

UNIVERSITY OF SHEFFIELD

**The energy costs of commuting: a
spatial microsimulation approach**

by

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“A finales del siglo XX, y gracias a su automovil privado, un simple trabajador podía residir en un lugar determinado pero desempeñar su trabajo, diariamente, en otro lugar que se encuentra a 50 o 60 km de distancia. Este hecho, que para tal ciudadano formaba parte de la rutina de su vida cotidiana, constituye, sin duda, uno de los más grandes enigmas de la antropología y la historia”

José Ardillo, *El Salario del Gigante*

“Towards the end of the 20th century, and thanks to the private automobile, a simple worker could live in one place but carry out their work, daily, 50 to 60 km away. This fact, which for the citizen formed part of their everyday routine, constitutes, without doubt, one of the greatest enigmas of Anthropology and History”

Author's translation

Abstract

Commuting is a daily ritual for a large proportion of the world's population. It is important materially, consuming large amounts of time, money and natural resources. As with many routine activities travel to work is often taken for granted but its energy consumption is of particular interest due to its heavy reliance on fossil fuels and the inflexibility of the demand for commuting. This understudied area of knowledge, the energy costs of travel to work, forms the basis of the thesis.

There is much research into commuting and transport energy use as separate fields, but they have rarely been combined in the same analysis, let alone at high levels of geographical resolution. The well-established field of spatial microsimulation offers tools for investigating commuting patterns in detail at local and individual levels, with major potential benefits for transport planning. For the first time this method is deployed to study commuter energy use between and within small administrative zones.

The maps of commuter energy use presented in this thesis illustrate this variability at national, regional and local levels. Supporting previous research, the results suggest that a range of geographical factors influence energy use for travel. This has important policy implications: when high transport energy use in commuting is due to lack of jobs in the vicinity, for example, modal shift (e.g. from cars to bicycles) on its own has a limited potential to reduce energy costs. Such insights are quantified using existing aggregate data. The main methodological contribution of this work, however, is to add individual-level factors to the analysis — creating the potential for policy makers to also assess the distributional impacts of their interventions and target specific types of commuters having high transport energy costs, rather than treat areas as homogeneous blocks. This potential is demonstrated with a case study of South Yorkshire, where commuting energy use is cross-tabulated by socio-economic variables and disaggregated over geographical space. The areas where commuting energy use is less evenly distributed across the population, for example in urban centres, are likely to benefit most from policies that target the specific groups. Areas where commuter energy use is more even, such as Stocksbridge (in Northwest Sheffield), will benefit from more universal policies.

The thesis contributes to human knowledge new information about the energy costs of commuting, its variability at various levels and insight into the implications. New methods of generating and analysing individual-level data for the analysis of commuter energy use have also been developed. These are reproducible (see the GitHub repository “thesis-reproducible” for example code and data) and will be of interest to researchers and policy makers investigating the energy security, resource efficiency and potential welfare impacts of interventions in personal travel systems.

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¹Sample code and data used can be found on github.com/Robinlovelace/. In particular, reproducible versions of the results can be found in the [thesis-reproducible](#) repository.

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Abbreviations

Acronym	What it Stands For
kJ	kilojoules (10^3 J)
MJ	megajoules (10^6 J)
GJ	gigajoules (10^9 J)
TJ	terajoules (10^{12} J)
PJ	petajoules (10^{15} J)
EJ	exajoules (10^{18} J)
kWh	kilowatt hour (3.6 MJ)
CO ₂	Carbon dioxide
EROI	Energy return on (energy) investment
IPF	Iterative proportional fitting
pkm	passenger-kilometres
vkm	vehicle-kilometres
TRS	Truncate replicate sample (integerisation method)
DECC	Department of Energy and Climate Change
Defra	Department for Environment Food & Rural Affairs
NTS	National Travel Survey
ONS	Office for National Statistics
OSM	Open Street Map
USd	Understanding Society dataset

Symbols

symbol	name	unit
dE	Euclidean distance	km
dR	route distance	km
E_{trp}	direct primary energy use per trip	J
ET	total energy use of all commuter trips in a given area	GJ
ET_{yr}	total primary energy per year	GJ/yr
E_{sys}	total primary energy use (direct and indirect)	MJ/km
E_f	Direct fuel (including electricity and food) energy use per kilometre	MJ/vkm
E_{fp}	Energy costs of fuel production	MJ/vkm
E_v	Energy costs of vehicle production per unit distance	MJ/vkm
E_g	Energy costs of guideway construction per unit distance	MJ/vkm
EM_v	embodied energy of vehicle production	GJ/vehicle
EM_g	embodied energy of guideway production	GJ/km
EI	energy intensity of transport per passenger kilometre	MJ/pkm
FE	fuel economy of vehicle	L/100 vkm
L_f	load factor of vehicle or mode	
L_g	lifespan of guideway	vehicle passes
L_v	lifespan of vehicle	vkm
m	mode of transport (e.g. car, train)	
O_c	occupancy, the number of people in each vehicle	people/vehicle
P	power	W (Js^{-1})
Q	circuitry: route distance divided by Euclidean distance	
η	energy conversion efficiency ($\frac{\text{Energy in}}{\text{Energy out}}$)	
Toe	tonnes of oil equivalent	

Chapter 1

Introduction

The research presented in this thesis focuses on commuting and its energy costs. UK datasets from the beginning of the 21st century form the empirical foundation of the work. Travel to work statistics are described, analysed and in later chapters modelled to assess the variability of energy use for this commuting. The underlying motivations are broader and play an important role throughout the thesis, from the choice of methodology (chapter 4) to the specification for scenarios of change (chapter 8). It is therefore important to lay out these wider issues at the outset, before highlighting the impact of commuting at the individual and national scale (in sections 1.2 and 1.3). These ‘big picture’ motivations also inform the research aims and objectives (section 1.5).

1.1 The ‘Big Picture’

Our increasingly interconnected global civilisation is facing challenges that are unique in the history of humankind. Environmental and social-economic changes are occurring to a greater extent and faster than ever before (Rifkin, 2011; Ehrlich and Ehrlich, 2013). Perhaps more importantly, this generation is in the privileged position of being able to monitor, predict and respond to these changes as they occur (Evans, 1998; Smil, 2008; IPCC, 2007). This work is firmly situated in the context of these changes and aims to contribute to humanity’s understanding of them. Following the academic tendency for specialisation whilst avoiding the pitfalls of dogmatic allegiance to any particular discipline or worldview (Kates and Burton, 1986), this thesis focuses on one ‘bite-sized’ yet important part of these wider issues.

Energy intensive transport contributes to pressing environmental, social and economic problems of the 21st century. Climate change, resource depletion, and growing levels of

economic inequality are global problems aggravated by energy use. Travel is a major energy consumer. Yet transport systems powered by fossil fuels have become integral to modern life: by the 1970s ‘automobility’ was central to social change (Illich, 1974) and since then motorised transport has become even more central to modern life (Rodrigue et al., 2009). This means that policy-makers, businesses, and individuals will have to make difficult decisions in the coming decades. According to some the situation is urgent: “Rapid decisions now need to be made so that the impacts of transport on the environment can be minimised and fossil fuel resources conserved” (Chapman, 2007, p. 354). *Rapid* decisions are not always *good* decisions, however: rational choices depend on good information about the world.

Because of the scale and complexity of the previously mentioned global problems, it is tempting to focus solely on the detail of energy use in commuting as one aspect of personal travel about which good datasets are available. It is however important to understand the wider context of transport energy use in order to decide the most useful applications of and directions for future research in this area. An introduction to the broader context that motivates this research is therefore provided, focussing on the three ‘big issues’ of climate change, peak oil, and economic inequality which are also long-term political priorities in the UK (UKERC, 2010).

1.1.1 Climate change

The Earth’s climate has always changed: it is a complex system with non-linear responses to internal and external drivers and a number of feedback loops (IPCC, 2007). The changes during the 20th and 21st centuries are, however, different from those observed in the paleoclimate record: “It is important to realize that the current change in atmospheric CO₂ is proceeding at a rate more than 200 times faster than any natural change in Earth’s past history, except the Cretaceous-Tertiary boundary event generally attributed to impact of an asteroid with the Earth” (Hay, 2011). The other major difference is that today climate change is caused by the combustion of fossil fuels by humans. Commuting, composed of millions of motorised trips to work and back each day, is a small yet important contributor. The desire to reduce these emissions, for the maintenance of a “safe operating space for humanity” (Rockstrom et al., 2009) provides an important motivation for this research. An underlying aim is to contribute ideas and information to the ongoing debate about how to mitigate anthropogenic climate change (Matschoss and Kadner, 2011).

This aim appears to be shared by others: academic interest in transport emissions has proliferated in recent years (Akerman et al., 2006; Chapman, 2007; Schwanen et al.,

2011), although less so in the specific area of commuting (chapter 2). Because energy use is directly related to greenhouse gas emissions (Mackay, 2009), this research is also about climate change.

UK greenhouse gas emissions

At the UK level, the emissions associated with commuter energy are subsumed within ‘transport emissions’. These include emissions from shipping, aviation and military transport, as well as the road and rail sectors (DECC, 2011c). Road transport dominates, accounting for more than 90% of the UK’s transport emissions (figure 1.1).

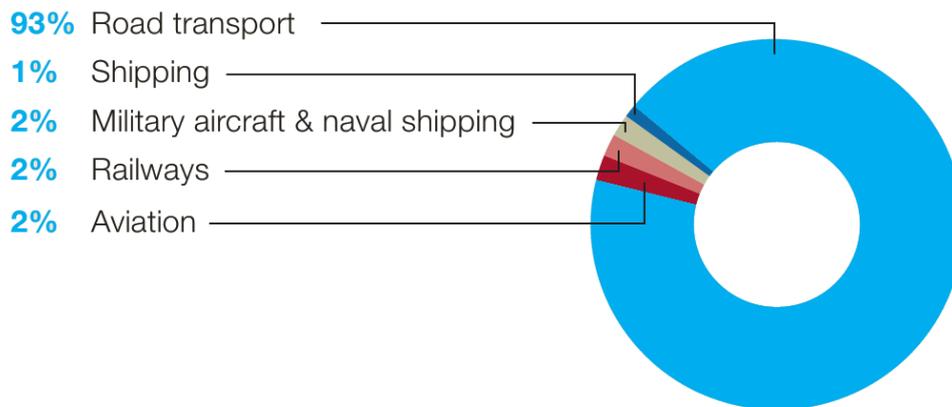


FIGURE 1.1: UK transport emissions by source in 2009 (DECC, 2011c).

An interesting feature of the UK’s emissions reporting strategy is that ‘transport’ is generally presented as a monolithic category (e.g. DECC, 2010), despite the wide variety of transport modes and purposes presented in figure 1.1. This makes it difficult to identify the specific drivers of growth in UK transport emissions since 1970 (Gasparatos et al., 2009) and stagnation since 1990. What is clear in both cases is that energy use and hence emissions from transport have increased (since 1970) or stagnated (since 1990) while those of other sectors have declined. Between 1990 and 2010, transport was the only sector other than housing in which emissions increased; transport now accounts for just over 20% of UK emissions (table 1.1, below). This research project quantifies the contribution of commuting to this total in terms of energy use, and provides evidence about which strategies may be effective for reducing the emissions due to transport to work.

The UK’s climate change commitments are unambiguous, agreed upon by all major parties, and legally binding: emissions in 2050 must be below 20% of their 1990 level (Committee on Climate Change et al., 2008). This means that the *total* permitted

emissions in 2050 across all sectors are roughly equal to the emissions from just the *transport sector* today. This fact underlines the scale of the proposed changes: transport to work represents a small but important component of this challenge that affects millions of working people every day.

TABLE 1.1: Top 5 UK sectors in terms of greenhouse gas emissions, 1990-2010 (MtCO₂e). Data from DECC (2011a)

	1990	2000	2010	% change	% emissions (2010)
Energy Supply	273.4	220.1	204.3	-25.3	34.8
Transport	121.5	126.7	121.9	0.3	20.7
Residential	80.8	90.1	89.9	11.3	15.3
Business	113.2	111.3	89	-21.4	15.1
Agriculture	63.1	58	50.7	-19.7	8.6
Other	117.4	65.8	32	-72.7	5.4
Total	769.4	672	587.8	-23.6	100.0

Emissions from transport to work

Of the 20% of UK emissions that arise from transport, only a small fraction are due to transport to work. How small? No official breakdowns of emissions are provided by reason for trips, but estimates can be made by analysing the make-up of the transport sector. As shown in figure 1.1, 5% of transport emissions can be accounted for by military vehicles, aviation and shipping: none of these are usually involved in transport to work. Also, 31% of road transport emissions arise from goods vehicles (HGVs and LGVs); the remaining 69% arise from road vehicles for personal transport – buses, motorcycles and cars (DECC, 2011b). From these figures, it is possible to estimate that 80 MtCO₂e result from personal travel in the UK. 19.5% of passenger kilometres travelled by all personal transport modes in the UK are due to travel to work (DfT, 2011b). Transport to work can be estimated to cause ~16 MtCO₂e of emissions or around 3% of the UK’s total. (In section 6.3 a more refined estimate of commuter energy use is presented, based on geographically disaggregated data: commuting was found to account for 4.1% of total energy use and 14.4% of transport energy use.)

It is important to undertake such ‘back of the envelope’ calculations at the outset of research into emissions reduction strategies or sustainable energy to ensure that time is not wasted on negligible issues such as phone chargers (Mackay, 2009). David MacKay, Chief Scientific Advisor at the Department of Energy and Climate Change (DECC), puts this argument in lay terms by proposing a rule for energy-saving interventions: “A gizmo may be discussed only if it could lead to energy savings of at least 1% ... because the public conversation about energy surely deserves to be focussed on bigger fish” (MacKay, 2009). Applying this reasoning more broadly to areas of energy use,

transport to work clearly deserves attention according to this rule, although emissions cuts in commuting will have to be matched in all other sectors for targets to be met. However, there are reasons to believe that making cuts in the transport sector generally, and in transport to work in particular, will be especially difficult, and therefore worthy of dedicated investigation. These include:

- The transport sector is overwhelmingly dependent on petrol and diesel: motorised transport (which accounts for most trips and the vast majority of the distance travelled, as shown in chapter 5) is 95% dependent on refined oil products (Woodcock et al., 2007). This is problematic because there are no commercially viable, low emissions alternatives to crude oil for liquid fuels. Biofuels are the only ‘renewable’ option on the table, but their potential contribution is low (Grady et al., 2006; Michel, 2012), they can conflict with food production (Pimentel et al., 2009), and currently used crops may increase greenhouse gas emissions due to land use change (Fargione et al., 2008).
- Linked with the previous point, low carbon technology is far less promising in the transport sector than in other large emitting sectors. For electricity generation and residential heating the technologies for renewable alternatives are becoming more commercially viable (Chu and Majumdar, 2012). By contrast, the penetration of electric, hydrogen, and biofuel-powered cars may be slow, largely due to their high cost (Proost and Van Dender, 2011; Vaughan, 2011).
- The current transport system is built around road (and to a lesser extent rail) infrastructure that took many decades and large capital investments to complete. The dependence of society on the car is deeply embedded, yet a low-energy (and hence low emissions) transport system may require a shift away from personal ownership of automobiles altogether (Mackay, 2009; Moriarty, 2010), something that will take decades to accomplish.

These difficulties make de-carbonising transport systems problematic compared with the other large energy users — electricity and heat production.¹ Despite these issues, transport is rarely framed in terms of energy use and greenhouse gas emissions (chapter 2). In addition to its impacts on climate change via direct and indirect greenhouse gas emissions, commuting is also vulnerable to the effects of climate change, as discussed in section 8.5.2.

¹These can convert more easily to renewable sources — e.g. via stationary wind turbines and solar hot water panels — than can transport systems. This is because transport systems are inherently mobile, therefore requiring a high energy density power source. Fossil fuels are unrivalled in terms of their energy density — almost 100 times greater than the best non-agrofuel commercial alternative: lithium ion batteries. Hydrogen fuel cells have been proposed as a solution, but these are still far from commercial viability, and have been precluded by DECC’s Chief Scientific Advisor on the grounds that they are highly inefficient (Mackay, 2009).

1.1.1.1 Climate change and energy

Most studies looking at the impact of one aspect of the economy on climate change do so through the emissions that it produces. These studies generally measure environmental impact in terms of kilograms of carbon or CO₂ equivalent caused by different modes of travel. This seems logical if one is concerned about climate change: it is the greenhouse gases that trap the heat (Houghton et al., 1990). However, others have suggested that the best way to tackle the problem is from an energy perspective: “climate change is an energy problem”, as a group of 18 prominent US academics put it (Hoffert et al., 2002, p. 981). What is meant by this is that energy use and greenhouse gas emissions are currently two sides of the same coin. More than 80% of commercial total primary energy supply (TPES) worldwide is provided by fossil fuels (Smil, 2008) and in the transport sector this is even higher. It is true that not all forms of energy have the same emissions. Yet, as illustrated in figure 1.2, CO₂ emissions per unit energy are in fact surprisingly similar across a wide range of transport fuels. In addition, even if it were possible to decarbonise electricity production in the near-term, the fact remains that uptake of low-energy sources will almost certainly be gradual (Smil, 2010b). Another issue is that technologies that have low emissions per unit of energy use during the usage phase of their lifecycle often have an energy intensive production phase. Because much modern food production depends upon fossil fuel energy, the energy approach can also help in the assessment of wide-boundary energy impacts. Some environmental impacts of transport such as noise, road-kill and the need to frequently resurface roads pummelled by powerful vehicles are not included in most emissions estimates. Energy use can to some degree encapsulate these additional impacts.

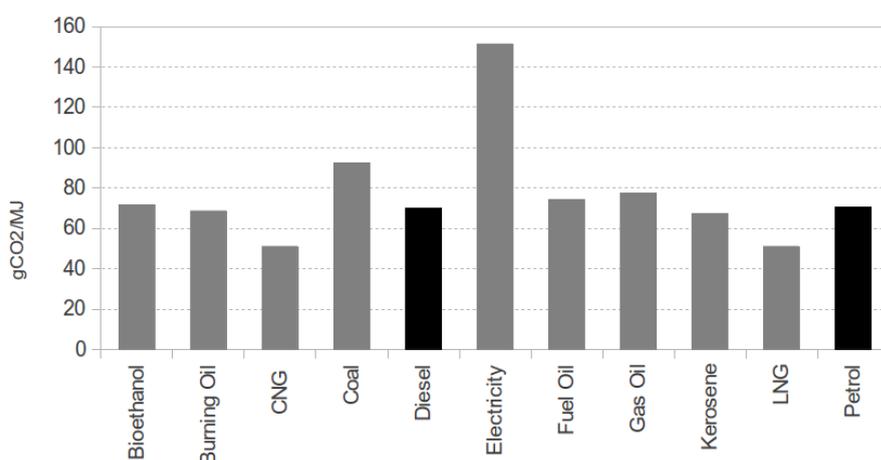


FIGURE 1.2: The greenhouse gas emissions per unit energy of various fuels. Data taken from Defra (2012) (additional sources for [electricity](#) and [biofuel](#) emissions were used) and converted into SI units. The dominant transport fuels are black for emphasis.

The reasons for advocating a focus on energy use, and not emissions directly, can be summarised as follows:

- Emissions can be variable depending on the energy/fuel source, whereas energy is constant across fuel sources.
- If energy use is reduced overall, carbon-intensive forms can be phased out. However, if emissions from one sector fall, they may well rise in another as fossil energy resources are freed-up.²
- Energy is the ‘master resource’ from which all others (including more energy) can be obtained; emissions are the end result of energy use.
- It can be argued that energy use is at the root of the linked ‘big picture’ problems mentioned in this chapter, not just climate change. Therefore tackling the energy problem could have numerous co-benefits.

All this suggests that the climate debate should be much more closely linked to the energy debate. Specifically, the carbon content of proven fuel reserves should be compared with the carbon dioxide content that can safely be burned. Doing this analysis, based on recently released data on fossil fuel assets, has led to an alarming finding: “for all the talk about finite resources and peak oil, scarcity is resoundingly not the problem. From the climate’s perspective, there is far too much fossil fuel” (Berners-Lee and Clark, 2013, p. 29). Berners-Lee and Clark (2013) show that for there to be at least a 75% chance that the global temperature increase remains below two degrees humanity can burn only around a half of economically viable reserves. In terms of personal transport, this means phasing out petrol and diesel and avoiding carbon-intensive electricity sources: a fundamental shift.

Most greenhouse gas emissions stem from fossil fuel use, and once extracted, these fuels are invariably burned. This has led to the conclusion amongst some that the solution must be top-down: fossil fuel companies must be forced to leave most of their assets untapped. This can be achieved either through plummeting prices of fossil fuels or through regulation. The former case is currently highly unlikely due to the surge of fuel demand from emerging economies, combined with the sheer utility of fossil fuels.³ The latter also

²For example, imagine if transport emissions rapidly dropped to zero due to electrification and rapid uptake of renewables. The additional load on the grid caused by this new user (Dyke et al., 2010) could lead to an increase in the emissions stemming from space heating because the total supply of renewable energy is fundamentally limited by the laws of physics (Mackay, 2009). Berners-Lee and Clark (2013) describe this problem with emission reduction plans overall as squeezing a balloon: savings in one area tend to bulge out in another.

³However, if governments, in coordination, prioritise minimising energy use while maximising uptake of renewable energy, the former possibility would become more feasible.

seems unlikely, following the failure of UN talks in Copenhagen to arrive at a consensus on legally binding and enforceable emission targets for the major emitter. This research is relevant in any case: if fuel prices remain high there is a strong economic incentive to reduce energy imports. If leaders worldwide agree to tackle climate change through top-down or bottom-up policies, there will clearly be a strong interest in how best to reduce reliance on fossil fuels in every sector that is vital for well-being. Regardless of the level of regulation (whether it occurs at the point of extraction or use of fuel), it implies high consumer prices for fuels, through policies such as taxes, a ‘carbon cap’ or even energy rationing.⁴ Another pragmatic benefit of the energy approach is that even if one questions the need to tackle climate change, the arguments to reduce dependence on finite fossil fuels for other reasons are very strong.

1.1.2 Peak oil and resource depletion

In addition to the impacts of climate change, depletion of our fossil energy resources is another non-negotiable reason for transition away from fossil fuels, to a “post-carbon” economy (Heinberg, 2005, 2009; Heinberg and Fridley, 2010; Kunstler, 2006). Oil is the most rapidly depleting resource yet motorised transport is almost entirely dependent on liquid fossil fuels derived from it (Gilbert and Perl, 2008). Multinational personal transport industries tend to downplay or deny the risks of peak oil, pointing to non-conventional oil resources and technological advance as reasons not to worry. Prototype biofuels, electric cars and hydrogen fuel cells are often cited as ways of overcoming high prices. This is ironic because each technology is highly dependent on oil for resource extraction, manufacture, distribution and waste disposal stages of their life-cycle: high oil prices could make the batteries for electric cars, to take one example, even more expensive, far out of the reach of the median global citizen. Each technology is still in the research phase of development, relies on scarce public subsidies to be commercially viable and cannot operate on the scale needed within modern transport infrastructures even if production lines producing them were scaled up before a major oil shock. Biofuels, to take the most heavily subsidised example, can only ever produce a small fraction of current transport energy demand even if all available resources were exploited to the maximum (figure 1.3).

For this reason peak oil is a major motivation for research into energy and transport. How will transport systems operate beyond 2050, when oil production will be a fraction of its current level? (Aftabuzzaman and Mazloumi, 2011). How will people get to work in the event of shortages? (Noland et al., 2006). These are just a couple of examples

⁴Interestingly, high prices of fossil fuels is also the end result of many scenarios of resource depletion, which has historically been another major driver of research into energy and transport (Berry and Fels, 1973).

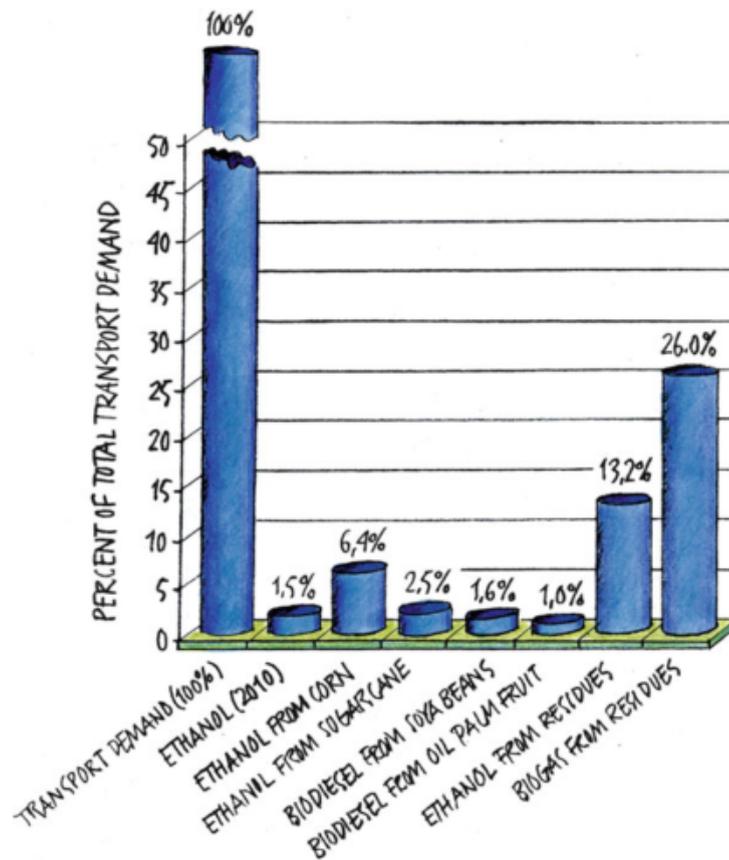


FIGURE 1.3: Biofuels' current (2010) and potential contribution to global transportation energy use (Alekkett, 2012, p. 228). Image used with permission of author. Data originally presented in Johansson et al. (2010).

of the kinds of questions that are being asked in preparation for declining oil supply. A parallel question (explored in section 8.4) is: how will commuters be affected by oil price shocks, depending on where they live and their socio-demographic characteristics? The potential problems posed by peak oil for motorised transport systems are severe and include collapse of complex economic activity due to the highly inter-dependent nature of the global economy (Friedrichs, 2010; Korowicz, 2011). For this reason an introduction to peak oil, and how it relates to commuting, will help to place this research in the wider context. Gilbert and Perl (2008) provide a comprehensive reference on the subject, from a North American perspective.

Peak oil is the point at which global oil production enters terminal decline due to depletion of large oil fields (Greer, 2008). It is an inevitable event during the 21st century, as oil is a finite resource, approximately half of which has been used (Alekkett et al., 2010). However, there remains controversy about the exact timing of the peak (Smil, 2008). An in-depth review by the UK's Energy Research Centre (UKERC, 2009) found that the weight of evidence suggests a peak in the near-term, before 2030. This is well before

the 20 years that the famous Hirsh Report (Hirsch, 2005) indicated would be needed to prepare for declining supplies of liquid fuel. The implications are stark: if peak oil does occur before 2030, as the evidence reviewed by UKERC (2009) suggests, urgent preparations must begin now.

As economists have long indicated (Solow, 1974), it is not only the amount of oil left in the ground that directly affects peoples' lives. It is the *price* of oil that affects transport systems, with knock-on impacts on human lives. Price is also affected by changes in demand and technologies for extraction and substitution (Perman, 2003). Over the past decade there has been increasing evidence that depletion plays a major role in determining global oil prices, however, with high and volatile prices likely in the future (Alekkett, 2012). The price of crude oil during the past 20 years has shown both volatility and (when smoothed by a rolling average function) a near inexorable upward trend figure 1.4.

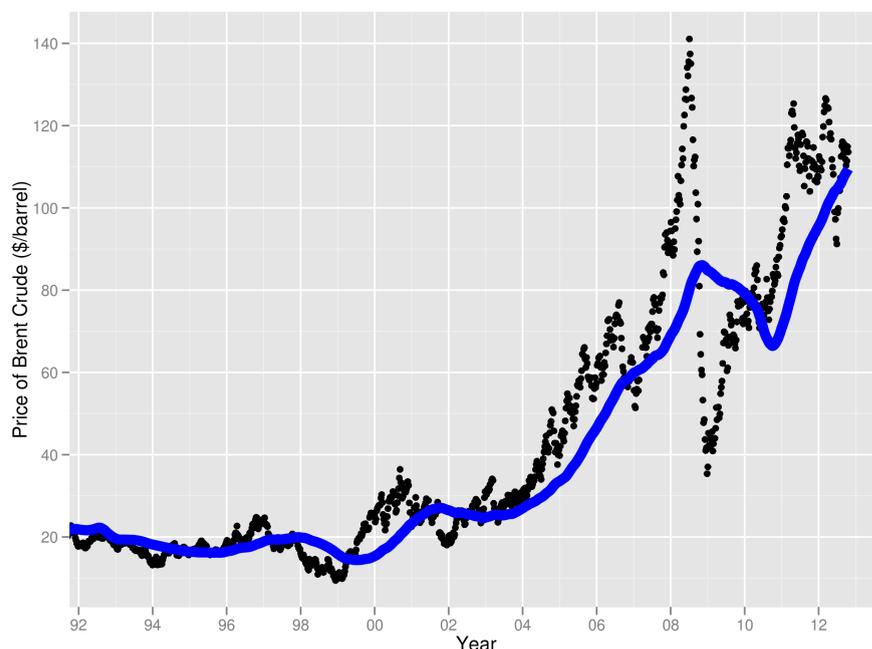


FIGURE 1.4: Average prices of Brent Crude oil spot prices per week, January 1992 until October 2012 (dots) and a 2 year rolling average (blue line) Data from the U.S. Energy Administration (http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm) plotted using the R package ggplot2.

Despite these upward trends, UK government energy policies are still largely based on the assumption that oil prices will remain below \$100 per barrel into the 2020s (UKERC, 2010). Thus methods that estimate the oil-reliance of households based on readily available commuter statistics could be highly relevant to politicians and planners making long-term decisions. The ability to quantitatively explore the impact of high oil prices

and other scenarios of change at the individual level is an output of this research that could have applications in transport policy evaluation and development. See chapter 7.

1.1.3 Inequality and well-being

Peak oil and climate change are important because we depend on the resources and processes of the natural environment to survive. Humans also depend on the relationships between each other, not simply for survival, but for quality of life. “It is only in the backward countries of the world”, wrote John Stuart Mill, “that increased production is an important object; in those most advanced, what is needed is a better distribution” (Mill 1857, in Perman 2003: p. 6).

With more than 150 years of hindsight, Mill’s statement seems all but Utopian: economic growth is still the number one priority of most governments worldwide, even in wealthy countries such as the UK where evidence suggests that further growth may do more harm than good, for people and the environment (Latouche, 2008). To such an extent does economic growth dominate modern decision making, regardless of consideration of how growth is distributed, that authors such as Charles Eisenstein and John Michael Greer refer to it as the founding story of our age (Eisenstein, 2011; Greer, 2009). In contrast to this dogmatic growth focus, evidence suggests that other things, including equality of economic and social opportunities, lead to quality of life (Jackson and Day, 2008; Jackson, 2009).

The growth-at-all-costs mentality, combined with our debt-based capitalist economy⁵ has caused inequalities to grow worldwide (OECD, 2011). The UK has one of the highest levels of inequality in Europe (figure 1.5).

This problem is important in the context of the energy costs of commuting because employment opportunities are greatly affected by one’s ability to find and affordably travel to work. Variable transport opportunities amplify social and economic inequalities: 38% of jobseekers say transport problems prevent them from getting a job (Social Exclusion Unit, 2002). “No jobs nearby” and “lack of personal transport” were the first and second most frequently cited barriers to getting or keeping a job in a survey of young people in the UK (Bryson et al., 2000).

Paid employment, and the economic independence it brings, is a foundation for life satisfaction (Jahoda, 1982). Work is “a principal source of identity for most adults”

⁵As explained by Eisenstein (2011), the very existence of positive interest rates ensures that those who have money tend to have more. According to this view, growing levels of economic inequality is built into the monetary system, and can only revert back to low levels with crises such as wars or depressions, planned debt annulments or (preferably for Eisenstein) negative interest rates.

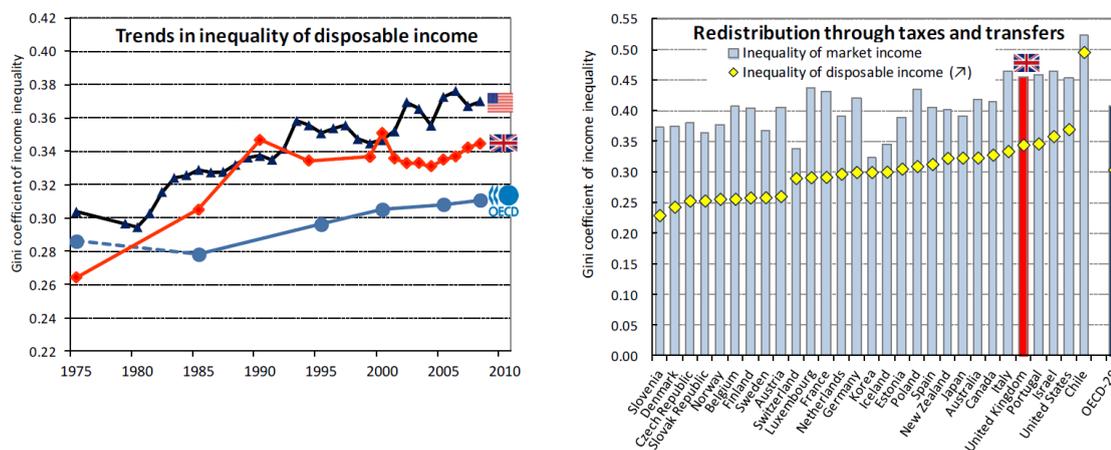


FIGURE 1.5: UK Gini index for market and disposable income in context (OECD, 2011).

(Tausig, 1999) and can promote good health (if the work is satisfying) (Graetz, 1993). By corollary unemployment, the proportion of working-aged people without a proper job, “is a crucial indicator of the welfare and economic performance of different areas” (Coombes and Openshaw, 1982, 141). Yet without accessible means of travelling to and from work each day, these benefits are impossible to reach.

Given the importance of work, and the high proportion of work that is undertaken outside the home, it should come as no surprise that people will commute even if it an arduous task damaging to their health. Taking a broad definition of health, these impacts range from those narrowly associated with breathing urban air to more subjective consequences for mental health including stress. From a human ecology perspective commuting can be understood as a stressful relocation from one’s ‘domestic habitat’ to a more hostile, hierarchical workplace. The trip to get there will often coincide with thousands of other commuters, all using the same road, railway or path. With these factors in mind, the finding that, “For most people, commuting is a mental and physical burden” should come as little surprise (Stutzer and Frey, 2007).⁶ The entrenched issue of inequality is tackled from the perspective of commuting by measuring it in energy (as opposed to purely monetary) terms (section 6.4) and providing methods for assessing the distributional impacts of future what-if scenarios (chapter 7 and chapter 8).

⁶The question “how much of a burden” is open to debate, however. The finding of Stutzer and Frey (2008), that subjective well-being declines proportionally with time, was not replicated in a recent analysis of data from the BHPS (Dickerson et al., 2012).

1.2 Commuter energy use: everyday realities

The large scale processes of change mentioned above tend to be thought of in the abstract, using inevitably simplified versions of reality. They are often best represented through statistics, inherently simplified and aggregated for visualisation. Seeing the issues quantitatively and at ‘arms length’ may be necessary to gain an objective understanding of their evolution. Yet this may also lead to lack of understanding of their local level manifestations and poor retention in memory: although physical reality may be best understood through numbers, human brains seem better able to retain information that has emotional or personal content (Laird et al., 1982; Green, 2012). When explaining my research to others, the following question has been found to effectively transform a purely academic and boring issue into something interesting and relevant: “What would a doubling of global oil prices mean for your family?” For this reason, and to introduce some themes that are used throughout this thesis in ‘layman’s terms’, this section is based on a brief personal story: that of Chris Fisher.

Chris was born and bred in Weobley, a small town nestled between Hereford, Leominster and Kington (figure 1.6). Since finishing at Weobley secondary school he has worked in a wide range of jobs in the local area, including for Weobley’s largest employer (and sponsor of the village football team) Primasil and a local restaurant called Joules. His current job, held for over 3 years now, is to provide manual labour in Tyrrell’s crisp factory.

Commuting and the economic cost it exacts has a large impact on Chris’s life. Ideally he would like to move to Hereford as that is where more of his friends live and because there is more going on in the city than in Weobley. However, Chris feels bound to continue living with his mum in Weobley due to the costs of commuting. The numbers work out like this: it’s an 8 to 9 mile round trip to work from Weobley, whereas the distance would approximately double if he lived in Hereford. The location of his job also essentially forces car ownership: there are no buses between Weobley and the Tyrrell’s crisp factory, car sharing options are limited and relying on a bicycle does not seem feasible for winter shifts that end at 6 am. In addition to location, other downsides include long hours (12 hour shifts for everyone, 4 days on, 4 days off), poor pay (£8 per hour) and unpleasant working conditions (the factory contains no windows, meaning that during some day shifts you do not see the sun for 4 days in a row). For these reasons Chris was tempted to quit when Tyrrell’s decided to move towards 24 hour production following increased demand from the USA: previous to this change 8 hour shifts were the norm; afterwards 12 hour shifts were implemented, broken up by three 20 minute breaks.

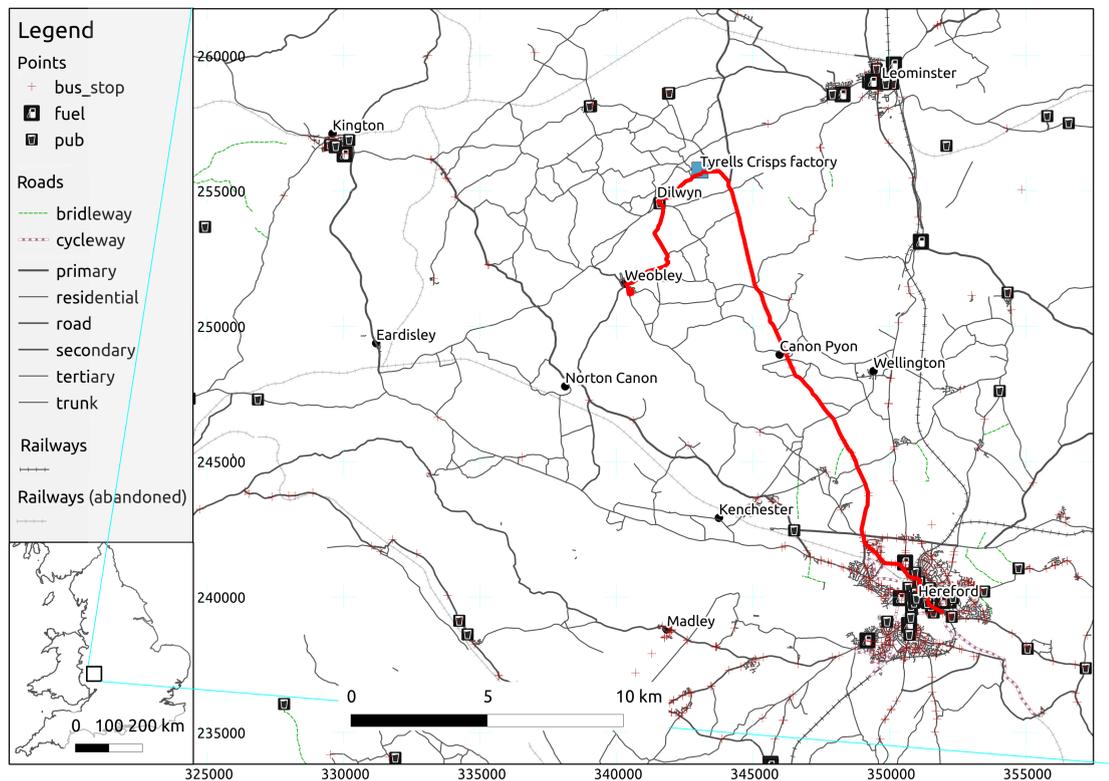


FIGURE 1.6: Commuting options to Tyrell’s crisp factory for Chris Fisher if he lives in Weobley (7 km one way) or Hereford (13 km one way), as illustrated by the thick red lines.

Despite these issues Chris has so far decided to stay on at Tyrell’s because “if you live in Weobley, there are not many jobs.” This context is important, because it illustrates how commuting interacts with everyday life dilemmas, in this case between moving house or staying put and between quitting an exploitative job or finding a new one. Ideally, Chris would like to sell his car, get a job in Hereford and be able to walk to work each day. However, he’s adapted to the new shifts, and enjoys the 4 days of freedom he is allocated out of every 8, using them to climb mountains, go to gigs and relax. The need to own a car (on which 20% of his income goes) and the expenditure on commuting (5 to 10% of his income) are disadvantages that can be endured for now.

Chris almost always drives to work. He has cycled a few times in nice weather and would like to cycle to work more frequently. However, the prospects for *modal shift* are not great at present: his bike is not much good, and the prospect of cycling 5-odd miles at 6 in the morning after a physically punishing 12 hour shift is not attractive. Chris is very interested in the cycle to work scheme, and believes he would cycle more if he had a decent bike — a friend was able to get a £900 bicycle through it. That’s the

semi-solution that will be pursued in the short-term, and that goes well with Chris's fitness hobbies. When asked about the impact of the commute on his quality of life Chris gave a short answer: "not a lot really." For him commuting is simply a means to an end — to get to paid employment — which in itself is just a way to earn a living.

The sheer complexity of commuting on a national scale is well illustrated by considering that Chris's commuting behaviour, plans and experiences are just one data point out of hundreds of thousands. Subtleties of his current behaviour, let alone the transient nature of his working hours, shift patterns, home location and employment status are not picked up by questions in the census or, to varying degrees, in the national travel surveys (see chapter 4). Nevertheless, the things that Chris allocated importance to — the distance to work, the time and money costs of the commute and the availability of alternative modes — indicate that quantitative analysis of these aspects of the problem of commuting is appropriate and relevant to everyday life.

There are certainly many unknown and highly varied individual circumstances, such as Chris's that can never be squeezed into simple numerical models. However, the variables about which good geographical data are available (mode and distance) and the variables which can be calculated with varying levels of uncertainty (e.g. economic costs, potential for modal shift), match the factors that held most sway for Chris, except for the location of his friends.

1.3 The importance of commuting

The previous two sections have illustrated the importance of commuting in terms of its impact at the individual level, and in the global context. In many countries, however, the importance of commuting can be investigated using a more detailed source of information: national transport statistics. This section introduces aggregate level travel to work statistics from the UK Census, which form the foundation of analysis in the coming sections, and outlines the variability of commuting patterns nationally. Based on these statistics, it also illustrates the importance of commuting in comparison with other reasons for travel.

1.3.1 Trips

Trips are the basic unit of travel, "a one-way course of travel with a single main purpose" (Department for Transport, 2011b, p. 6). The data presented in figure 1.7 (and henceforth) therefore counts the daily journey to work and back as two trips. The value

for commuting provided by this dataset (150 trips per year) may therefore seem surprisingly low, implying that people only work an average of 75 days per year — Hall et al. (2011) estimate that roughly 400 commuter two-way trips are made per capita per year worldwide. However, the National Travel Survey samples all citizens, including children and the elderly; the average number of trips made by commuters — the focus in this thesis — is estimated to be double this figure, around 320 (section 5.4.1).

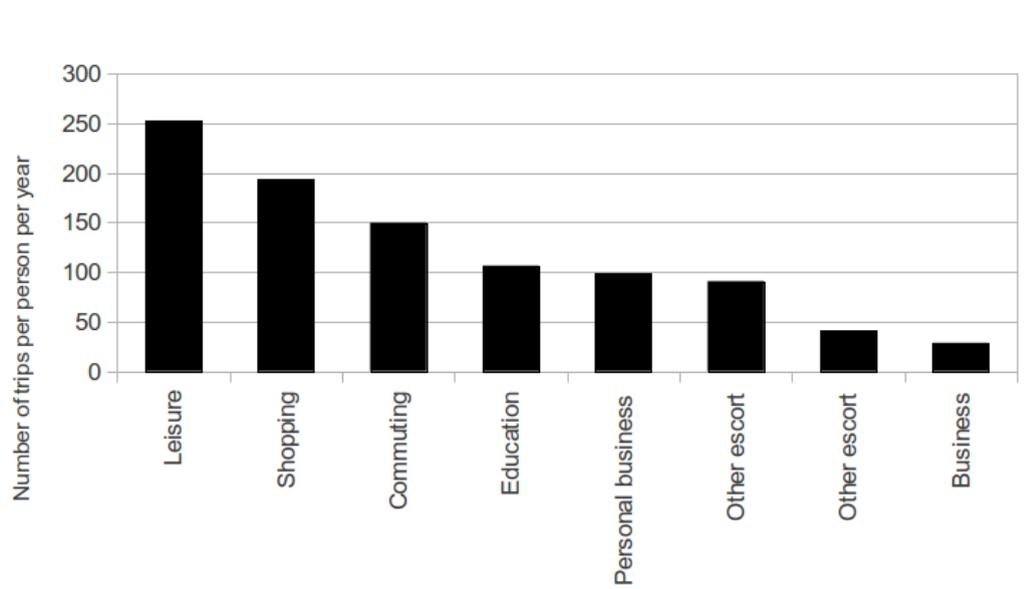


FIGURE 1.7: Average number of trips per person per year across Great Britain.

1.3.2 Distance

The distance made by all trips is their number multiplied by their average distance. Commuter trips averaged 14.2 km in 2009/10, slightly longer than the 11.3 km average for all trips in Great Britain and the third longest, following holiday and business trips. The average length of the latter are greatly increased by flying. This information are illustrated in figure 1.8.

The average distance of each trip helps characterise commuting as relatively long-distance compared with other trip purposes such as shopping (6.9 km). However, total travel distance is more important from an energy perspective: long leisure trips, for example, are comparatively unimportant in energy terms if they are infrequent. The data shows that leisure travel⁷ dominates trip distances, despite the sporadic nature of international holidays. Commuting is in second place, responsible for 2160 km of personal

⁷Leisure trips include holidays and social trips, in the 2010 National Travel Survey (Department for Transport, 2011b).

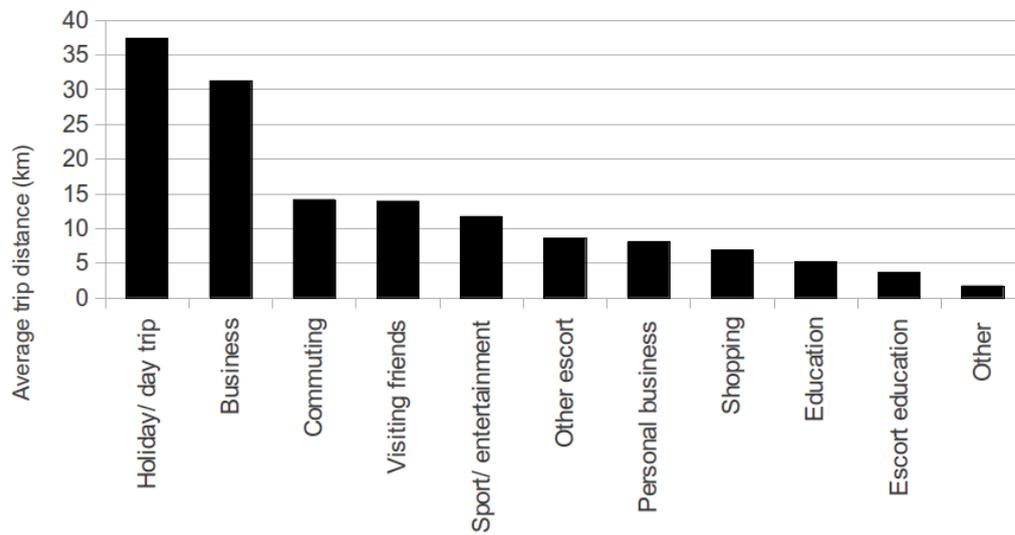


FIGURE 1.8: Average trip length by purpose in Great Britain.

travel each year for UK citizens, including those under 16. For commuters, the average total distance of commute would be approximately double this value (figure 1.9).

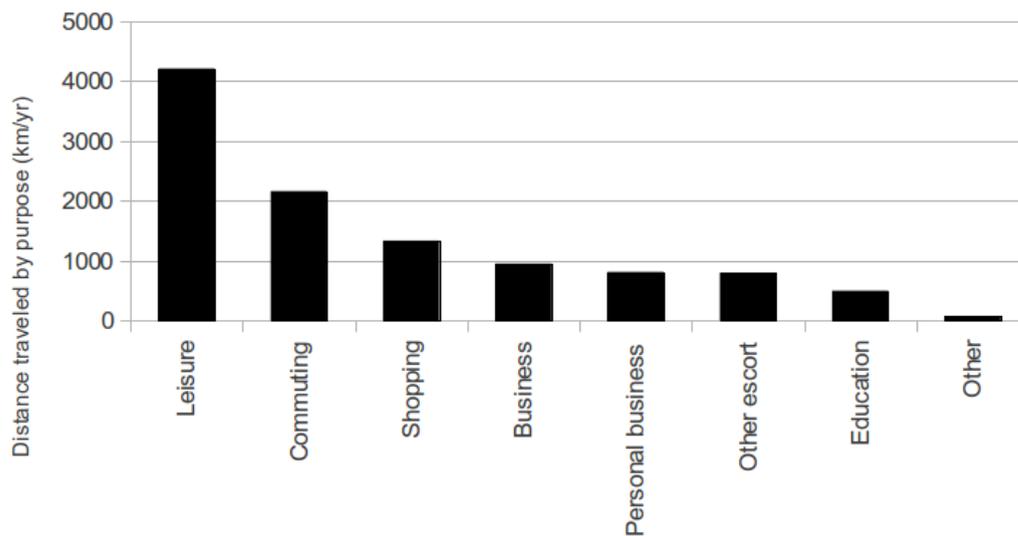


FIGURE 1.9: Total distance travelled by mode in Great Britain.

1.3.3 Time

From the commuter's perspective, the number and distance of commuter trips made may seem relatively unimportant: in the formal economy, time is money and people

are increasingly rushed to face up to professional and family commitments (Eisenstein, 2011). Therefore, time is another measure of importance that should receive attention in any introduction to commuting. Overall commuting is the most time-consuming reason for personal travel in the UK, accounting for 19% of trip time, consuming 70 hours per year. Because both the numerator and the denominator in this measure (hours per year) have time units, travel to work can also be presented as the percentage of one's life spent travelling to and from work⁸ (figure 1.10).

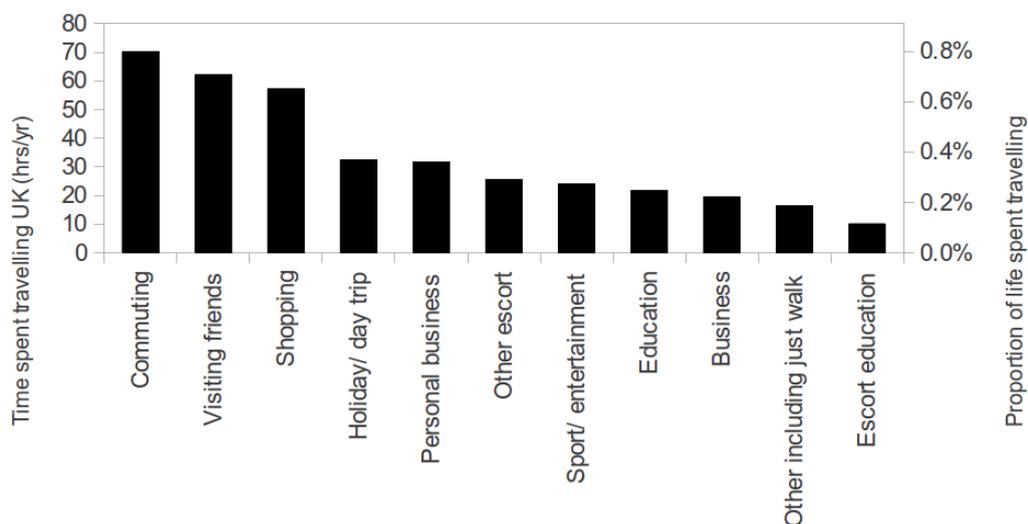


FIGURE 1.10: The average time spent by citizens of Great Britain travelling to work and back each year. The right hand axis illustrates the same information, this time as a proportion (data source: National Travel Statistics, 2012).

There is pronounced regional variation in the average time spent travelling to work. This variation is linked to the average time per commuter trip (high total work travel time values are influenced by how frequently people work), the distance to workplace, and, of prime importance, levels of congestion.

1.4 Thesis overview

The thesis is divided into 9 chapters which can be classified into four parts: introduction, methods, results and conclusions. Chapters 1, 2 and 3 provide background to the research. The present chapter provides context. The purpose is to show how the thesis is motivated by and informs some of the grand debates of the 21st century: environmental, economic and social. Chapter 2 is a more conventional academic literature review,

⁸This is a potentially poignant metric for those who spend more than 5 hours per working day or more than 10% of their life simply getting to work and then turning around going home again!

focusing on the research that is most closely related to the thesis topic rather than its wider context. Chapter 2 tackles the following questions: what is the range of methods used to investigate energy use in transport from a policy perspective? To what extent is the literature coherent in its assessment of the reasons for energy intensive transport behaviour and appropriate solutions? Chapter 3 is the methodological literature review. It traces the various incarnations and uses of spatial microsimulation and related methods. The purpose is to illustrate the reasons for choosing to apply the technique to the research questions outlined in chapter 2.

Chapters 4 and 5 are methodological. The data available to analysts interested in commuting are explained in detail in chapter 4, with reference to an ideal dataset. Later in the same chapter, the underlying theory and computer code developed and used to generate spatial microdata is described in detail. The aim is to allow the results to be replicated by anyone provided with the same input data as used in the thesis. To this end numerous script files are provided which allow many of the analyses performed to be re-run on any computer using free software.⁹ Chapter 5 describes and analyses the factors affecting energy use in personal transport. Methods for converting CO₂ emissions data (the best official source on the matter) into energy cost values per unit distance are described and put to work on the best available data. Chapter 5 culminates in a table summarising the best estimates for the efficiency of each commonly used mode of travel to work.

The subsequent three chapters present the results and conclusions. Chapter 6 harnesses the data and methods described in previous chapters to calculate the energy costs of travel to work at a range of levels, in England and within the case study region of South Yorkshire. (A brief detour in section 6.5 compares English and Dutch commuter energy use to illustrate the international applicability of the methods.) There is some discussion of the links between energy use and other variables under investigation such as home-work distance, mode of travel, age, sex and socio-economic class. However, most of the results at this stage are descriptive: no attempt is made here to evaluate political implications of the results. The desirability of the commuting patterns that have been observed is more the topic of chapter 7, which discusses inequalities in commuter patterns. In chapter 8 the attention is turned to the future. The analysis is informed by ‘what if’ scenarios made possible through spatial microsimulation and a case study of ‘oil vulnerability’ in Yorkshire and the Humber. The former creates quantitative scenarios to describe futures of high cycling uptake and a shift to Finnish levels of telecommuting. Based on these assumptions, the total energy savings from each scenario is estimated and the spatial and social distribution of the impacts analysed. The latter investigates

⁹Sample code and data used can be found here: github.com/Robinlovelace/

the likely impacts of high oil prices on different social groups and places and is designed to show the policy-relevance and usefulness of the methods.

Chapter 9 draws together the various threads of the thesis to arrive at overall conclusions about the energy costs of commuting: current patterns are not as simple as first-impression thinking may indicate and neither are the solutions. A particularly surprising result for the author was that cycling can only make small savings in the current context compared with the relatively overlooked options of telecommuting and car sharing.

1.5 Aims and objectives

This chapter has argued that the energy costs of commuting is an important and policy-relevant area of research, that links with some of the major issues of the age. This recognition of the potential applications of the research is reflected in the aims and objectives. These, which have helped to guide the research throughout, are as follows:

1.5.1 Aims

- A1 Investigate the energy cost of transport to work, its variability at individual and geographic levels, drivers, and policy implications.
 - A1.1 Examine the variation of energy cost of trips to work, at geographic, household and individual levels, and over time.
 - A1.2 Identify and explain the geographic and socio-economic factors most closely associated with high and low energy use.
 - A1.3 Formulate and analyse scenarios of change to inform decision makers about how commuter energy use can be reduced.
- A2 Explore and evaluate the potential of spatial microsimulation models for the social and spatial analysis of the energy costs of commuting.

1.5.2 Objectives

- O1 Conduct a review of literature pertaining to the socio-economic and geographical factors of energy use and identify studies most relevant to the aims of this thesis.
- O2 Calculate the energy costs of transport to work at different geographic levels and interpret the results.

- O3 Develop and use a spatial microsimulation model to simulate the characteristics of different types of commuter and estimate the variability of energy costs at the individual level.
- O4 Identify the links between individual characteristics, geographic variables and energy use and analyse them further using the microsimulation model.
- O5 Apply the energy use formula described by (Fels 1975) to individual level commuting data to create estimates of the energy costs of transport to work in Yorkshire (A1, O2).
- O6 Formulate and test ‘what if’ scenarios of future change in variables associated with commuter behaviour with the use of microsimulation and identify the likely energy impacts of policy measures for commuters.
- O7 Discuss the results in the context of high future energy prices and the desire for reduced dependence on fossil fuels.

1.5.3 Methods

- M1 Descriptive statistics, time-series analysis, and GIS mapping (A1.1, O2).
- M2 Development of a spatial microsimulation model (A1, A2, O3, O4).
- M3 Use the spatial microsimulation to investigate the impact of change on commuter behaviour and energy consumption (A1.3, A2, O6, O7).

Chapter 2

Personal transport, energy and commuting

The traditional preoccupation with the supply side of transport policy — the provision of additional road, air and rail infrastructures — is no longer appropriate socially, economically and environmentally.

(Peake, 1994, p. 5)

Any review of research into the energy consumption of commuters is bound to encounter wider issues such as transport infrastructure, the spatial characteristics of labour markets (Ballas et al., 2006), population densities of settlements (Breheny, 1995) and the price of oil (Sexton et al., 2012). Transport research is often multidisciplinary (Hoyle et al., 1992). This element is even more important in the present study because commuting and energy use in transport are not academic disciplines, or even established fields, of their own right. Rather they are issues, tackled from a range of perspectives using various methods.

As illustrated by the quote that opens this chapter, research into energy in transport is contested. Almost 20 years since it was written there has undoubtedly been much more focus on the demand side; social and environmental considerations have increasingly been taken into account; and transport studies have become more multi-disciplinary. Yet fundamental differences in the methods used by researchers persist. Battle lines can be seen emerging in the literature, for example, between those who advocate a greater role for the social sciences (Schwanen et al., 2011) and those who advocate a scientific approach (Simini et al., 2012; Marshall, 2008). The transport-energy nexus has also received attention from disciplines not traditionally associated with either issue, such as computer science, physics and psychology. It is therefore necessary to impose some kind

of order on the mass of work that is related to the topic. With this aim in mind, the literature reviewed is divided into six sections:

- the ‘sustainable mobility’ paradigm (section 2.1)
- commuting research, at various scales (section 2.2)
- energy use and emissions in personal transport generally (section 2.3)
- energy impacts of commuting specifically (section 2.4)
- ‘tools of the trade’ — methods for studying energy and commuting (section 2.5)
- key concepts in energy and commuting (section 2.6)

These sections initially deal with commuting and transport energy use as separate entities, because they have rarely overlapped. The studies that do tackle the interface between these issues are generally conducted from within pre-existing disciplines, such as economics or transport geography, rather than adopting a completely multidisciplinary approach or attempting to start a new field in ‘transport and energy’, let alone ‘energy use in commuting studies’. Section 2.4 therefore focuses on two studies that deal with energy and commuting from two different perspectives: transport geography and economics. Because this research area is quite specific, the section is the only one in which comprehensive coverage is attempted. The other sections attempt only to outline influential strands of research and highlight findings of direct relevance to this project. Section 2.5 provides an overview of the techniques used in the research areas covered, and introduces one of the main methods: spatial microsimulation. (The spatial microsimulation literature is covered in more detail in chapter 3.) The current chapter concludes with a summary of important knowledge gaps in the area of commuter energy costs, and promising research directions that are related to the thesis (section 2.7).

2.1 The sustainable mobility paradigm

As outlined in chapter 1, energy use in transport is bound up with a number of issues — climate change, energy, inequality. Diverse as these are, they all fall within the umbrella term of sustainability. It is not surprising, therefore, that much of the work linking transport and energy use has been conducted within the context of sustainability, especially since the 1990s when sustainability became a buzzword in politics and academia. Here is not the place to discuss of what sustainability does and does not mean.¹ For the

¹See (Pezzey, 1997) for an attempt to define the term rigorously or (Steg and Gifford, 2005) for a discussion of ‘sustainable transportation’.

purposes of this section, suffice to say that sustainability relates to *long-term* environmental, social and economic well-being. According to Banister (2008), in a paper with the same title as this section, sustainable mobility is an approach to transport research and policy that differs from conventional transport planning priorities in the following ways:

- its focus on people and social outcomes rather than infrastructure, vehicles and traffic
- localised and specific in its approach to intervention, rather than large scale and homogeneous
- a focus on potential scenarios of the future rather than univariate ‘modelling’
- travel modes placed in a hierarchy with pedestrians and cyclists at the top, rather than a focus on motorised transport
- multi-criteria assessment methods used for project assessment rather than just economic valuation

On all counts, the world-view adopted in this research project fits firmly into the sustainable mobility paradigm, so this is the starting point for the literature review. Energy use in personal transport may seem a technical consideration, suitable for consideration only by traffic engineers and natural resource economists. Yet the energy intensity of transport systems has a direct impact on resource depletion (and therefore economic sustainability), the natural environment and, by amplifying inequalities in access to physical and cultural resources, people’s lives. The energy costs of commuting are therefore of critical importance to the ability of modern economies to sustain themselves.

Probably the most high-profile UK government report written from the perspective of the sustainable mobility was published by the Sustainable Development Commission (SDC) (Kay et al., 2011).² ‘Fairness in a Car Dependent Society’ takes a broad perspective when analysing personal transport. As advocated by Banister (2008), it focuses on people rather than traffic and infrastructure, while also mentioning the potential for environmental and (long-term) economic gain. The report urges the prioritisation of “quality of life, safety and the environment” for all members of society affected by personal travel systems over the speed and convenience of wealthy travellers (Kay et al., 2011, p. 5). The report’s findings are especially powerful because it provided a very

²This report, incidentally, was published just before the SDC was dissolved by the coalition government in March 2011. No follow-up research in the area has been conducted.

large body of evidence to support its findings, rather than to simply repeat the ‘anti-car’ mantra expounded by some based on the strength of rhetoric, social theory and a smattering of technical facts (e.g. Dennis and Urry, 2009).

Kay et al. (2011) is also useful as a source of inspiration about future interventions, as it provides strong and specific policy recommendations. The most general of these, that can be applied to nearly every intervention affecting transport, is that a clear order of priorities should be followed by transport policy-makers (figure 2.1). Incidentally, this is the same order of priorities that would be followed if reducing energy use were the primary objective of transport policy, as the evidence presented in chapter 1 suggests it should be.

This thesis is therefore closely related to the SDC study (and the sustainable mobility paradigm more generally) in a number of ways. It begins from the same world-view as Banister (2008), but focuses on energy as a way to include all the various factors affecting sustainability. The purpose of this research mirrors that of Kay et al. (2011): to highlight the wider impacts of personal mobility. The methods are quite different, however: based on the knowledge that a range of social, economic and environmental ills are associated with energy intensive transport highlighted in chapter 1, the focus is on energy use. This thesis does also highlight the wider costs to society of personal travel advocated in the ‘sustainable mobility paradigm’, but indirectly, via energy use, and with a focus on only one type of trip: commuting.

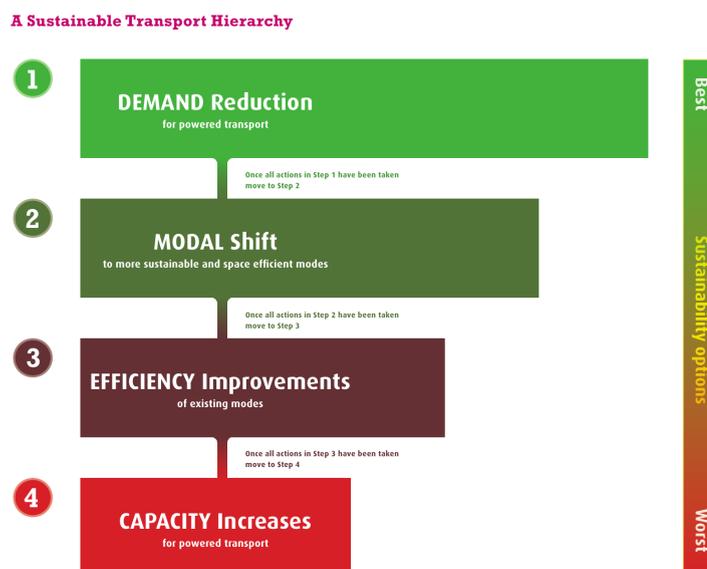


FIGURE 2.1: The sustainable transport hierarchy (Kay et al., 2011).

2.1.1 Active travel

Although not always explicitly part of the sustainable mobility paradigm, many of the studies from the loosely defined ‘active travel’ literature³ make reference to the sustainability benefits of walking and cycling. For the purposes of this literature review, research into non-motorised modes is therefore considered as part of sustainable mobility, although the term has been used in different contexts.⁴ Much of the active travel literature has a clear health agenda (e.g. Jarrett et al., 2012); here the focus is on studies that also report energy and emissions implications.

Woodcock et al. (2007) investigated the links between transport, the environment and health by projecting the rate of active travel up to 2030 in London. The outcome of policies to encourage cycling were found to be wide ranging, including positive impacts on road injury rates (a ‘neglected epidemic’), physical inactivity and associated degenerative diseases, climate change and pollution, ‘community severance’, as well as difficult-to-measure impacts on energy security and rates of transmission of infectious diseases. Clearly it is not possible to accurately measure each of these impacts in a single study, but it is useful to bear in mind the broader benefits of walking and cycling, which are also particularly energy efficient. In a similar vein, Jacobsen et al. (2009) provided evidence to suggest that as well as competing with healthier and lower-energy active travel modes for trips and space, motorised traffic also discourages walking and cycling through perceived danger levels. Although their methodology was relatively rudimentary (a review of statistics from the academic and policy literature), Jacobsen et al. (2009) provide the basis for an interesting hypothesis: that strategies to reduce car use may be more effective than pro-active travel measures in terms of energy and health outcomes. The case study comparing commuter energy use between the UK and the Netherlands presented in section 6.5 provides some empirical support for this hypothesis.

With the emergence of newly available datasets from GPS devices, mobile phones and bicycle rental schemes, more sophisticated methods have emerged in the realm of active travel research. Ogilvie et al. (2010), for example, provide details of how GPS measurements for individuals can be used estimate both physical activity levels and CO₂ savings

³This area of research has also been referred to ‘non-motorised transport’, or simply ‘walking and cycling’. The term ‘active travel’ is preferred as it is more concise and encapsulates all methods of travel to work that rely on human muscles rather than mass-produced motors as prime-movers (see Smil, 2008 for more on the contrasts and surprising similarities between the two). The rare but growing category of muscle-motor hybrid vehicles such as electric bicycles is ambiguous in this regard: as the ratio of motive energy provided by personal exertion and inanimate energy sources will vary between zero and infinity from case to case. The approach taken here is to exclude it from active travel completely as motors and their energy supply must be included for a realistic energy assessment.

⁴Lawrence Burns, who directs the Program on Sustainable Mobility at Columbia University’s Earth Institute, uses ‘sustainable mobility’ primarily to describe shifts in car technology and use, including driver-less cars and electrification Burns (2013). Aftabuzzaman and Mazloumi (2011) uses the term to describe a transport system resilient in the face of peak oil.

of active travel. In-depth questionnaires were also used to estimate “physical activity energy expenditure (PAEE) and total energy expenditure (TEE)” (Ogilvie et al., 2010, p. 7). GPS data was combined with accelerometer data by Cooper et al. (2010) to estimate physical activity. Although this metabolic energy consumption of the human body is not generally seen in the same light as energy use by vehicles, both can be measured in the same units and compared directly. It is argued in chapter 5 that this fact is a further benefit of the energy approach to commuting: substituting motorised energy use with muscular energy has a direct impact on obesity and chronic inactivity levels. Thus energy measurements can encapsulate (to some degree) health as well as environmental impacts of travel.

In line with this new abundance of data, advances have been made in characterising and modelling active travel patterns as well. Millward et al. (2013) used GPS data to supplement survey findings on walking trip characteristics in a US city. The combination allowed for accurate characterisation of both quantitative variables such as speed, time and distance of travel as well as qualitative information about the reason for the trip. Of particular relevance to scenarios of future change, is work looking at the ‘impedance functions’ of active travel modes with respect to distance under various conditions (Iacono et al., 2010). Here, impedance refers to the disincentive to make trips by active travel per unit distance. Impedance influences p , the proportion trips that take place between A and B made by walking or cycling. Due to the impedance or ‘resistance’ to travel associated with these modes being highly dependent on distance compared with faster and less physically demanding motorised modes, the proportion of trips made by them can be expressed as a function of distance ($p = f(d)$). Based on this reasoning p should be high for the shortest trips, dropping rapidly as the distance increases beyond a few kilometres and levelling-off towards 0% after around 5 km for walking and 15 km for cycling. This hypothesis has indeed been born-out in practice. Based on travel survey data, Iacono et al. (2010) calculated the rate at which the proportion of trips made by bicycle and walking decreases with increasing distance for different trip reasons, including shopping and commuting figure 2.2. The average proportion of trips (p) made by a particular mode in a particular context (e.g. bicycles for shopping in a given settlement) was found by Iacono et al. (2010) to take the following functional form:

$$p = \alpha \times e^{-\beta \times d} \quad (2.1)$$

where α , the proportion of made for the shortest distances and β , the rate of decay are parameters to be calculated from empirical evidence. This equation is interpreted in chapter 8 as a proxy for the probability of car-bicycle modal shift.

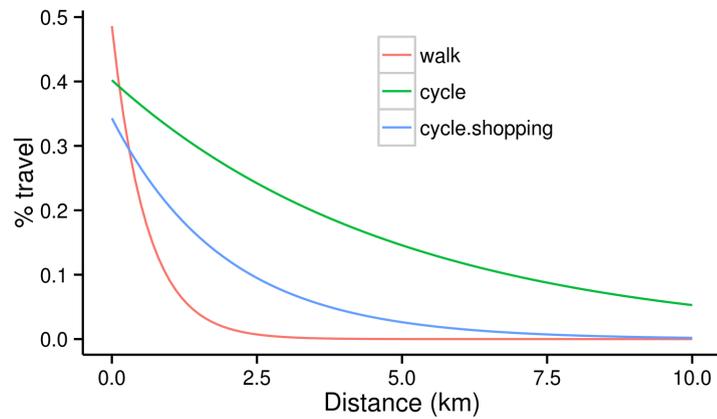


FIGURE 2.2: Proportion of trips made by active travel by distance and mode. Functional form from equation (2.1); parameter values taken from (Iacono et al., 2010).

In summary, the sustainable mobility literature provides a strong foundation for investigating energy costs in commuting. The emerging field of active travel also has a strong interest in energy, although this is rarely linked to the energy use of motorised modes. Sustainable mobility provides both a world-view and methodological guidance for the thesis, yet is still only a minor influence on commuting research overall, as shown in the subsequent section.

2.2 Commuting research: individual to national levels

The energy costs of commuting depend on commuting behaviour. As Smith (2011, p. 297) put it regarding CO₂ emissions from travel to work, they are “essentially a weighted combination of the mode-choice and travel distance patterns.” Understanding the factors driving travel behaviour is key, therefore, to understanding energy costs. ‘Behaviour’ can be understood from a range of perspectives, from the internal workings of the mind to the macro-economic forces driving the type and spatial distribution of jobs (figure 2.3). This section is structured to reflect the multiple levels that affect commuter patterns.

Many important factors influencing the decision of whether, how and how far to travel to work depend on the global economy, which is largely beyond anyone’s control (Eisenstein, 2011): the price of crude oil, industrial production⁵ are all determined outside the sovereignty of any person or even country, yet these factors, determined by the global

⁵Production of cars, trains and machinery, for example, is a prerequisite for the construction and maintenance of transport infrastructure.

economic system, clearly have large knock-on effects on commuting patterns. National-scale physical factors also play a role. The transport network, shifting vehicle fleet efficiencies and the nation’s topography all help determine the ease with which different commutes are undertaken, and their energy costs. Large-scale political and economic processes, such as congestion charges, fuel taxes and house price gradients also affect commuting behaviour. Zooming in on the local scale, the strength and nature of the local economy will decide whether suitable jobs are available locally or whether one’s job search must go further afield. Community and family ties could both make commuting distances shorter (by providing support to family and friends searching for work — the “home-field advantage” identified by Simini et al. 2012, p. 100), or longer (by creating a disincentive for people to move closer to where they work Green et al., 1999). At the simplest level, however, the decision to get up in the morning and commute to work is ultimately made by individuals figure 2.3).

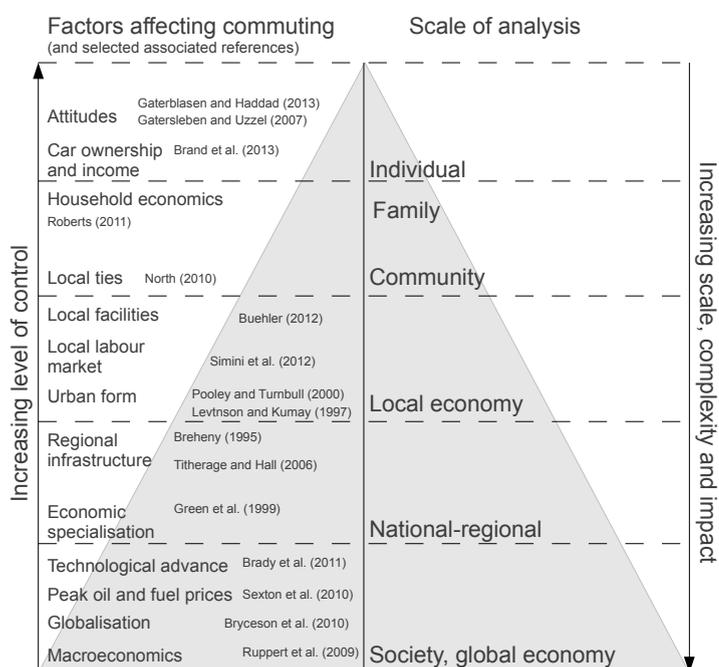


FIGURE 2.3: Schematic for organising research commuting research by scale.

2.2.1 Personal factors: psychology, family and community

As Chris Fisher’s story demonstrated (section 1.2), human beings are not merely economic machines motivated solely by money. We make decisions based on a wide and interrelated range of factors (Pinker, 1997). Some are instinctive, others are carefully

planned (Kahneman, 2012). While money plays an important role, it is within an array of factors along with family considerations and proximity to friends and home.

In some ways, long-distance commuting is the ultimate manifestation of the conflict between work and family life. If money were the only objective, people would be far more mobile, willing to pack their bags and leave to live near better salaried jobs whenever opportunities arrive. This is obviously not the case: “job relocation almost always involves a move not only of one individual’s job, but also of his/her household’s home and of jobs/schools for other household members” (Green et al., 1999, p. 52).⁶ Over the past 50 years, perhaps due to the perceived social costs of this upheaval, job relocation has increasingly *not* led to house relocation, but longer commutes instead (Green et al., 1999; Nielsen and Hovgesen, 2008).

This trend has been labelled the ‘commuting paradox’ due to the seeming irrationality of the decision to spend much of one’s time travelling to work and back (Stutzer and Frey, 2008), in face of evidence of negative impacts on well-being (Novaco et al., 1990). Approaching the problem at the individual level makes sense: people are not economic machines, yet assuming that people make a personal cost-benefit analysis for each available option allows the powerful tools of microeconomics to be used. Applied to commuting, each individual would evaluate all work-home (and hence commuting) options and select the best (Stutzer and Frey, 2008).⁷

Research into commuting at the individual level generally uses psychology (e.g. Van Lange et al., 1998) or microeconomic theory (e.g. Van Ommeren et al., 1999) to explain *why* people choose their commuting behaviours. Yet the level of analysis is generally weaker when it comes to describing *how* commuting patterns — the aggregate pattern of many individual flows — are configured and how much energy or other resources these patterns use relative to other activities. The relationship between commuting and larger scale processes is generally not considered in individual level studies, although there is a move towards more holistic understanding of individuals. One study that analysed both environmental and psychological determinants of individual level commuting behaviour found conclusive evidence (from a sample of 130 university students) that “cognitive variables play a more important role in the prediction of active commuting than do environmental variables” (Lemieux and Godin, 2009, p. 9). Because

⁶This decision, to move for personal reasons rather than work, is also well-expressed in everyday speech: “I’d much rather have a crap job and be with Richard than have a good job and be miserable”, as one person told me (Emma, 2013, personal communication).

⁷Mysteriously, as the authors of the ‘commuting paradox’ point out, this cost-benefit analysis is often performed in a less than rational way, leading to commuting costs (predominantly on unquantified well-being) that far outweigh the benefits in many cases (Stutzer and Frey, 2008).

of the non-geographical nature of this study and its small sample size, however, it provides little evidence on the factors related to *aggregate level* variability in commuter flow patterns. Local, regional and national level studies are needed.

2.2.2 Behavioural economics and its impacts on commuting

Behavioural economics seeks to explain a large part of human behaviour in advanced capitalist societies where making money is often (implicitly or otherwise) seen as the number one *raison d'être* of life (Eisenstein, 2011). The underlying assumption that human beings are rational beings has of course come under attack from many quarters. To take one example, “There is probably no other hypothesis about human behaviour [than economic rationality] so thoroughly discredited on empirical grounds that still operates as a standard working assumption in any discipline” (Anderson, 2000; cited in van Excel, 2011, p. 34). Despite these criticisms it is easier to create testable models in economics than the social sciences (Perman, 2003).

Indeed, many economists would be quick to point out that the term ‘economics’ has been conflated with what is in fact ‘neoclassical economics’ in the public consciousness and in other academic disciplines. It has been argued that it is only with the recent focus on money exclusively (instead of the physical reality that underpins its value) that utility and profit have been conflated (Porritt, 2007; Eisenstein, 2011). Clearly, it is not money per se that affects commuting energy costs, but its indirect influence on behaviour. It is for this reason that behavioural economics is the branch of the discipline with most insight into travel to work patterns. At its most tempered, modern behavioural economics completely accepts that much of human behaviour follows a rationality other than the profit motive. Many behavioural economists acknowledge the findings of Nobel Laureate Daniel Kahneman, neatly summarised in the book *Thinking, Fast and Slow* (Kahneman, 2012), which explains that humans are servants to both cool rational thought processes (when ‘system 2’ is dominant) and also to quick-fire decisions based on spontaneous urges and heuristic reasoning (when ‘system 1’ is dominant). The caveat in the quantitative analysis underlying economic analyses becomes “when humans are acting rationally, with the objective of maximising profit” which is only some of the time.

If these limitations are understood, behavioural economics can provide a powerful framework for explanation. The framework is consistent with anecdotal evidence about the reasons behind travel behaviours (e.g. Chris Fisher’s decision not to move to Hereford because commuting to the Tyrrell’s crisp factory would then become too expensive) and the observed behaviour that people react predictably to price signals. The framework

can also be called upon to explain more general (and less testable) trends, such as the increasing dominance of the car throughout the 20th century: “One important reason for the automobile’s increasing dominance in passenger transport is that ... the price of car travel relative to public transport has largely remained steady while the (system) quality of car travel has considerably increased relative to public transport” (van Excel, 2011, p. 149). Far from assuming humans are soulless economic machines, such explanations, taken as descriptors of aggregate behaviour, assume citizens are simply careful with their cash. Such explanations are supported by multiple studies of transport elasticity (e.g. Goodwin et al., 2004).

2.2.3 The local and regional economy

The idea that localised environmental factors can influence behaviour patterns has a strong tradition in geography. In terms of the impact of local factors on commuting, existing research has focussed on transport infrastructure, the built environment,⁸ topography and local economies, as well as the more abstract concept of ‘urban form’.

A common research strategy for exploring these links is to take aggregate travel behaviour in different areas as the dependent variable and set-up a multiple regression model to identify which factors can best explain its variation. This strategy has provided a number of insights into commuting behaviour and its dependence on geographical factors:

- Buehler (2012) ran a logistic regression model and found that the provision of showers and bicycle parking by employers (which had not previously been included in regression models of commuter behaviour) were significantly related to the chances of respondents cycling to work. The provision of bicycle lanes and free car parking also had large impacts on the odds ratio of a person cycling in the expected direction, supporting past literature on the matter. Significantly, this study also combined household level variables; it was found that a high number of bicycles (and low number of cars) per household member also increased the propensity to cycle, as did high income and ‘white’ ethnicity.
- Titheridge and Hall (2006) used distance of commute as the dependent variable in their study of commuter patterns in the East of England. It was found that distance from London, social class and level of car ownership in each ward affected

⁸The built environment is defined as “equipment, facilities or infrastructures in one’s environment” that influence travel behaviour by Lemieux and Godin (2009, p. 2). The built environment can thus be seen as a superset of transport infrastructure, which includes features such as parks, street lights and even showers designed to encourage running or cycling to work.

distance in the expected ways. Population density, which would be expected to be associated with lower energy costs based on the ‘compact city’ concept, was positively associated with commuting distance in their model. This contrasts the idea that bunched-up living is a panacea for travel costs and was explained by Titheridge and Hall (2006) in terms of accessibility to transport infrastructure.

- Muñiz and Galindo (2005) performed a regression analysis exploring the impacts of urban form on the ‘ecological footprint’ (which is closely related to energy use) of commuting in Barcelona Metropolitan Region. It was found that, for the 163 municipalities that constituted the case-study area, low population densities, high ‘accessibility’ (which seems to have been defined simply as distance from central Barcelona) and high average income all were positively associated with the dependent variable. Although this study was conducted at only one scale (it may suffer from the ecological fallacy and does not prove causality), the authors concluded that factors relating to urban form “have a greater capacity to explain municipal ecological footprints variability than other factors” (Muñiz and Galindo, 2005, p. 511).

Such studies, which use geographical zones as the unit of analysis, have revealed some of the factors that are closely related to certain commuting patterns. Some of these, such as propensity to cycle and distance to workplace, have important energy implications. When the independent variables include factors over which policy makers have some degree of influence, such as employers’ provision of showers investigated by Buehler (2012), the findings can be used to predict changes resulting from new policies. Even in cases where the independent variables are largely beyond anyone’s control — such as population density and home-work distances — regression analysis can be useful: it can be used to identify anomalies where commuting patterns differ greatly from what would be expected based on explanatory variables alone. In these cases, it must be acknowledged that other processes are in operation, which can lead to new avenues for research. However, regression analysis used in this way is limited: causality is not proved; relationships may not hold at different levels of analysis; and standard regression does not take space into account (spatially weighted regression can be used to tackle this problem). Partly to overcome these limitations, a number of other strategies have been used to explore the geographical determinants of commuting behaviour.

In a study of commuting behaviour in northern Sweden, descriptive statistics and maps were used to characterise commuter patterns in the region (Sandow, 2008). Making use of the abundant anonymous spatial microdata made available by the Swedish state, an individual level logit model, with long or short distance commute set as the binary variable, was used to explore the reasons for and impacts of the observed patterns. It

was found that people living in more sparsely populated areas were more likely to travel far to work than those living in dense areas. This was as expected (but in contrast to Titheridge and Hall (2006)). The individual level data allowed for the investigation of socio-demographic variables: education and income were associated with longer commutes. Interestingly (in contrast to UK data), commuting distance decreases with every age group above the 16-25 band. Gender differences were also apparent: men travelled further than women and the impact of marriage and children on the probability of commuting far was greater on females. Thus it was concluded that family commitments “constrain women to a higher extent than men” (Sandow, 2008, p. 24).

2.2.4 National and global considerations

While regional approaches have tended to focus on detailed sub-regional factors affecting commuting, national approaches tend to be broader. The large quantity of data available (albeit often at a high level of spatial aggregation and low temporal resolution) make the national level well suited to analysing shifts over time and persistent patterns within commuter flows. Larger study areas also shift attention towards universal concepts, that should, in theory, apply anywhere with similar underlying conditions.

In the context of the compact city debate, an individual level regression model involving 47,000 people across the US was undertaken by Levinson and Kumay (1997) to ascertain the impact of population density on travel to work distance and time (and hence average speed also). A wide range of individual and geographical factors (the latter aggregated at the level of Metropolitan Statistical Areas (MSA), roughly equivalent to county level in the UK) were used as explanatory variables. These were carefully selected based on theory and previous findings. They included a measure of polycentricity (the number of ‘activity centres’ — meaning employment centres — in each MSA), population growth rate and three variables to quantify the transport technology in use in each area. It was found that for car drivers, travel speed and distance were negatively associated with density. Time, which had received little attention in the compact city debate previously, was found to be negatively associated increased residential density up to a certain limit and then actually increase above this threshold. It was concluded that this indicates diminishing returns as the density of settlements increased if cars are the main form of transport, due to congestion. Public transport users, by contrast, “displayed a negative relationship between travel time and density both above and below the 10,000 ppsm density threshold”, suggesting that these modes are less affected by traffic (and hence more attractive) in dense urban areas (Levinson and Kumay, 1997, p. 168).

Building on these findings, Levinson (2012) returned to the question of the factors affecting commute time in US MSAs with updated datasets and more sophisticated tools for analysis. It was found that accessibility was the major determining factor of travel to work characteristics at the MSA level, and had a strong negative association with average time and mode share of cars. Accessibility (a slightly refined version of which was used in the final model) was defined, for given time thresholds, as follows:

$$a_t = \pi \times \left[\frac{V_n \times t}{Q} \right]^2 \times p_{emp} \quad (2.2)$$

where V_n is average network velocity, Q is circuitry — see page xix for definition and figure 5.13 for illustration — and p_{emp} is the urban density (measured in jobs per km²). A number of other mathematical entities were used to define the transport network, the most influential of which were treeness (roughly speaking, the proportion of the network going to new places), connectivity (measured in five metrics, from alpha to gamma) and circuitry. The relevance of (Levinson, 2012) for this thesis is that it provides strong evidence to suggest key aspects of the journey to work are influenced by road and settlement factors, and a set of tools for measuring and assessing the effects of these factors. These techniques are not used in a model of commuter energy use in the case studies presented in this thesis, but could be in the future.

Commuting has been studied and understood from a wide range of perspectives. For the purposes of this thesis, insights are taken from economics, ecology, and transport geography. The first assumes commuters to be free thinking utility maximisers (Sexton et al., 2012); the second sees humans as “mobile, interacting animals” who “are no different from our fellow species” (Brockmann, 2012, p. 40). Transport geography tends to be agnostic in its explanatory framework, taking insights from the spatial structure of transport networks, supply and demand centres, and the physical environment (Rodrigue et al., 2009). Interestingly, considering the ubiquity of commuting worldwide, no research into commuting as a global phenomenon could be found, let alone systematic comparisons between nations. This suggests that there is a research gap in the area of international commuting studies, which may be partially filled by a comparison of the UK and the Netherlands later in this thesis section 6.5, as recommended in the conclusions (see section 9.4).

2.3 Energy use and CO₂ in transport studies

The traditional reasons for interest in commuting and personal transport more generally include its links to urban structure, industrial location, productivity of workers and

quality of life. Economic factors have tended to be dominant in past research, but energy use and its environmentally destructive impacts, predominantly quantified in the form of greenhouse gas emissions, are increasingly becoming a focus for transport researchers (Chapman, 2007). Although CO₂ production is a direct result of energy consumption, depending on emission factors (Defra, 2012; see figure 1.2), some studies continue to treat them as separate issues. Boussauw and Witlox (2009), for example, calculate the energy costs of commuting in Flanders, but nowhere does the paper mention the link to climate change: results are also, in essence, a map of CO₂ emissions due to commuting, relevant to EU targets. On the other hand, it is possible and equally valid (if one's primary concern is climate change) to only quantify CO₂ emissions and acknowledge that the results essentially show energy use (Smith, 2011).

Simonsen and Walnum (2011) harness the knowledge that energy use and greenhouse gas emissions are two sides of the same coin to use the same energy analysis model to quantify both. In their analysis of cars in Norway, it was found that only electric vehicles powered by renewable sources (hydro-electric plants in this case, which are bountiful in Norway) performed well. The approach taken in this thesis follows Simonsen and Walnum (2011) in seeing the link between energy and emissions. Moreover, it is assumed that the former is a close enough proxy of the latter at the system level that only energy use needs to be calculated to gain an understanding of both.⁹ This prevents the complexity of having to report two (very highly correlated) sets of indicators for the energy and emissions impacts. They are assumed to be essentially the same thing.

Underlying drivers of this interest in energy use in transport and associated emissions include peak oil and climate change (chapter 1). This attention has led to methods and findings directly related to the thesis. Although there has been a recent proliferation of interest in the contribution of transport energy use to climate change (Schwanen et al., 2011), the topic has received attention, intermittently, over many years. Interest seems to have peaked during the 1970s, following the major oil crises of that decade (Greer, 2009). Since then the topic has largely been confined to the following fields:

- Urban sprawl: the phenomenon of low density housing, also known as suburbia, is highly car dependent and has attracted attention investigating its impacts on transport energy use. The antithesis to this is the 'compact city'. Investigation of continuum between these two extremes has led to many insights on the impact of urban form on transport energy use.

⁹'At the system level' in this context means emissions arising from knock-on impacts of interventions in the transport system are taken into account. For example, if rapid uptake of electric cars leads to slower phasing out of fossil fuel fired power plants, this would constitute additional emissions at the system level that are not included in official emissions inventories.

- The energy costs of transport modes: quantifying which modes of transport use most, and least energy per unit distance, typically per passenger, vehicle or tonne kilometre: *pkm*, *vk*m or *Tkm*.
- The climate impacts of transport, usually quantified through estimates of the quantity of CO₂ directly emitted by vehicles.

Transport and energy use is a broad area of research, so it is inevitable that not all of it fits neatly into these four categories. A fifth category, miscellaneous studies on transport and energy, will emphasise this diversity of approaches, and touch on the interdisciplinary nature of the work.

2.3.1 The energy costs of urban form: urban sprawl and compact cities

The links between urban form and consumption of fossil fuels (primary energy) have been of interest since at least the 1940s, especially amongst utopian town planners (Steadman, 1977). Of the various types of urban form under consideration, from the fictional ‘City of Efficient Consumption’ (Goodman and Goodman, 1947) to the ‘compact city’ (Breheny, 1995), none have received more critical attention than that of urban sprawl (Marshall, 2008). Urban sprawl has long been identified as an energy intensive settlement pattern, with social and environmental knock-on effects: “Urban sprawl not only consumes more natural ecosystems and has a higher cost per unit of development in both money and materials, but once completed it requires higher inputs of energy and generates more air and water pollution” (Bormann, 1976).

Such statements may seem obvious, yet without evidence questions about the extent of the problem, and how to mitigate it, remain unanswered. This is a key motivation behind methods which seek to measure aggregate energy use over space, and provide breakdowns of how much energy is used where, and insights into why. One implicit assumption underlying much of this research is that energy use is *the* defining variable of a settlement and hence requires most attention. This reasoning was stated explicitly by Marique and Reiter (2012), who note that despite the primacy of the transport sector in driving up energy use in sprawling suburbs, “transport energy consumption is rarely taken into account” (p. 1). In response to this negligence, the authors quantify the average transport energy costs in four settlements, based on travel statistics. Their analysis shows commuting to be the most important determinant of transport energy consumption in Belgium. Commuting consumes more than double the amount of energy (4000 to 6000 kWh/p/yr) than the next largest transport energy user (trips to school) (Marique and Reiter, 2012). These findings lend support to the topic of this thesis and encourage further analysis of energy use in personal travel overall.

Despite the use of census data, Marique and Reiter (2012) present their findings only at high levels of aggregation, for entire settlements. The *distribution* of energy consumption within the areas is not considered. Nor are the *types* of people responsible for high energy use for commuting. These gaps in their research suggest more detail would be welcome: providing a method to calculate the energy costs of commuting at lower geographies that is capable of providing breakdowns of energy use at the individual level would constitute a step forward for this research.

2.3.2 The energy costs of different transport modes

The relative energy use of different ways of travelling per unit distance or time has been of interest to researchers at least since the 1800s when Tredgold (1835) was taking measurements from railway engines to ascertain their coal consumption. A more universal approach to energy use in transportation was taken by Von Karman and Gabrielli (1950), who characterised the energy performance of different modes, for given speeds and loads. This model included jet fighters, helicopters and even a horse, as well as more traditional vehicles such as cars, bicycles and trains. Although largely unnoticed by the academic community (it has been cited 11 times according to Google Scholar), this paper was seminal in its approach to comparing widely varying forms of transport, and the findings still largely hold today (although efficiency gains have been made) (Yong et al., 2005). An updated analysis, which uses a simpler energy performance metric, kilogram-metres per Joule, multiplied by speed ($kg * m^2/J/s$) applied the method to a wide range of modern vehicles, confirming the relatively poor energy performance of cars in comparison with trains and bicycles (Radtke, 2008, figure 2.4). This is a recurring theme in chapter 5.

Von Karman and Gabrielli (1950) and their successors made large advances in understandings of the relative energy costs of widely different transport modes. It is therefore surprising that methods and findings stemming from this work are not more frequently used in transport studies. One limitation of the research area is that it omits indirect energy impacts from the analysis. This is problematic because vehicle and infrastructure manufacture obviously require large amounts of energy: inclusion of direct energy costs only “might lead to serious faults in estimating environmental impacts of new infrastructure or modal shift policies” (Wee et al., 2005, p. 23). A pioneering paper that sought to overcome this issue quantified both the direct and indirect energy costs per unit kilometre of the main US modes of personal travel shortly after the 1973 oil shock (Fels, 1975).

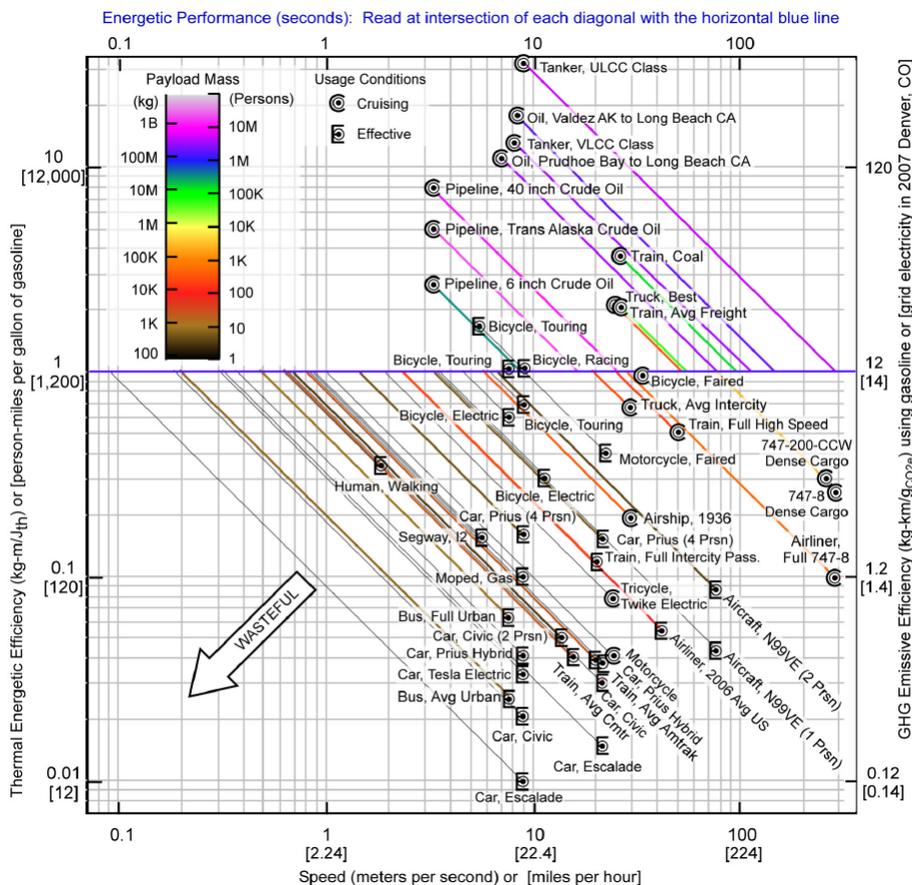


FIGURE 2.4: Energy performance of different modes, from (Radtke, 2008).

In hindsight, Fels’ research seems to have stood at the beginning of a research area, dedicated to assessing the wide-boundary energy impacts of personal travel. Key papers in this area include Lenzen (1999), who used updated versions of Fels’ early methodology to calculate the total energy and emissions impacts of the Australian transport system and Ramanathan (2000) used a new method (‘data envelope analysis’) to investigate the relative energy costs of Indian road and rail transport. Another group of researchers have researched essentially the same issue, but with different methodologies and terminologies (the ‘well-to-wheels’ approach) from the life cycle analysis (LCA) perspective (e.g. Wang, 2002; see section 5.3.1). Because research rooted in LCA tends to be concerned with emissions rather than energy use per se, it is of slightly less relevance to this thesis. Surprisingly, there seems to be limited overlap between the well-to-wheels approach and the aforementioned system level energy use studies. Despite the activity of these research areas, there has been limited uptake of system level energy cost estimates in transport studies overall. Direct emissions and their climate impacts have received more attention.

2.3.3 The climate impacts of transport

Since 1985, when Professor James Hansen of NASA's Goddard centre testified to the US congress about the threat posed by climate change, there has been a growing concern about the issue from all quarters, including the media (Boykoff and Boykoff, 2007). While media insistence on 'balance' seems to have actually led to bias in climate change reporting, providing excessive coverage to contrarian views (Boykoff and Boykoff, 2004), academia has largely risen to the challenge in practical terms. A multitude of articles has been written on how to reduce emissions in everything ranging from catering (Gössling et al., 2011) to the Indian cement industry (Kumar Mandal and Madheswaran, 2010). Acknowledging that transport is responsible for roughly a quarter of emissions, researchers in the sector have been no exception. Modelling scenarios of future change proposing new policies for emissions reductions are now common themes in the transport literature (see reviews by Chapman, 2007 Ross Morrow et al., 2010).

Without delving further into this large and diverse body of literature, a few generalised criticisms of it can serve to highlight where improvements can be made. It is acknowledged that these observations do not apply to all research into transport and climate change. The reason for voicing these concerns, summarised in the bullet points below, is that they help focus attention on areas within the field lacking in coverage.

- Transport and emissions studies have tended to focus exclusively on direct emissions, to the detriment of understanding of the system level or 'embedded' emissions resulting from transport policies, such as road construction and vehicle manufacture (Lenzen, 1999; Wee et al., 2005).
- Because of the focus on the national level, papers in the area could be argued as offering little in the way of support to local and regional transport planners. This is an important oversight because local and regional level transport planners vastly outnumber national policy makers (in staff, if not in terms of political influence).
- The various scenarios of the future often appear to be overly academic, arbitrary and unrealistic. This is problematic because impenetrable models and scenarios may prevent engagement and interaction with the possible futures presented, by either the public at large or policy makers. To overcome this issue, participatory models such as that published online by the Department of Energy and Climate Change (2050-calculator-tool.decc.gov.uk) have been advocated (Fulton et al., 2012).

Despite these issues, this thesis fits within the field: although the emissions benefits are not calculated explicitly, it is not a large jump from energy costs to emissions (CO_{2eq}

output would be easy to estimate, based on the emissions factors present in chapter 5). The efforts to estimate system level energy costs of different modes presented in the same chapter are aimed at overcoming the focus on direct emissions alone, prevalent in the transport-climate change literature. Regarding scale, in some ways it makes sense that many of the studies in the area operate at a large scale because climate change is inherently a global issue. The problem is that there is an excess of studies that operate only at the national level, with relatively little work focussing on larger or smaller geographical unit of analysis. The methods presented in this thesis are well-suited to smaller geographical unit areas, although they can also be applied to nations (chapter 6). The methods presented in this thesis are not participatory (unless one is willing to learn to code in R and apply it to spatial microsimulation!). However, effort has been made to make the code and data underlying the models as accessible as possible.¹⁰

2.4 The energy impacts of commuting

The intersection between these two study areas, each large in its own right and with substantial interaction, is surprisingly small. As described in the previous two sections, major advances in understanding commuting behaviour and energy use in transport have been made. The problem is that these insights into commuting are often not translated into energy use estimates.¹¹ Or, conversely, existing estimates of energy use of different modes and other personal variables are not combined with readily available commuting statistics. The energy cost of commuting is not a ‘pure’ research area, in the sense that it relies on combining data from sources that often are not linked.

The study that most closely fits the title of this section was based on aggregated census data from Flanders. Without relying on regression analysis or sophisticated statistics Boussauw and Witlox (2009) provided a detailed account of the factors linked to areas with high and low average commuter energy costs. By mapping average energy consumption per person per day (ranging from almost zero to above 30 kWh/p/d) for small administrative zones, the impacts of modal split (minimal), distance (“paramount”) and urban morphology and infrastructure on energy use for commuting were determined. These are new and important findings that need to be tested in other countries and at different scales before they are accepted as ‘universal’ relationships that can form the basis of policies worldwide. It was concluded that “the energy performance of the transport system is an important approximate indicator for the sustainability of a spatial

¹⁰See <http://rpubs.com/robinlovelace>, which contains links to reproducible result, via sample code and data. Github has also been used to make some experimental analyses available.

¹¹This step is in fact relatively straightforward, once the energy use of different modes is well-known (chapter 5).

structure” (Boussauw and Witlox, 2009, 590). This observation was a major motivation for the subject matter of this thesis. The political implications of the research are wide-ranging: the prevailing focus on mode-split in Belgium (and in many other countries, including the UK where uptake of cycling has become a major political issue) seems to be misguided. Governments should instead focus on enabling their citizens to live closer to their place of work.

Boussauw and Witlox (2009) did not provide ‘further research’ type conclusions. However, the arguments made throughout for a greater role for energy-based metrics of transport system performance and sustainability clearly imply that more research measuring energy use in commuting is needed. The paper therefore provides a strong intellectual foundation on which this thesis is built. The methodological guidance was limited as the analysis was quite simple. From this was taken the importance of seeing method as a means to an end, rather than an end in itself, an issue that has been debated in academia for many years.

While Boussauw and Witlox (2009) were writing from the perspective of transport geography, the primary concern being spatial variation of energy costs, the issue of energy costs has also been tackled from the perspective of mainstream economics. Sexton et al. (2012) set out to test a hypothesis: that the 2008 sub-prime mortgage crisis was triggered by high liquid fuel prices. The mechanism for this was commuting energy costs — those who live closer to their place of work were found to be less affected. This was shown through a number of maps illustrating the change in average house prices over space. Areas furthest from employment centres had the greatest falls, whereas house prices in more central locations were relatively unaffected. This study demonstrates the importance of energy costs of commuting, not just in abstract terms of environmental impact or global resource depletion, but in terms of direct impacts on peoples’ lives. No attempt is made to replicate the economic methods used by Sexton et al. (2012) in this thesis. However, section 8.4 was heavily influenced by the paper. It takes from Sexton et al. (2012) the need to assess potential future impacts of high oil prices on different social groups.

2.5 Commuting and energy use research: tools of the trade

The previous section illustrates that energy use in commuting can be seen in at least two different ways: a dependent variable influenced by geography, or an explanatory variable affecting household expenditure. Many other ways of looking at commuter energy use are possible and each would suit different methods for describing and explaining energy

use. While research methods and explanations can be closely bound together,¹² different research methodologies can also be used to investigate the problem from a single perspective. For this reason the methods discussed below are considered separately from the other sections of this literature review. Theories are hypotheses about how the world *should be*, based on experience, concepts and intuition, while the methods help uncover facts about how the world *is*. This is the standard model of science, which progresses by falsifying ideas which fail to explain observed reality, and leads to the acceptance of systems that have most explanatory power (Popper, 1959).

In some ways, this scientific approach can be seen as a tool of the trade in itself: it provides a framework within which competing theories can be impartially compared, and provides a mechanism to discard ineffective explanations, ‘sorting the wheat from the chaff’ in terms of ideas about the world. For this reason the scientific method, as it has been intermittently applied to research into commuting, is discussed as the primary, and most broadly defined, tool of the trade. Visualisation techniques have progressed alongside advances in data availability and analysis are considered as a key method in the research area. Finally, the ‘data deluge’ precipitated by the widespread adoption of handheld GPS devices and traffic monitoring technology is briefly considered. This source of information may, one day, rival official commuting statistics as a dataset from which to understand the energy costs of work travel.

2.5.1 ‘Scientific’ approaches to energy and transport

Science is a contested concept but has undoubtedly had a large impact on methods of researching energy use in transport. Rather than be restricted to Popper’s narrow definition of science (as any knowledge that can produce falsifiable hypotheses), the literature is more usefully seen as falling into a continuum, ranging from “scientific” on the one side, to “not scientific” on the other. This is not to make a value judgement about which research is ‘better’. (Indeed, one could argue that commuting is not a research area that is amenable to true science at all, due to the complexity of human decision making and the impossibility of controlled experiments.) It is simply to say that some methodological approaches borrow more heavily from the formalisation of theory and emphasis on quantification and testability of science than others.

A well-established ‘scientific’ theory about commuter patterns is the gravity law. The law is falsifiable (and has been falsified on numerous occasions!) because it predicts the

¹²Simini et al. (2012), for example, harness a vast commuter dataset covering the USA to support their general numerical model of commuting: the model to a large extent contains explanation implicitly.

number of trips (T) from location i to location j using the following formula:

$$T_{ij} = \frac{m_i^\alpha n_j^\beta}{f(r_{ij})} \quad (2.3)$$

where m_i and n_j are the populations of the start and destination settlements respectively, r is the Euclidean or ‘straight line’ distance of the journey, and α and β are parameters to be calculated based on evidence. The functional form of the denominator is open to interpretation, making the gravity law more of a modelling framework. Proponents have claimed that the framework can predict commuter flows between two settlements, once the functional form of equation (2.3) has been learnt.

This is quite a sweeping statement. Clearly, the model cannot be correct all the time because it is deterministic. It can, however, produce a sufficiently close fit with reality, across a number of transport flows, that it has become “the prevailing framework with which to predict population movement, cargo shipping volume and inter-city phone calls, as well as bilateral trade flows between nations” (Simini et al., 2012). The gravity law has been applied to commuting on a number of occasions with results pertinent to energy use. Gargiulo et al. (2012) presented a spatial interaction model based on the gravity law. It was configured using a single parameter (β in equation (2.3)), and was used to calculate the probability of individuals travelling from their home to workplace zones. Although no energy implications were investigated by Gargiulo et al. (2012), the model could be used to predict energy costs via trip counts between different zones. In a related paper, Lenormand et al. (2012) presented results of a model that calculates commuter flows between zones about which the number of incoming and outgoing commuters is already known. From this input dataset could be estimated the flow between each zone pair, to a high degree of accuracy. The authors compared the results of a stochastic implementation of a spatial interaction model, described in (Gargiulo et al., 2011) and based on the ‘gravity law’ (see section 2.5.1), against the ‘radiation model’. It was found that the former outperformed the latter, in terms of reproducing the known origin-destination matrix of commuter flows. It is to this radiation model, another scientific approach to commuting, that attention is directed below.

The gravity law has been recently criticised by Simini et al. (2012), who proposed an alternative that they refer to as a ‘radiation model’. In this model, the flow rate between two zones is defined probabilistically. The average flux is estimated as follows:

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})} \quad (2.4)$$

where s_{ij} is defined as the total population living within a circle, the centre of which lies in the centroid of zone i and the radius of which is the distance between zones i and

j. Thus, the greater the population living within the commute distance, the lower the estimated flow rate. This is key to the radiation model: it accounts not only for the characteristics of the origin and destination zones, but also the surroundings. Not only does this model have strong theoretical underpinnings, it also performed well against commuting data from US counties: the flow between each county pair was predicted with a high level of accuracy, based solely on the population of each. The potential utility of this model in energy applications is considerable: it is highly flexible so could be used in its raw state, before adding refinements to explain the impact of infrastructure. Also, the concept of impedance (introduced towards the end of section 2.1.1) could be used to create modified versions of equation (2.4) for each commonly used form of transport. With both modifications in place, such a model should be able to predict the energy implications for commuters of both new settlements and new infrastructure.

Another area where the mathematical formalisation of theory has been useful in energy-transport research is in the creation of future scenarios. Köhler et al. (2009) used an agent-based model to create scenarios of behavioural change and uptake of new transport technologies between the years 2000 and 2050. The novelty introduced by their model was use of different ‘agents’ — people (‘consumers’) interacting with higher level ‘niches’ and ‘regimes’ to determine the final outcome. The modelling framework is flexible, and allowed for complex dynamic behaviour to be simulated. A downside of the model was that it depended heavily on user input to set initial parameters. These parameters were set in a “scenario storyline of a successful transition” (Köhler et al., 2009, p. 2988), in which hydrogen fuel cell cars become widely available by the 2040s. Clearly, this scenario of the future is more the product of human imagination than the scientific method, and the future may take an entirely different technological path than that imposed by the authors. However, the sophistication of the approach shows that scenario creation can go beyond simple population models (Lovelace et al., 2011) or user-defined snapshots of the future (Akerman et al., 2006).

2.5.2 Visualisation methods

People tend to think visually and often lack the concentration or ability to read through long verbal descriptions or understand mathematical formulae. For this reason visualisation is important: “A picture really can be worth a thousand words, and human beings are very adept at extracting useful information from visual presentations” (Kabacoff, 2011, p. 4). A list of some of the main visualisation techniques for representing is therefore timely at the outset, to provide context and justification for the use of figures in this thesis:

- Choropleth maps are very common in geographical commuting research, providing an insight into the areas where particular behaviours are most prevalent. A minor difference between the maps used in most previous research and this is the use of continuous colour scales in this thesis, instead of bins for communicating energy costs (see chapter 6). This can be problematic if a distribution is highly distorted by outliers, in which case bins would be preferable, but can provide additional information to the reader if neighbouring zones have values at the opposite ends of a single colour bin.
- Geographical flow maps, with thickness of lines joining origin-destination pairs proportional to the flow (e.g. Smith et al., 2009). This technique is employed in section 7.3 to illustrate the importance of knowing *where* commuters are travelling to for local transport decisions that consider commuter energy use. Often these maps lack direction, however, leading to the use of arrows or asymmetries in lines being added (e.g. (Nielsen and Hovgesen, 2008))
- On-line visualisations have become increasingly common as software such as Processing, OpenLayers (for maps) and an R package called Shiny have become increasingly available and user friendly. Although no on-line visualisations have been created for the main thesis, ‘Google Fusion Tables’ and ‘Geoserver’ options were considered to make the results more accessible.¹³

2.5.3 Harnessing the ‘data deluge’

The increasing market penetration of hand-held GPS devices, in dedicated packages (Oliver et al., 2010) and more recently embedded within ‘smartphones’ (Gong et al., 2011), has led to an ‘overabundance’ of spatial data which must be filtered, prioritised, ordered, sorted and analysed to provide meaningful results.¹⁴ This ‘data deluge’ is still in its early stages (Bell et al., 2009), yet is already having an effect on approaches to geospatial data analysis (Jiang, 2011). The data analysed come from more conventional sources (primarily the Census and official surveys). However, it is important to be aware of the potential for this research to contribute to knowledge about commuter energy use.

¹³A presentation on this topic was given by the author at the FOSS4G (Free Open Source Software for Geospatial) annual conference 2013. The slides can be viewed [online](#).

¹⁴This was the topic of the Sixth International Workshop on “Geographical Analysis, Urban Modeling, Spatial Statistics”, held in Salvador de Bahia, Brazil, June 2012. The problem neatly summarised on the conference’s web-page: “During the past decades the main problem in geographical analysis was the lack of spatial data availability. Nowadays the wide diffusion of electronic devices containing geo-referenced information generates a great production of spatial data. Volunteered geographic information activities (e.g. Wikimapia, OpenStreetMap), public initiatives (e.g. Spatial Data Infrastructures, Geo-portals) and private projects (e.g. Google Earth, Microsoft Virtual Earth, etc.) produced an overabundance of spatial data, which, in many cases, does not help the efficiency of decision processes” (http://www.unibas.it/utenti/murgante/geog_an_mod_11/index.html, accessed February 2012).

2.6 Concepts in energy and commuting

The diversity of research on energy and commuting is great, yet within this body of work lies a set of concepts that appear repeatedly. The purpose of this short section is to summarise some of these ideas and to help tie together the literature reviewed in this chapter. The first two will act as points of reference in later sections.

- *Circuitry* (Q): This is the ratio of network distance to Euclidean distance between two places (Levinson and El-Geneidy, 2009):

$$Q(i, j) = \frac{dE(i, j)}{dR(i, j)} \quad (2.5)$$

Circuitry is important due to its impact on energy use (Levinson, 2012) and because other metrics of the transport network's performance can be derived from it (Barthélemy, 2011). Circuitry impacts energy use because in highly circuitous networks, more energy must be expended to go the same distance. In addition, if circuitry is low for energy intensive modes (e.g. the route between settlements joined by a motorway), these modes will be preferred.

Circuitry is also important practically: the distance bins used to disseminate UK census data measure Euclidean distances, whereas the actual distance travelled depends on network distance: to calculate energy use, the circuitry factor Q , must be used to translate between the two. The second reason for circuitry's importance is that other useful metrics of transport system performance can be derived from it. These include the *accessibility* of a location (how circuitous is the average route to that place), and the *global efficiency* of the network. These additional concepts which grew out of the understanding of circuitry have strict mathematical definitions and could be used to quantify the impact of network structure on scenarios of the future, including the likely resilience of different parts of the travel network under scenarios of natural disaster Barthélemy (2011). This is a research area with great potential for the future. In this thesis, however, circuitry is the only quantitative description of the transport network to be implemented: in 5.4.4 circuitry is described as a mechanism to map the Euclidean distances reported in the census to the route distances reported in survey data.

- *Efficiency* (η): Efficiency is an important concept in transport and energy studies. As with its everyday use, often its meaning is not strictly defined in the transport literature. "This is not an efficient use of time" is a typical use of the term, meaning that the benefits (outputs) are low considering the time input.

Regarding energy use, the meaning is the same, although the mathematical definition allows for precision:

$$\eta = \frac{E_{out}}{E_{in}} \quad (2.6)$$

Where E_{out} is energy that is useful (e.g. electricity), and E_{in} is the primary energy input (e.g. calorific content of petrol). Of course, the definition of ‘useful’ is open to interpretation (Patterson, 1996), leading to various measures of efficiency, ranging from pure thermodynamic definitions¹⁵ through to economic-thermodynamic definitions¹⁶, to purely economic definitions¹⁷. The concept of efficiency — and related concepts of fuel economy and energy intensity — is well established in research on the energy requirements of freight transport (Kamakaté and Schipper, 2009). It has rarely been used to compare the performance of different transport modes, however (Fels, 1975; Lovelace et al., 2011).

A general principal of energy efficiency measures is that they should reflect the purpose of the process they describe (Patterson, 1996). In commuting, the transport of *people* is the aim, so the commonly used fuel economy metric (l/100 km) is not an appropriate measure of the performance of the system (Mackay, 2009). The preferred energy metric for this research is therefore energy intensity:

$$EI = \frac{MJ}{pkm} \quad (2.7)$$

The energy intensity of passenger transport modes are described (after a large body of evidence on the matter is considered) in section 5.7. In everyday speak when transport modes are described as ‘efficient’ people are generally referring to energy intensity rather than thermodynamic efficiency. Following this convention, ‘efficiency’ when used in this thesis also generally refers to energy intensity.

In terms of the energy costs of commuting, the preferred metric is the average energy costs per commuter per two-way commuter trip (MJ/trp). This is similar to the units of kWh/p/day used by Boussauw and Witlox (2009), but the denominator is the number of commuters in this study, not the number of people (making the results impervious to variable unemployment rates) here. To translate MJ into kWh, multiply by 3.6. The energy per trip results are presented in chapter 6 at a variety of scales.

¹⁵The efficiency of electricity production, for example.

¹⁶For example, the efficiency of freight transport can be defined as tonne-kilometres per unit energy input (tkm/MJ) (Simongáti, 2010). This hybrid economic-thermodynamic measure is more commonly expressed as fuel economy of freight, its reciprocal (MJ/tkm).

¹⁷This is measured as the proportion of an activity’s monetary cost that is spent on energy — the proportion of bus a bus fare that goes towards diesel costs, for example.

- *Resilience*: this is measure of a system’s capacity to function after enduring external shocks (Holling, 1973)¹⁸. Despite its origins in Ecology, the concept is applicable to any complex system, and is especially relevant to the relationships between the economy and the natural environment (Holling, 2001). In the sustainability literature, the term is rarely quantified (see Bridge, 2010). However, there has been progress in defining resilience mathematically for networks, which could theoretically be used to calculate the impacts of large collapses, such as blackouts, or, by corollary, failure of the transport network (Barthélemy, 2011). At present however, this quantitative branch of the resilience concept lacks empirical application. The term is harnessed to discuss the long term sustainability of commuter systems and their capacity to function in the event of oil shortages.
- *Inertia*: in its original physical definition, inertia is the characteristic of mass by which it “endeavours to preserve [itself] in its present state, whether it be of rest or of moving uniformly forward in a straight line” (Newton, 1848, p. 73). In the context of transport systems, inertia is used to describe ‘lock-in’ to the current transport system in the short term, and its resistance to change: “Transport systems and urban lay-outs have great inertia and take years to change” (Chapman, 2007, p. 365).

2.7 Summary of the literature

This chapter has highlighted the range of methodologies and disciplinary diversity of studies investigating the energy costs and greenhouse gas emissions of personal travel. The sustainable mobility paradigm provides a useful label that can be applied to much of this research, differentiating it from the traditional supply-side approach bemoaned in the opening quote. The majority of the literature in transport and energy is not concerned with such high level discussion, however, generally preferring to ‘let the facts speak for themselves’. The area of study is quite new (except for a flurry of work following the 1970s oil shocks, exemplified by Fels (1975)), perhaps explaining why geographical studies into energy use for transport are still largely descriptive (e.g. Marique et al., 2013; Boussauw and Witlox, 2009), content to explain spatial variability intuitively rather than with the use of a predictive model. This thesis takes a similar approach and is primarily concerned with *describing* the variability of commuter energy costs at geographic and individual levels. This appears not to have been done before in the UK.

¹⁸The seminal definition of resilience is that it is “a measure of the persistence of systems and of their ability to absorb change and disturbances”, while maintaining their functionality (Holling, 1973, p. 14).

Transport and energy use has been investigated from a wide range of disciplinary perspectives, from psychology and economics through to engineering and physics. This is because energy use depends not only on the efficiency of transport technologies, but also the behavioural factors that determine how they are used. Following this diversity, the research presented in this thesis is also explicitly multi-disciplinary: claiming allegiance to any one discipline would likely be at the expense of another, potentially hindering understanding of the complexity of factors at work.

The energy costs of transport, and their underlying causes, have been explored at a range of different scales. Individual factors including family and career commitments have an important role to play, but whether or not these can be modelled using quantitative data from surveys remains to be seen. At the regional level, geographical factors influencing energy use in transport have been explored with reference to the ‘compact city’ hypothesis. CO₂ emissions and energy studies have tended to operate at large national or regional levels, despite the fact that most transport planners and other decision makers implement policies (especially in the realm of active travel) at the local level. This suggests a gap in the literature and highlights the need for energy and transport studies focussed more locally. Moreover, because the factors affecting commuting behaviour operate at many levels, there is a need for further development of methods that allow factors operating at individual and geographical levels to be taken into account simultaneously.

Chapter 3

Spatial microsimulation and its application to transport problems

The modellers' task is to predict how people and organisations will live in 'good' and 'sustainable' cities; how the infrastructure will, or should, grow; and how activities and traffic flows are, where appropriate, best managed, priced and regulated.

(Wilson, 1998, p. 3)

Microsimulation can have variable meanings depending on whether you are a geographer, transport planner, or economist (see Ballas et al., 2005d; Liu et al., 2006; Bourguignon and Spadaro, 2006 for examples). This chapter reviews existing work that uses individual level data and modelling techniques to investigate transport and related problems. It also introduces static spatial microsimulation, a particular type of microsimulation that is central to the thesis. The method enables individual level and geographical variation in commuting behaviour to be analysed in tandem. Operational definitions, based on established research, are important for clarity, repeatability and to show how the work presented here builds on past research. A number of key terms will be frequently used throughout the thesis, so this chapter begins with definitions. This is followed by an overview of the history (section 3.2) and current state of the art (section 3.3) of the technique as it relates to transport issues such as travel to work.

As implied in the quotation above, transport does not happen in isolation from other phenomena. It is part of the complex web of social relations, the environment, infrastructures, economics, policies and decisions that define modern settlements. From this perspective, spatial microsimulation for transport applications is just one branch of a long-standing tradition of urban modelling (Wilson, 1970; Batty, 1976, 2007). Other branches

include dedicated transport modelling techniques (e.g. SATURN Software, 2012), integrated land-use transport models (Wegener, 2009) and agent-based approaches (Gilbert, 2008). These research areas are related to the thesis and in some cases have the potential to build on its results. In this chapter they are grouped together under the broad term ‘urban modelling’ and discussed in section 3.4. The final section of this chapter (section 3.5) summarises the literature and explains how it relates to methods implemented in the thesis.

3.1 Definitions: what is spatial microsimulation?

Microsimulation, as its name suggests, refers to the modelling of individual units — e.g. people, household, companies — which operate in a wider system. Used in this sense, the term originates in economics, where it signified a theoretical turn away from aggregate level analyses and towards a focus on individual behaviour. “This shift of focus, from sectors of the economy to the individual decision making units is the basis of all microsimulation work that has followed from Orcutt’s work” (Clarke and Holm, 1987, p. 145; see section 3.2.2 for further reference to this work). Microsimulation overall therefore has a wide meaning, from individual vehicles in a transport model (Liu et al., 2006; Ferguson et al., 2012) to the inventories of competing firms over time (Bergmann, 1990). The term has a narrower definition in this thesis, however, that is more concerned with modelling the distribution of behaviours of individuals over space than over time. This thesis is predominantly concerned with only one subset of microsimulation: spatial microsimulation, modelling the distribution of individuals over space. Within the category of *spatial* microsimulation, different types can be specified (section 3.3.1).

Spatial microsimulation of the static kind can be formally defined as follows: the simulation of individual level variables within the geographic zones under investigation (Ballas and Clarke, 2003; Ballas et al., 2007). The models that perform this operation have also been referred to as ‘population synthesizers’ (Mohammadian et al., 2010). This term is useful in the context of transport applications, because small area micro-population generation is only one stage of a wider process of individual level transport modelling (Pritchard and Miller, 2012; figure 3.1).

During static spatial microsimulation individuals are sampled from a non-geographical dataset via reweighting, based on what have become known as ‘constraint variables’ from early combinatorial optimisation work (Williamson et al., 1998). The key feature of these variables is that they are present in both individual level and geographically

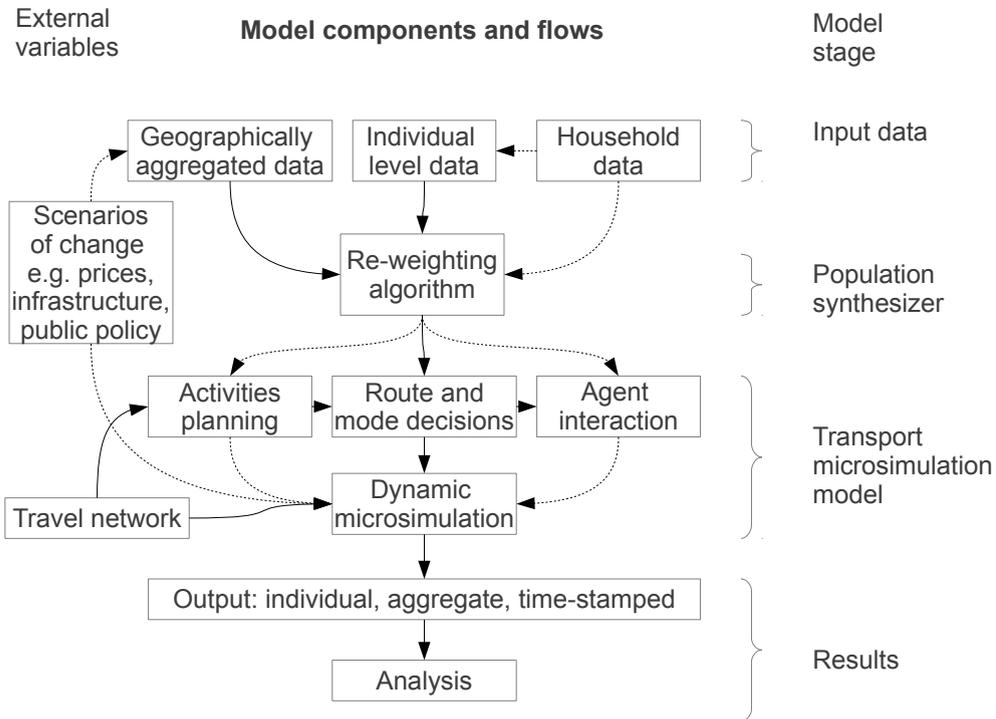


FIGURE 3.1: Schematic of the components of a complete transport simulation model such as TRANSIMS, after Nagel et al. (1999) and Mohammadian et al. (2010). This thesis is primarily concerned with the first two stages.

aggregated data sets.¹ Figure 3.1 shows the technique in the wider context of transport modelling. Spatial microsimulation here refers to only the top two stages in the diagram. It represents a computationally small but important (for social analysis at least) part of the wider simulation process. It is important to clarify this distinction, as the meaning of ‘spatial microsimulation’ can be ambiguous. It can refer either to the process of population synthesis (Chin and Harding, 2006; Ballas et al., 2005a; Hynes et al., 2008), or the entire urban modelling process that builds on the spatial microdata (Wegener, 2011). Spatial microsimulation here refers to the former case. The results could thus be harnessed as inputs into more complex dynamic models in which individuals interact with each other and other entities in a wider urban model. The terms *dynamic spatial microsimulation* or *agent-based models* will be used to refer to the wider modelling process.

¹Constraint variables must be categorical variables (such as ‘male’, ‘age: 16 to 19’ or ‘works 0 to 2 km away from home’) that are shared between the micro level data and known geographical aggregates, usually from the census. Continuous variables have not been used in the microsimulation literature reviewed, although they could theoretically be used, by constraining variables’ spread, skewness and central tendency.

Static spatial microsimulation (generally and henceforth referred to simply as spatial microsimulation) involves sampling rows of survey data (one row per individual, household, or company) to generate lists of individuals (or weights) for geographic zones that expand the survey to the population of each geographic zone considered. The problem that it overcomes is that most publicly available census datasets are aggregated, whereas individual level data are generally much more detailed (Ballas and Clarke, 2003). The ecological fallacy, whereby relationships found at one level are incorrectly assumed to apply to all others (Openshaw, 1983), for example, can be tackled to some extent using individual level data allocated to geographical zones (Hermes and Poulsen, 2012). This ‘spatial’ or ‘small area’ microdata is the output of spatial microsimulation.

Despite its ability to output geolocated individuals, spatial microsimulation should never be seen as a replacement for the ‘gold standard’ of real, small area microdata (Rees et al., 2002, p. 4). From the perspective of social scientists, it would be preferable for governments around the world to follow Sweden’s example and release such small area microdata anonymously. However, this prospect is unlikely to materialise in the UK in the short term, adding importance to the process of model validation. In any case, the experience of spatial microsimulation development and testing can help prepare researchers for the analysis of real spatial microdata. Also, the technique’s links to modelling make spatial microsimulation useful for investigating the impacts of policy or other changes in the real spatial microdata (Clarke and Holm, 1987). The method’s practical usefulness (see Tomintz et al., 2008) and testability (Edwards and Clarke, 2009) are beyond doubt.

Assuming that the survey microdataset is representative of the individuals living in the zones under investigation,² the challenge can be reduced to that of optimising the fit between the aggregated results of simulated spatial microdata and aggregated census variables such as age and sex (Williamson et al., 1998). These variables are often referred to as ‘constraint variables’ or ‘small area constraints’ (Hermes and Poulsen, 2012). The term ‘linking variables’ can also be used, as they *link* aggregate and survey data. Based on the literature, the technique seems to have been used for five main purposes, to:

- model variables whose spatial distribution at the aggregate level is otherwise unknown (e.g. Ballas et al., 1999).
- estimate the individual level distributions of variables within small areas about which only aggregate counts or summary statistics are known (e.g. distance travelled to work)

²The suitability of this assumption is further discussed in chapter 8.

- understand the spatial distribution of discrete behaviours (such as visiting ‘stop smoking’ centres — Tomintz et al., 2008) and thus the likely local level effects of policy change (Ballas and Clarke, 2001)
- project future changes at the local level, based on past trends (Ballas et al., 2005b)
- provide a foundation for agent-based models, which rely on discrete individuals (Ballas et al., 2007; Pritchard and Miller, 2012; Wu et al., 2010)

The main purposes of spatial microsimulation here are related to bullet points one and two above. However, elements from each will be harnessed at some point. In essence, spatial microsimulation merges individual level data (a list of individuals, each with their own ID) with geographical data (a list of zones, each with its own ID). It therefore relies on two types of input data:

The *microdataset* is the individual level data from which individuals are weighted or probabilistically selected. It is referred to as the survey dataset (Wu et al., 2008) or simply as ‘individual data’ (Simpson and Tranmer, 2005). The input microdata should be as representative of the zones being studied as possible³ and sufficiently diverse.

The *constraint variables*, ‘small area constraints’ or ‘linking variables’ are the aggregate level variables that link the zonal and individual datasets together. They must (for current methods, at least) be categorical and the categories in the two datasets must be the same (re-categorisations may be needed).

Target variables are the variables that spatial microsimulation seeks to estimate. Typically they are not reported at all at the small area level (e.g. income), leading to the term ‘small area estimation’ being used to describe spatial microsimulation when it is used to estimate the average values of unreported variables for small areas. But spatial microsimulation can also be used to simulate the distribution of variables that are already known. Thus, although distance is a constraint variable in our model, it is also in some ways a target variable: little is likely to be known about its distribution within each distance bin. Finally, counts of interaction variables (e.g. male, over 50, high social class and car driver) are typically not reported from the Census. These can therefore also be referred to as target variables. Overall, target variables is the term given to the information targeted for estimation by the spatial microsimulation model.

³For example, the date of survey data collection should be close to date of at which the zonal data was collected. Also, the survey data should preferably be from the same geographic region as the zones under investigation, or at least weighted so that individuals from the region under investigation are more likely to be sampled (Ballas et al., 2005c). An alternative way of making the survey dataset more representative is to preferentially sample individuals from areas with the same classification as the their zone being modelled.

Reweighting is the process by which individuals are assigned a weight for each of the zones under investigation. Harland et al. (2012) provide an overview of the methods available for this process, which is also known as ‘population synthesis’. The higher the weight for a particular area, the more representative is the individual of that area, compared with the rest of the survey dataset. Combinatorial optimisation and deterministic reweighting are the two main methods for reweighting (Hermes and Poulsen, 2012).

Combinatorial optimisation is an approach to reweighting that uses repeated randomised sampling to repeatedly select individuals from the survey microdataset and allocate them to zones (Williamson et al., 1998; Voas and Williamson, 2000). Based on the fit between simulated and known aggregate counts after each iteration, the parameters of the resampling algorithm can be adjusted (e.g. via simulated annealing).

Deterministic reweighting refers to non-random methods of allocating weights to individual-zone combinations (Ballas et al., 2007; Tomintz et al., 2008). Iterative proportional fitting (IPF) is a widely used deterministic reweighting algorithm and is used in the spatial microsimulation model throughout. Whole cases are generated using integerisation.

Integerisation is the process by which integer weights are generated from the non-integer weight matrix (see section 4.7).

Cloned individuals are rows in the survey microdataset that have been replicated more than once in the spatial microdataset for a particular area (Smith et al., 2009). The cloning of individuals can be represented by an integer weight above one, or simply by repeating identical rows multiple times. In practice these two forms of representing data are interchangeable; the latter takes up more disk space (Holm et al., 1996) but may make certain types of analysis easier.

3.2 The history of spatial microsimulation

This section outlines the history of spatial microsimulation. It would be easy to repeat past work here.⁴ To avoid this, the focus is on developments that influence the way spatial microsimulation is and can be used for transport applications. These include:

- the influence of location on individual behaviour via transport costs
- the question of data vs theory driven approaches
- converting a spatial microdataset into a behavioural model

⁴Readers interested in a comprehensive history of the field are directed towards Ballas and Clarke (2009).

- the impact of rapidly advancing computers and data sources

These themes are present throughout the section, which is ordered roughly chronologically.

3.2.1 Pre-computer origins

The theoretical origins of spatial microsimulation stretch back to before the turn of the 20th century. It was only with the emergence of large scale data sets, methods of analysis and conventions of mathematical notation that quantitative analysis of variables that vary over time and space could actually occur (Ballas and Clarke, 2009). Despite (or perhaps partly because of) the absence of these pre-requisites for the analysis and simulation of large populations at the individual level, much progress was made in thinking about how individuals behave within environments that vary in predictable ways over space before computers were available. Consideration of travel costs (which were much higher before most people travelled by motorised modes) was integral to both Christaller's central place theory and Von Thünen's concentric agricultural zones. Lacking reliable data with which to test their ideas, the early quantitative geographers had to make do by developing theories based on personal observation. Some of these theories are still influential today (Clarke and Wilson, 1985). Ideas developed in the pre-computer age can be seen as the theoretical forefathers of the microsimulation models of transport behaviour, and frameworks for interpreting the results, that are in use today.

One explanation for the greater theoretical focus of pre-computer work is that empirical data seldom fit into any neat model and therefore distract from explanation. This point was made as early as the 1970s, accompanied by the warning that the accelerating deluge of new datasets and quantitative methods was leading some to conflate quantification with theory (Wilson, 1972). Much theoretical work has been done since this cautionary tale. Yet the same problems of being blinded by new information (to the detriment of deductive thinking) face modellers now, probably to a greater extent. This, in combination with the fame enjoyed by early theoretical geographers (as opposed to more recent empirical geographers who modified or rejected their work), goes a long way to explain why researchers continue to cast back to the pre-computer age for theoretical insight. Two of the early theories that are most pertinent to simulation of travel patterns are Von Thünen's, on the spatial distribution of agricultural activity and Christaller's central place theory.

Von Thünen's work in the early 1800s is a seminal example of this early theoretical thinking. His model of concentric zones of agriculture was described verbally and in

the evolving language of mathematics but rarely tested on real data (Moore, 1895).⁵ Von Thünen's work exerts a strong influence, even in the 21st century (e.g. Lankoski and Ollikainen, 2008) due to its use of geographically defined variables, strictly defined assumptions and extensibility (Sasaki and Box, 2003). The approach describes individual units based in Cartesian space, that can be seen both as discrete zones, or as a continuous variable (as an input into the cost of travel) (Stevens, 1968). The model's insight into the variability of individual level behaviour depending on their zone of habitation can therefore be seen as a direct precursor to spatial microsimulation models. These also seek to describe the characteristics and behaviour of individual units living in geographical zones.

Walter Christaller's central place theory of the 1930s provided an integrated theory of spatially variable behaviour (primarily shopping) and the location of settlements of varying sizes (Matthews and Herbert, 2008). Based on the assumption of a continuous and even geographical space ready for urban growth, the theory proved fertile for hypothesis testing and extension to other sectors. Following Von Thünen, Christaller attempted a 'scientific' explanation of the behaviour of individuals based on where they live. The mechanistic nature of the approach has since been superseded by more advanced and probabilistic models yet central place theory continues to influence many areas of spatial modelling (Wilson, 1972; Sonis, 2005; Farooq and Miller, 2012). Applied to commuting, the theory provides a ready made model about where people travel to work: the settlement that can provide the best pay, minus travel costs. Of course, both pay and travel costs vary greatly depending on a number of individual and geographic variables that cannot be known in every case. However estimates can be made (even in the absence of now readily available data) and applied stochastically. This theoretical approach has subsequently helped explain spatial distributions in travel to work patterns, using models based on Christaller's ideas (Tabuchi and Thisse, 2006). Christaller was a major advocate of explaining theories in mathematics: "the equilibrium of the location system ... can only be represented by a system of equations" (Christaller, 1933; quoted in Wilson, 1972, p. 35). More recent research suggests that urban systems are rarely in equilibrium (Batty, 2007). In any case, Christaller provided a hypothesis about why some settlements grow more than others, attracting more people, trade and commuters. More prosaically, Christaller's theory also helps explain why long-distance commuting appears to be more common into large cities than small ones (see chapter 6).

The preceding discussion provides only a small snapshot of pre-computational spatial analysis, based on two influential thinkers. The focus was on deductive reasoning, rather

⁵For example, "although [Von Thünen] claims that his advantage over Ricardo consists in his ability to reduce the co-operation of capital to terms of labour, the validity of that claim has not been tested" (Moore, 1895, p. 126).

than inductive methods, whereby large amounts of data are processed in the hope of finding some underlying pattern. This emphasis can provide a lesson for the future: despite the clear disadvantages faced by researchers before the digital revolution, one advantage they seem to have had a clear theoretical focus and this may have been due in part to absence of large and distracting datasets and computers. The danger that this historical perspective flags is that the masses of micro level data now available could distract from explanation. As Wilson (1972) emphasised, it is explanation and theory development, not mere description, that enables a discipline to progress.

Despite this risk, the emergence of powerful computers have allowed theories to be developed and tested in ways that were previously impossible. The digital revolution can thus be seen as the single most important event in the history of spatial simulation.

3.2.2 The digital revolution

At the present time, the speed and capacity of electronic computers would still put economic limits on the number of units that could be handled in the above fashion.

(Orcutt, 1957, p. 120)

After World War II a number of factors drove interest in modelling human behaviour and transport. Important among these were a couple of influential new technologies: the mass produced car and electronic computers. The former expanded rapidly in the West before the oil price shocks of the 1970s, during a sustained period of stability and economic growth. Nowhere was this more apparent than in the USA, where the rapid uptake of the car was forcing planners to reconsider city layouts in order to cope with the influx. Linked to this pressure, the broadly defined art/science of ‘Urban Modelling’ also began, originating in the USA (Batty, 1976) and continuing to this day in a paradigm that can be described as the ‘science of cities’ (Batty, 2012).

In the early phase of this research program, planning for the future of cities in a resource-constrained world was a research priority for some, even before the severity of environmental problems such as climate change was fully understood (Rouse and Smith, 1975). The potential of numerical models to tackle the mismatch between economic development and resource and energy issues was not overlooked, although models were also used to investigate how best to accommodate anticipated growth in populations, economies and car use (Irwin and McNally, 1973). Still, there were calls to harness these newly discovered methods for consideration of the relative performance of radically different options from first principles (Manheim et al., 1968; The Urban Institute, 1972).

Beyond changing mobility patterns (the impact of which was largely to provide motivation, but not method), it was the appearance of computers that drove forward and facilitated progress in the field. Although many now take fast and efficient processors for granted, for example by using hand-held computers to play ‘Angry Birds’ and check Facebook accounts, computers increasingly are used in vital areas of daily life, from education to the design of traffic lights. The digital revolution should not be seen as a single transformative event: it is an ongoing and accelerating set of changes in the way information is stored, processed and communicated. Combined with the internet, the digital revolution has ongoing impacts on society (Rushkoff, 2011), including travel to work patterns (Orloff and Levinson, 2003) and of course the methods available to investigate human behaviour over space.

As with other areas of rapid technological progress, there is no fixed point at which there is ‘enough’ computing power to solve the most pressing issues: an interesting phenomenon with computing power is that, much like the problem of roads driving demand for driving up, the more there is the more demand grows. Throughout the 20th century computing power was often seen as *the* limiting factor preventing accurate simulation of social systems.⁶ This is no longer the case: “Modern computing is now sufficiently powerful to deal with most [urban] models ... models based on individuals are now feasible both in terms of their computation and their representation using new programming languages” (Batty, 2007, p. 5).

Regardless of our insatiable thirst for processing power, these external factors — the digital revolution and wider societal changes embodied in the car — undoubtedly drove forward research seeking to understand and model transport systems in detail. The aim was to harness the marvel of computing power to better understand the rapid shifts taking place. This was most apparent in applied urban modelling: “Increasing car ownership during the 1940s and early 1950s led to the growing realisation that cities with their traditional physical form could simply not cope with the new mobility” (Batty, 1976, p. 6). The new methods formed an important tool for enabling planners to deal with this shift. Some of the descendants of this early transport modelling work are described in section 3.4.1.

⁶This is well illustrated by the quote that begins this section. To put the quote into its proper context, consider the following: the IBM 704 had the equivalent of 18,432 bytes of RAM. This was the first mass produced computer and was considered as the state of the art at the time of Orcutt’s paper: subsequently in the article it was referred to as a ‘powerful giant’ (Orcutt, 1957). Now one can purchase a laptop with 16 Gigabytes of RAM for approximately 5% of average UK wages (£1,000). This is 1,000,000,000 times more memory than was available to the IBM, operating millions of times faster and costing thousands of times less in real terms. Yet still people complain about lack of computing power! In other words, as computing power has advanced exponentially, approximately by Moore’s law — which accurately predicts the exponential shrinkage of electronic components, by a factor of 0.7 every 3 years (Kish, 2002) — our hunger for more and faster processing has increased even faster.

3.2.3 Statistical methods for estimation

In statistics too, more sophisticated methods were being considered during and after World War II. Increasingly large and complex datasets were an additional driver of advancement here: the increased automation and rigour of data collection led to new data management problems. Placing his seminal work on iterative proportional fitting (IPF) in context, Deming (1940, p. 427) provides the following example of this data-driven methodological development: “in the 1940 census of population a problem of adjustment arises from the fact that although there will be a complete count of certain characters for the individuals in the population, considerations of efficiency will limit to a sample many of the cross-tabulations (joint distributions) of these characters.” In other words, IPF was developed not to simulate populations but to fill in empty cells in situations where storing all possible cross-tabulations of categorical data was not feasible or where internal cells needed to be updated based on new marginal constraints: “The iterative proportional fitting method was originally developed not for fitting an unsaturated model to a single body of data but for combining the information from two or more sets of data” (Bishop et al., 2007, p. 97). To provide a concrete example of this “classical” use of IPF, Bishop et al. (2007) reproduce Friedlander (1961) who updated cross-tabulations of counts of women by age and marital status from the complete 1957 table by 1958 margins. More than 50 years later, IPF was still in use, to tackle the same issue (Jiroušek and Peučil, 1995).

Parallel to these developments the concept of ‘entropy maximisation’ emerged. This method aims to “produce the maximum-likelihood estimate — the distribution [of cell values] that is most likely to occur given no other constraints [on their marginal totals] than those imposed” (Johnston, 1985, p. 95). Originally proposed and formalised mathematically in the field of statistical mechanics (Jaynes, 1957), the concept was used to estimate probability distributions that satisfy all conditions without making any further assumptions about the data. “Mathematically, the maximum entropy distribution has the important property that no possibility is ignored; it assigns positive weight to every situation that is not absolutely excluded by the given information” (Jaynes, 1957, p. 623). This definition is very similar to the maximum likelihood estimate attained through iterative proportional fitting. The mathematics underlying entropy maximisation is complex, involving Lagrangian multipliers and a series of interrelated equations containing exponentials (Jaynes, 1957). Its relevance here is that it is a way of estimating unknown probability distributions, based on a limited set of constraints. In the language of spatial microsimulation, this means calculating internal cell values based on marginal constraints. Thus entropy maximisation can be used to estimate the maximum likelihood of individual level attributes for areas about which only counts are available.

Because of this, iterative proportional fitting has been shown to be a specific form of entropy maximisation (Beckman et al., 1996; Ye et al., 2009; Rich and Mulalic, 2012).

It was not until the 1990s that IPF (and, often unconsciously, entropy maximisation) was discovered by human geographers and ‘put on the researcher’s desk’ (Norman, 1999) for spatial microsimulation.⁷ An early advocate was Wong (1992); early applications that produced spatial microdata included Birkin and Clarke (1988), who used IPF in combination with Monte Carlo sampling to create completely synthetic microdata. Ballas et al. (1999) used IPF to allocate individual level survey data to areas. Mitchell et al. (2002) used IPF to create cross-tabulations of categorical marginal totals to investigate the changing geography of health inequalities in the UK.

Deming’s methodological innovation was not especially outstanding in the context of rapidly advancing 1940s statistics, but it is worth considering in more detail. The IPF procedure that it was built upon (Deming, 1940) is now frequently used in spatial microsimulation models for automatically allocating individuals from a survey dataset to the zones for which they are most representative. New applications and refinements to Deming’s method continued in the proceeding years within statistics (Stephan, 1942; Friedlander, 1961), although the term ‘iterative proportional fitting’ was only used to describe it after Fienberg (1970). Since then, IPF has continued to be refined and applied to various statistical problems involving the estimation of missing data, but these advances are generally contained in a literature that is separate from the body of work that is the focus of this chapter.⁸ The reasons for using IPF instead of combinatorial optimisation or other related methods of discrete multivariate analysis described in Bishop et al. (2007) include speed of computation, simplicity and the guarantee of convergence (Deming, 1940; Mosteller, 1968; Fienberg, 1970; Wong, 1992; Pritchard and Miller, 2012). Rich and Mulalic (2012) endorsed IPF over alternatives in the context of transport modelling. Summarising past literature, they state that IPF can arrive at the same (maximum likelihood) result as other maximum entropy (ME) approaches, but faster: “The popularity of the IPF is therefore mainly due to the fact that it provides a solution which is equivalent to that of the ME approaches, but attained in a much more computationally efficient way” (Rich and Mulalic, 2012).

⁷There were a few earlier exceptions, including its application to model the diffusion of Dutch Elm disease in the UK (Sarre, 1978).

⁸As a relevant aside, history of IPF provides an interesting example of fragmentation in academic research, as the statistical community continued to use Deming and Stephen’s method of estimating internal cell values based on known marginal subtotals, but using a totally different name: “The methodology became known as ‘raking’ and found widespread application in sampling, especially at the US Census Bureau and other national statistical offices” Fienberg and Rinaldo (2007). It is important to note this divergence, as the statistical uses of IPF (or ‘raking’) have the potential to aid the technique’s usage in spatial microsimulation.

It was only with the intervention of Guy Orcutt that such methodological advancements were combined with new computing capabilities to provide new possibilities for social science, based on the simulation of individuals. Although Orcutt is often cited as one of the founders of social simulation, arguably his most important contribution was to place computerised methods in a wider conceptual framework of policy analysis. Instead of using a single ‘representative agent’ with averaged values, the microsimulation method enabled the evolution of multiple micro units to be traced, under different scenarios (Mitton et al., 2000, p. 176). This helps explain why Orcutt (1957; 1961) is frequently cited as one of the founding fathers of the field (e.g. Clarke et al., 1989; Wu et al., 2008; Ballas et al., 2012). Granted, he successfully exported the concept of manipulating individual level variables based on estimated probabilities of change, but Orcutt was not particularly interested in spatial analysis.⁹ Building on Orcutt’s methods, simulation grew popular in the increasingly quantitative social sciences. Uptake was greatest in economics, where the technique gained a strong following as a method for evaluating the impact of changing policy and economic conditions at the individual level (see Merz, 1994 for an overview). The branch of microsimulation associated with spatial problems emerged later (Tanton and Edwards, 2013a), although it has clear links with earlier shifts towards modelling within the wider field of quantitative geography (e.g. Clarke and Wilson, 1985).

The shift to the practical application of microsimulation to explicitly *spatial* problems was not to happen until around 30 years after the 1960s applications. This can partly be attributed to the computational limits emphasised by Guy Orcutt at the outset of this chapter, but partly also to a disinterest in quantitative models on the part of geographers. A seminal paper (Clarke and Holm, 1987) reviewed the limited experience of microsimulation models for spatial applications up to that point. The authors warned of “the possibility of the method being reinvented by different researchers independently” if the new techniques continued to be ignored by geographers (Clarke and Holm, 1987, p. 145) and provided a coherent argument in favour spatial microsimulation, culminating in the following conclusion: “With micro-modelling it is possible to use and formulate theoretical concepts and hypotheses about social action on at least the same level of detail as sometimes found in other social sciences without neglecting the apparent and

⁹Although Orcutt was instrumental in advocating and demonstrating micro level methods for policy evaluation, he was more concerned with time than he was with space. Neither IPF nor combinational optimisation, two of the main tools used for generating spatial microdata in spatial microsimulation research today, are mentioned in his seminal works (Orcutt, 1957; Orcutt et al., 1961). Instead, he laid down the tantalizing possibilities of simulating society, in very general (and seldom validated) terms, using the newly available mainframe computers. The following is a typical example of the clarity, enthusiasm and sense of purpose of his vision: “The following method is feasible, readily comprehensible and may serve to illustrate still further the proposed model. Using this approach the model would be simulated on a large electronic machine, such as the IBM 704 or the UNIVAC II, or some improved successor to these powerful giants” (Orcutt, 1957, p. 119).

important elements of spatial interdependence seldom found in studies outside geography” (Clarke and Holm, 1987, p. 163). Thus the gauntlet was laid down to future researchers entering this emerging field: develop spatial microsimulation models to take advantage of newly available computers, programming languages and datasets. Since then “the speed of development has gathered pace” (Clarke and Harding, 2013, p. 259). Spatial microsimulation is now a field of social and spatial analysis in its own right, with an expanding range of applications.

3.2.4 Modern spatial microsimulation

Geographers are not generally taught computer programming. This, and the ‘erosion of quantitative literacy’ (ESRC, 2013) helps explain why spatial microsimulation has been limited to a small field within geography and related disciplines. Spatial microsimulation now constitutes “a relatively small community” that can be considered a field in its own right (Wilson, in Tanton and Edwards, 2013b, p. vi).

This community can roughly be identified as those with links to the International Microsimulation Association (IMA), who publish spatial microsimulation work in peer reviewed journals¹⁰ and whose work is referred to in recent overviews of the field (Tanton and Edwards, 2013b; O’Donoghue et al., 2013). In summary, spatial microsimulation has emerged from pre-computer origins and mid 20th century theoretical quantitative geography to tackle the research challenge set out by Clarke and Holm (1987). Since powerful computers became available at the turn of the 21st century, methods and applications have proliferated and accelerated. Spatial microsimulation now provides small-area estimates of individual level variables and projections of future change. Transport, along with a number of other phenomena, has been identified as an area for future application of the modelling framework (Clarke and Harding, 2013).

3.3 Spatial microsimulation: state of the art

Spatial microsimulation can now be seen as a field in its own right, with roots in Economics, Geography, Statistics and Regional Science. It is evolving, so any rigid definition of the ‘state of the art’ is likely to become obsolete quickly. Instead, the scope of spatial microsimulation is explained below in terms of the types and applications of models in use, the variety of reweighting algorithms and recent transport applications.

¹⁰The following journals are common places for the publication of spatial microsimulation research: *Computers, Environment and Urban Systems*, *The international Journal of Microsimulation*, *Journal of Artificial Societies and Social Simulation* and *Environment and Planning A*. Applied spatial microsimulation research is also published in a wide range of regional science and geography journals.

3.3.1 Types of spatial microsimulation models

The wide range of methods available for spatial microsimulation can be divided into static, dynamic, deterministic and probabilistic approaches (Table 3.1). Static approaches generate small area microdata for one point in time. These can be classified as either probabilistic methods which use a random number generator and deterministic reweighting methods, which do not. The latter produce fractional weights. Dynamic approaches project small area microdata into the future. They typically involve modelling of life events such as births, deaths and migration on the basis of random sampling from known probabilities on such events (Ballas et al., 2005a; Vidyattama and Tanton, 2010); more advanced agent-based techniques, such as spatial interaction models and household level phenomena, can be added to this basic framework (Wu et al., 2008, 2010). There are also ‘implicitly dynamic’ models, which employ a static approach to reweight an existing microdata set to match projected change in aggregate level variables (e.g. Ballas et al., 2005c).

TABLE 3.1: Typology of spatial microsimulation methods

Type	Reweighting technique	Pros	Cons	Example
Deterministic	Iterative proportional fitting (IPF)	Simple, fast, accurate, avoids local optima and random numbers	Non-integer weights	(Tomintz et al., 2008)
	Integerised IPF	Builds on IPF, provides integer weights	Integerisation reduces model fit	(Ballas et al., 2005a)
Re-weighting	GREGWT, generalised reweighting	Fast, accurate, avoids local optima and random numbers	Non-integer weights	(Miranti et al., 2010)
Probabilistic	Hill climbing approach	The simplest solution to a combinatorial optimisation, integer results	Can get stuck in local optima, slow	(Williamson et al., 1998)
	Combinatorial optimisation	Simulated annealing	Avoids local minima, widely used, multi level constraints	Computationally intensive (Kavrouidakis et al., 2012)
Dynamic	Monte Carlo randomisation to simulate ageing	Realistic treatment of stochastic life events such as death	Depends on accurate estimates of life event probabilities	(Vidyattama and Tanton, 2010)
	Implicitly dynamic	Simplicity, low computational demands	Crude, must project constraint variables	(Ballas et al., 2005d)

In practice, the typology presented in table 3.1 is an oversimplification. The spatial microdata generated during the same spatial microsimulation project can be used for both static and dynamic applications and different reweighting algorithms can be applied to the same dataset with similar results. Spatial microsimulation can thus be seen as an evolving process rather than a ‘once-through’ analysis. A typical spatial microsimulation

project, for example, may involve some or all of the following four steps (the first four are from Ballas and Clarke, 2003):

- construct a micro-dataset, usually from surveys
- reweight the individual level data to create a spatial microdataset
- static what-if scenarios (implicitly dynamic scenarios in table 3.1) to assess the impact of instantaneous change
- agent-based modelling, to better understand how the individuals in each zone interact with the environment and each other

3.3.2 Reweighting algorithms

To run a spatial microsimulation model, a prerequisite is a mechanism by which individuals from the survey are selected to ‘populate’ the areas under investigation. For the technique to be worthwhile, it is vital that individuals who are in some way representative of each area should be selected (Ballas et al., 2005b). Doing this manually is clearly not feasible, so a number of computerised techniques have been developed to create weight matrices automatically. This section provides an overview of the reweighting techniques that have been used in published research; the findings fit directly into the choice of microsimulation model used in this research.

Reweighting algorithms allocate individuals counts or weights for target areas based on a number of matching or linking variables that are shared between area and survey datasets. A number of options are available and these can be broken down into the following categories: deterministic/randomised, integer/ratio and count/weight. The option used in this thesis is deterministic sampling based on IPF. This reweighting procedure was chosen due to the repeatability of the results,¹¹ relative simplicity and past experience with the technique.

Randomised (combinatorial optimisation) sampling strategies have the advantage of robustness against local optima, which may mean that deterministic models may not always arrive at the optimal solution (Williamson et al., 1998). Also, a combinatorial optimisation sampling strategy has the inherent advantage of keeping individuals as integers (as opposed to deterministic reweighting, which results in fractional weights). This makes it easier to understand the simulated population, analyse the results (e.g. the

¹¹ “One advantage of a deterministic model is that the estimated population distributions will be the same each time the model is run” (Smith et al., 2009). Thus, the results of any model to be replicated without the need to “set the seed” of a known list of Pseudo-random numbers (Robert and Casella, 2009): this makes results easier to test and update when new data emerges.

Gini Index calculation is more straightforward if integer weights are used) and select subsets of the simulated population with certain characteristics. In addition, integer weights are needed for agent-based models. On the other hand, integer results can be associated with large differences between simulated and actual cell values (Ballas et al., 2005b).

In order to calculate the probabilities of survey individuals appearing in statistical areas, iterative proportional fitting (IPF) has been used. By altering the cell values in a 2 dimensional matrix, IPF is used to match “disaggregated data from one source with the aggregated data from another” (Norman, 1999, p. 1). This is done iteratively: each iteration brings the column and row totals of the simulated dataset closer to those of area in question.

Another, more fundamental, disadvantage of IPF is its inability to simulate individuals based on data at multiple levels, for example household and individual: “it can control either for agent level or for group level attributes but not for both simultaneously” (Axhausen and Müller, 2010, p. 5). This problem has long challenged researchers because “working at the household/family and person levels simultaneously can introduce conflicts between the competing goals of achieving good fit at both levels” Pritchard and Miller (2012, p. 694). Pritchard and Miller (2012) have tackled this problem by matching either individuals to known family attributes, for example based on conditional probabilities of the spouse sharing given attributes (age, level of education). These results offer the promise of allowing family level microdata generation from deterministic reweighting algorithms such as IPF.

Despite the wide range of reweighting options available and even wider range of implementations, there has been relatively little work comparing different approaches. Most model experiments evaluate goodness-of-fit for only a subset of reweighting algorithms, changing just one or two variables at a time (Voas and Williamson, 2000; Smith et al., 2009; Rahman et al., 2010). Another problem is the wide range of evaluation tools on offer, leading to confusion about which method is appropriate for a given application: “Different researchers use different methods to test the reliability of their results. This makes it more difficult for ‘outsiders’ to evaluate the value of a model or set of artificial population data” (Hermes and Poulsen, 2012, p.282). This issue is tackled with respect to the problem of integerisation in section 4.7 and discussed in more general terms in section 4.6.2. One group of ‘outsiders’ that could benefit from more accessible code and reproducible testing of it is the transport community, who are increasingly turning to spatial microsimulation to meet the need to include social factors in scenario evaluation.

3.3.3 Transport applications

It was mentioned in section 3.1 that ‘population synthesis’ is a synonym for (static) spatial microsimulation. The term is used by transport modellers to describe the process of generating individuals as inputs into wider transport models. Thus spatial microsimulation is used in transport applications. Whether to classify any given transport study as spatial microsimulation for transport analysis, or a transport model with spatial microsimulation ‘bolted on’, is a question of semantics not dwelt on here.¹² In any case, there is clearly a large degree of overlap between the two approaches. This section describes transport research that focuses on the individual (human, not vehicle) level, primarily through spatial microsimulation. Section 3.4.1 outlines dedicated transport models, which can also harness spatial microsimulation data as an addition to assess social impacts.

Transport modelling has a long history with strong links to engineering,¹³ strategic planning (Wilson, 1998) and hence large contracts. Aggregate economic return on income has thus played a central role in project evaluation and has become a focus of various modelling efforts (Masser et al., 1992). Perhaps due to this narrow technical and economic heritage, traffic models have tended to omit people from the analysis. Technical questions, such as ‘how much congestion will intervention x alleviate?’, predominate, rather than social questions more common in spatial microsimulation research such as ‘which groups will benefit most from intervention x?’. Thus it has been rare for socio-economic variables to be included in the model-based evaluation of transport projects, although social impacts are increasingly considered (Masser et al., 1992; Tribby and Zandbergen, 2012). This explains growing interest in spatial microsimulation for transport applications. It is in this context — a divide between the transport community, with its focus on traffic and aggregate economic performance and the spatial microsimulation community, with its focus on distributional impacts and public policy — that these studies are conducted.

Pritchard and Miller (2012) advocated harnessing spatial microsimulation for methodological reasons, including the computational benefits of sparse data storage for transport

¹²Ballas et al. (2012) treat activity-based transport models as an add-on to spatial microsimulation methods. The approach taken here is to deal with spatial microsimulation models that have some transport considerations added-on (this section) separately from dedicated transport models that also simulate individuals (section 3.4.1).

¹³The strength of engineers’ influence is emphasised in the following passage: “If the main brief of the planners is to recommend the ‘shape’ of cities, then it is usually left to the engineers to design, build and manage the transport systems. Engineers, therefore, can use models as design tools: for predicting loads ... network optimisation ... they will have concerns with project appraisal” (Wilson, 1998, p. 16).

models.¹⁴ These efficient data structures have origins in early spatial microsimulation research (Clarke and Holm, 1987; Williamson et al., 1998) and have the additional benefit of providing ready-made inputs into agent-based transport models such as ILUTE (see section 3.4.1).

PopGen is a program used to generate spatial micro-data on the characteristics of individuals living, and using transport services, in the study region (Ravulaparthi and Goulias, 2011). It is essentially a static spatial microsimulation model that combines non-spatial survey data with ‘marginal tables’ (constraint variables). Three input files can be used at each level — individual, household and optional ‘groupquarters’ (these are generally students living away from home) — leading to a high level of detail. The use of iterative proportional updating (IPU) is key to the ability of PopGen to simultaneously match individual and household level characteristics, during the process of allocating individuals to household (Ye et al., 2009). PopGen is made freely available to anyone from Arizona State University and has been used as a population synthesizer for other transport studies (Pendyala et al., 2012).

Popgen-T is a different (albeit confusingly similar in name) population synthesiser developed specifically for the purpose of analysing the distributional impacts of new transport schemes such as congestion charges (Bonsall and Kelly, 2005). The method uses IPF to combine data from a very wide range of sources, although the exact mechanism is not explained.¹⁵ Since the 2005 paper, no further implementations of the Popgen-T method could be found.

3.4 Microsimulation in urban modelling

Urban modelling goes beyond the estimation of individual level characteristics, as performed in spatial microsimulation. It attempts to include influential factors from the entirety of urban experience, from house prices and the labour market to the transport network and land-use. It is therefore inherently an ambitious project, that could claim to encapsulate transport models and explain travel to work patterns in their wider context. Only recently have data and computational power emerged to make this ‘dream’

¹⁴Sparse storage here refers to data structures whereby only non-zero values are stored and replication weights are used instead of repeating statistically identical individuals multiple times. This also avoids problems associated with arbitrary categories, e.g. for age: “Complete array storage is proportional to the number of categories used for each attributes, while the sparse storage scheme is not affected by the categorization of the attributes” (Pritchard and Miller, 2012, p. 691).

¹⁵In the 2005 paper, the following information on data sources was provided: “The data sources used in this application include the Household Census, the National Travel Survey, the Journey to Work Census, the Household Income Survey, The Household Expenditure Survey, the New Earnings Survey and a number of local travel surveys” (Bonsall and Kelly, 2005, p. 410). The data are further explained in a 2002 working paper, but this could not be found.

reality; many of the approaches to urban modelling are related to this research. The most relevant are outlined below.

Five entities central to any urban model have been identified by Wilson (2000) and it is the interaction between these that determines the final model outcome. The importance of each for influencing commuter flows, level of data availability and ease of incorporation into quantitative models is presented in table 3.2. Ultimately, these considerations should determine whether, and at what stage, each of these entities are included in urban models. Based on the basic multi-criteria analysis presented in table 3.2, the following

TABLE 3.2: Five entities central to urban modelling, after Wilson (2000)

Entity	Data availability	Importance for commuter flows	Ease of model inclusion
People	High: commuting data collected in the Census and surveys	High: personal behaviour	High: individuals are basic unit of analysis
Organisations	Low: rapid change (especially in private sector operators) and poor accountability in many cases	Medium: councils and companies influence travel patterns	Low: organisations often diffuse bodies
Commodities, goods, services	Low: petrol sales and bus ticket data not publicly available	Medium: travel is affected by price of fuel	Medium: can be defined by price of oil; depends on elasticity
Land	High: maps of terrain and land use readily available	Medium: network distance and terrain alter travel behaviour	Medium: via influence of topology and distance
Infrastructure	Medium: Open Street Map and Ordnance Survey data	High: personal travel depends on infrastructure	Medium: can influence local travel decisions

hierarchy of entities for inclusion was established, in descending order of priority:

people > infrastructure > land > commodities > organisations.

This priority list was considered when compiling the data in chapter 4, although only the first and second are included in the methods of this thesis. Due to the importance of road network planning, much of the research in the broader field of urban modelling is dedicated to the development of dedicated transport models, which focus on the second element of Wilson's (2000) list.

3.4.1 Dedicated transport models

Transport modelling is a large field within the wider framework of urban modelling. It has a long history, but has undergone a rapid evolution in the last decade, largely due to the emergence of the internet, which allows large collaborative software projects to flourish. Three dedicated transport models, of increasing levels of sophistication have been selected from the vast array of options to illustrate the state of transport modelling and its relation to this thesis (see Rasouli and Timmermans, 2012 for a technical review).

SATURN is a commercial transport model, originally developed at the University of Leeds (Boxill and Yu, 2000). Its current incarnation is version 11, a stable package running only on Windows (SATURN Software, 2012). The SATURN model is a mature tool for determining traffic loads on road networks given a known origin-destination flow matrix, and is used for this purpose in local authorities in the UK (Boyce and Williams, 2005).

OpenTraffic addresses many of the issues arising from commercial, closed-source traffic simulation models such as SATURN: “Most commercial traffic simulation packages primarily offer only ready-to-use functionality and do not facilitate the addition of new functionality by users or provide a transparent picture of how the underlying components are implemented” (Tamminga et al., 2012, 44). This recently developed simulation framework has a modular design and is therefore useful in a wide range of applications, from ‘car follow’ to activity planning (Tamminga et al., 2012).

MATSim is a more mature open source transport model that improves on previous transport modelling programmes in a number of ways (Rieser et al., 2007). The model allows individual attributes to be maintained throughout agent-based simulation and ensures that trips made throughout the day are realistically inter-dependent (see figure 3.2 for the model’s structure). For example, being late for one trip will have an impact on the start-time of the next (Balmer et al., 2009). Since the project was first made available as a free open source project in 2006 (see sourceforge.net), uptake has been rapid with applications ranging from agent-based modelling of trips for leisure and shopping (Horni et al., 2009) to intensive performance testing, in which MATSim is shown to accurately model real world travel patterns (Balmer et al., 2008; Gao et al., 2010). MATSim has also been used to model commuter patterns in Pretoria, South Africa, incorporating previously omitted trip-chaining behaviours (der Merwe, 2011).

Because MATSim builds on Kai Nagel’s experience as a computer scientist, who also developed the highly successful TRANSIMS model (described below), it has several advantages over competitors. These include:

- “MATSim is consistently constructed around the notion that travellers (and possibly other objects of the simulation, such as traffic lights) are ‘agents’, which means that all information for the agent should always be kept together in the simulation at one place” (Balmer et al., 2009, p. 9). This allows demographic data on each traveller to be instantly available, rather than being completely unavailable (as in most transport models), or available in a fractured file system (as in TRANSIMS).
- MATSim is fast to run in comparison with other transport models with similar specifications.
- Strong user community. As of May 2013, there is a comprehensive new tutorial on how to install and use MATSim (see MATSim.org’s tutorials site), and daily commits to the source code (see sourceforge.net).

For these reasons, and due to its accessibility to anyone with a modern computer, MATSim has been identified as the most appropriate pre-existing model for interacting with the data and methods presented in this thesis. MATSim was carefully designed from the ground up to be the most powerful, user-friendly and fast agent-based transport model

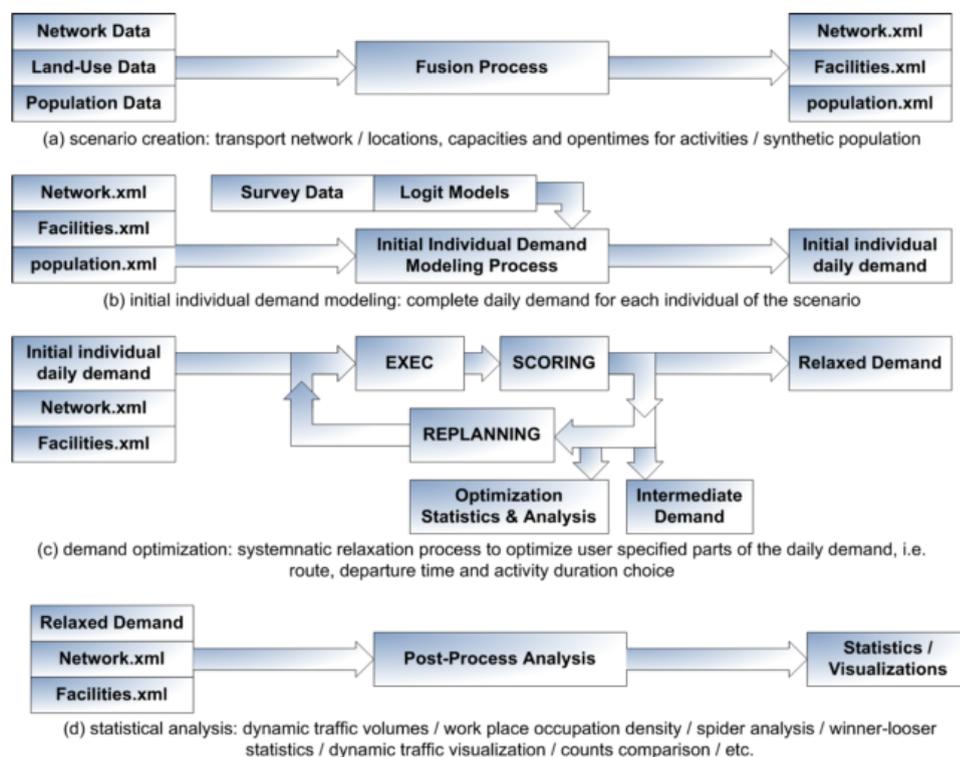


FIGURE 3.2: Schema of the MATSim model (Balmer et al., 2009). Thanks to Michael Balmer for permission.

available. It is important to recognise that in order to avoid trying to ‘re-invent the wheel’.¹⁶

3.4.2 Land-use transport models

Researchers now have decades of experience modelling individual agents (Ortuzar, 1982), transport flows (Wilson, 1970) and the land-uses that lead personal transit to take place (Batty, 1976). Of course, each of these elements depends to some extent on the others, so integrated land-use transport models have long been regarded as the holy grail in urban modelling. It is only recently that the computational requirements of this task have been available.¹⁷ Despite the daunting complexity and data and computational requirements of such models, their design and implementation has been theorised and attempted since the 1960s, with limited levels of success (Timmermans, 2003). The author of this critical review went so far as to suggest that the costs invested in ambitious land-use transport models generally outweigh the benefits. On the other hand, some have argued that it is only with modern computers and software that integrated land-use transport models can move from a mere ‘dream’ (Timmermans, 2003) into reality: “recently, the development of large-scale integrated land-use and transportation microsimulation systems such as ILUTE ... ILUMASS ... and UrbanSim has generated a new excitement in the field” (Pinjari et al., 2011, p. 935). These models, and TRANSIMS, are outlined below.

ILUTE represents the ‘third wave’ of transport-land use models based on individual level data: “[it] represents an experiment in the development of a fully microsimulation modelling framework for the comprehensive, integrated modelling of urban transportation-land use interactions and, among other outputs, the environmental impacts of these interactions” (Timmermans, 2003, p. 15). Thus *ILUTE* can be used to analyse a wide range of phenomena: it is an integrated urban model in the fullest sense of the word and has been even been used to analyse the distribution of house prices in and large city over time (Farooq and Miller, 2012).

UrbanSim, like *ILUTE*, is a micro level integrated land-use transport model, aimed at “incorporating the interactions between land use, transportation, the economy, and the environment” (urbansim.org, 2012). The source code (written in Java and Python) is open source and remains under continued development (Nicolai, 2012). Perhaps because the software is free for anyone to download, use and modify, it has been used for a range

¹⁶See section 7.3 for a crude attempt to integrate the road network in the spatial microsimulation — a MATSim implementation may have been more appropriate given sufficient time.

¹⁷The memory requirements alone of storing a detailed transport network in RAM are large. Combining this with complex polygons defining administrative zones, a detailed microdataset and then performing calculations defining how each model object changes from one moment to the next in high temporal resolution is clearly a taxing computational task.

of applications including as a tool to aid planners in the evaluation of transport projects (Borning et al., 2008). Although UrbanSim does not contain an advanced transport module, work has been done to integrate the dedicated transport MATSim model (see section 3.4.1) into it, via a plug-in (Nicolai, 2012).

TRANSIMS was developed at the Los Alamos National Laboratory with an ambitious objective mirroring that of ILUTE: “to model all aspects of human behaviour related to transport in one consistent simulation framework” (Nagel et al., 1999, p. 1). The model, which is based on cellular automata, has been given a public licence (the NASA Open Source Agreement Version 1.3), is cross-platform (with Windows and Linux binaries) and has been widely adopted.¹⁸ The encouragement of community contributions and an experienced development team has led the model to be extended various ways. For example, *TRANSIMS* can be configured to take advantage of parallel processing (in which one CPU is allocated to each area being modelled) (Nagel and Rickert, 2001), or external programs for the visualisation of results (<http://sourceforge.net/projects/transimsstudio>). The sub-modules of *TRANSIMS* include a micro level population synthesizer, a trip generator, route planner and microsimulator (which determines the location and behaviour of each individual at each time step). The model is being increasingly adopted by Municipal Planning Organizations (MPOs) in the USA (Lawe et al., 2009; Ullah et al., 2011) and has successfully simulated the entirety of Swiss travel flows (around 10 million trips), using a ‘Beowulf cluster’ of parallel computers (Raney et al., 2003).

The modular design of *TRANSIMS* means it can be used in conjunction with the spatial microsimulation methods presented in this paper. The small area microdata could, when allocated home-work pairs, be used as an input forming the baseline situation at time zero. The potential for combining the spatial microsimulation methods presented in this thesis with additional modelling tools is described in chapter 8.

3.5 Summary: research directions and applications

Over time the uses of spatial microsimulation, in its broadest sense, have expanded from a way of providing quantitative geographers and others with individual level data, into a more general modelling strategy harnessed to tackle many problems. In this thesis, however, a narrower definition is used: spatial microsimulation here refers to the process of generating spatial microdata, analogous to ‘population synthesis’ in transport models. As in many fields, the rate of change has also increased, due to increased availability of sophisticated software, large datasets and powerful computers. One could make the

¹⁸“*TRANSIMS*” was cited 166 time in Google Scholar in 2012 publications, many of which implemented the model for their own applications.

argument that the uses of spatial microsimulation, as defined above, have become more specialised as it is adopted by various fields for their own purposes, sometimes under different names. This fragmentation is aggravated by the fact that many do not make the code used for their analysis available, a practice prevalent across the sciences (Ince et al., 2012). However, there are also signs of integration. With the continued growth of open source software and the greater dissemination of code (e.g. through sites such as Github), a kind of evolutionary process can be observed: winners are picked and then generalised to be applied to a range of problems.¹⁹

The rate of change is fast, yet it is important to make use of more than 30 years . Looking back, it is possible to reflect on what works and what does not work so well in spatial microsimulation research. Summarising a large body of experience, Holm and Mäkilä (2013, p. 197) created the following ‘wish list’ of factors that future spatial microsimulation researchers should consider when creating new, or updating existing, models:

- use the most modern software
- use standard methods, shared by many users
- backward compatibility (so keeping our old models and subsystems running)
- avoid relearning
- develop solutions that are theoretically well designed
- transfer knowledge and know-how to new colleagues

It is interesting to note that this list could have been as applicable 30 years ago as it is now, indicating key areas of continuity in the field. Effort has been invested throughout to comply with these principles. It is hoped that the focus on the final point, dissemination of methods, will enable spatial microsimulation to be used by policy makers.²⁰ Indeed, its potential for policy evaluation, at individual and local levels, was one of the major reasons for choosing the spatial microsimulation approach to tackle the problem,

¹⁹A good example of this positive-feedback process of picking winners, whereby the most promising projects receive much new attention and then grow most rapidly as a result (of peer feedback and new collaborators), is MATSim. Released as an open source project in 2006, the project has rapidly gained users, contributors and policy applications. MATSim also illustrates the wide appeal of microsimulation software, finding applications as ranging from a ‘plugin’ to pre-existing urban simulation models to a framework for modelling leisure and shopping trips (Nicolai, 2012; Horni et al., 2009).

²⁰To this end, experiments to improve the performance of IPF and some other script files that may be of use to others have been put online via the dissemination portals www.rpubs.com/robinlovelace and www.github.com/robinlovelace . Knowledge transfer was also behind the publication of a user manual alongside Lovelace and Ballas (2013).

helping to fill the ‘scale gap’ between academic studies and policy interventions described in chapter 2.

The literature summarised in this chapter should make it clear that the methods used are not new: researchers have been modelling transport problems at the individual level over two decades (Ortuzar, 1982), and developing the theory behind individual level behaviour for even longer (Wilson, 1970). The novel contribution made in this thesis is the practical *application* of the existing method of spatial microsimulation to the problem of unsustainable commuting. Approaching the issue from a quantitative geography and spatial microsimulation perspective allows the focus on spatial variability and social inequalities in transport energy use, highlighted in chapter 6 to chapter 8 of this thesis. This is in contrast to the transport modelling perspective, which is still largely traffic-orientated. Before proceeding to apply the method, however, it is vital to understand precisely how the spatial microsimulation model used in this thesis works and the input data. That is the task of the next chapter.

Chapter 4

Data and methods

4.1 Introduction

To fully describe and understand the energy used in travel to work, a large amount of data is needed. Behavioural, technical, infrastructural and even economic data would be required at a high level of spatial and temporal resolution over a wide area and a long timespan to provide a complete picture of the flows within the transport-to-work energy system. The ideal dataset would also contain grid references of both the origin and destination of every trip to and from work, the route distance (which may change from one day to the next), the specifications of the primary vehicle used and, ideally, measurement of the food or fuel consumed as a result.

It is worth briefly considering what this giant dataset would look like: the methods can be seen as an attempt to approximate a simplified version this omniscient information source, through modelling. Figure 4.1 illustrates the numerous connections to additional datasets not traditionally included in travel surveys that would be needed for the most detailed view. The thought experiment led to the imaginary Comprehensive Commuting-Energy Database (CCED). This main dataset would be part of a wider ‘data schema’ of connected tables (Obe and Hsu, 2011) as it would depend on detailed additional information about individuals, the vehicles they drive, up-to-date information on where they live and work, as well as detailed information on every single trip to work they make for an accurate assessment of energy costs and the factors influencing them. To gain an understanding of the complexity of this dataset, let us picture its size for the UK. Assume that 30 million people are employed,¹ making, on average, 200 home-work round trips per year. This would mean the CCED would need to contain 12 billion

¹During the 3rd quarter of 2012, there were 29.86 million employed people in the UK according to the Office for National Statistics

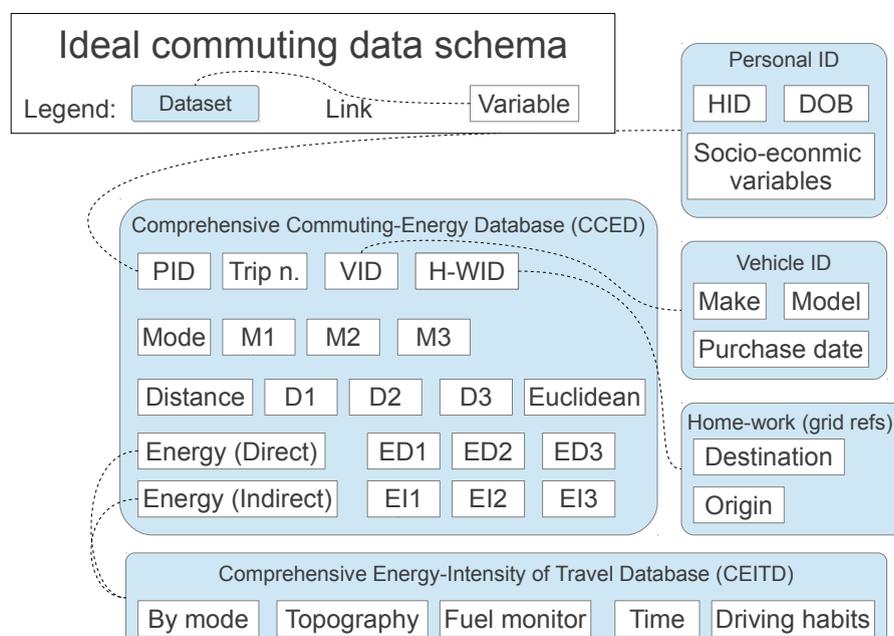


FIGURE 4.1: Idealised data schema for studying energy use in commuting. The imaginary CCED database would need to link to other, equally detailed datasets to work.

rows of data each year. Even ignoring the complexities added by the linked datasets,² keeping this dataset updated live would be far beyond the government’s current official data collection capabilities. The largest microsimulation run performed for this research was of ~ 2 million commuters in Yorkshire and the Humber, over 3 orders of magnitude smaller than the CCED for a single year. Given that the analysis was unwieldy, it seems such a large dataset would pose major problems to current mainstream computer hardware.

Of course, the available datasets do not match the detail of the imaginary CCED. Budgets for data collection, confidentiality and technical considerations combine with the practical difficulties of monitoring the energy used by hundreds of thousands of unique vehicles. Based on these difficulties, one could argue that the data limitations are insurmountable and that more qualitative approaches are needed. This research is based on the opposite view: that the inherent data limitations mean that the datasets that *are* available are absolutely critical. Systematically collected data has a much better

²The CCED would need to link to the constantly changing home-work locations (currently untracked by the government, except during the census), household composition, energy use data and vehicle ownership datasets. This would require constant, probably automated monitoring and computer infrastructure that is currently beyond most local authorities to store, analyse and interpret. Large data management organisations such as Google and Facebook have shown that such vast ‘live’ databases are possible, however. A state-controlled online data-logging system, which harnesses near-total smart-phone penetration, could conceivably move towards this vision.

chance of meeting the research aims, as set-out in section 1.5 than purely qualitative information. Without good statistics, one would have to resort to personal observation and anecdote, sources that are unlikely to be representative of the system as a whole (Little and Rubin, 1987). Because the available datasets cannot be changed, whereas the methods used to analyse and model them can, the approach taken here is *data-driven* (as opposed to model driven) (Anselin, 1989): the starting-point is the available data. After the introduction, this chapter describes the input datasets (section 4.2 to section 4.4) and then explains the methods used to process them and evaluate the outputs (section 4.5 to section 4.6). The final section explores methods for generating integer results, which are useful in agent-based applications (section 4.7).

Due to its policy relevance, the methods are treated primarily as means rather than ends in themselves throughout the majority of the thesis. In this chapter the emphasis reverses, and the methods (and the datasets on which they depend) become the focus. It would be an exaggeration to say that the data and methods are seen here as ends in themselves, as they all contribute towards the aims. Yet effort has been made to explain them in general terms. An additional aim of this chapter is to illustrate clearly how the methods were implemented, allowing others to replicate the results. It should also be clear by the end of this chapter that the methods could be harnessed for purposes other than assessment of the energy costs of travel to work. They could be used for a more conventional economic evaluation of work travel, as the basis of agent-based models of employee behaviour (see section 4.7 on integerisation) or for the analysis of individual level processes based on aggregate data more generally.

As discussed in chapter 3, reproducibility of methods is one of the cornerstones of scientific advancement yet it is often missing in spatial microsimulation and related fields. Therefore, this an important chapter from an academic perspective: it allows others build on the analysis, by applying the methods to new datasets and extending or modifying the methods for their own purposes. There have been some methodological advancements — such as a new algorithm for the integerisation of IPF weights and the allocation of origin-destination co-ordinates to individuals simulated using spatial microsimulation.³ However, much of the work simply applies existing methods in a new context.

The advantages of spatial microsimulation over purely aggregate or individual level analyses are described in general terms in the previous chapter. The reasons behind the choice of spatial microsimulation for this particular application relate to the available datasets, and should become clearer as they are described. Essentially, there is no single,

³Individuals have been allocated locations and other characteristics in existing micro level transport models such as MATSim (chapter 3). However, these models focus on transport: individual level attributes provide an optional add-on. The methods presented in this thesis operate the other way around: micro level characteristics generated by spatial microsimulation form the foundation; transport patterns are the add-on.

comprehensive dataset on travel to work patterns in the UK and its energy implications, such as the imaginary CCED described above. Various datasets are available, each with its own advantages and disadvantages. Spatial microsimulation can be used to combine the main official and un-official sources of data, and provide individuals whose travel patterns can be modelled. The main datasets used in this thesis are:

- transport energy use data
- the 2001 Census of UK population
- the Understanding Society dataset (USd)
- the 2002-2008 National Travel Survey (NTS)
- transport infrastructure from Open Street Map (OSM) and other sources

The first data source to be described is on direct energy use in transport, in section 4.2, as good energy data are vital to the results chapters. Although energy use can be calculated based on mode, distance and other variables, this official source provides energy data directly. Because of the limitations of these official energy use data (in terms of coverage of modes, lack of disaggregation by reason for trip and course geographical resolution), good data on commuting *behaviour* are needed to calculate energy costs indirectly. This information is reported in section 4.3. Social survey data are made available both as geographically aggregated counts from the census (section 4.3.1) and more detailed individual level variables from nationwide surveys which take a representative sample of the UK population (section 4.3.2 and section 4.3.3). The final type of data considered provides geographical context — the location of roads, railways and other infrastructures, as well as information about elevation and other geographical variables. These datasets are described in section 4.4.

Each data source has advantages and disadvantages. The census dataset is the most geographically comprehensive (covering virtually every commuter in the country) but is limited in terms of the number of variables on offer (mode and linear distance of home-work travel) and the fact that it is geographically aggregated count data, providing little sense of individual level variation. This can be supplemented by datasets that operate at household, individual and (in the NTS) trip, stage and vehicle levels. The Understanding Society dataset (USd) is a general purpose national survey, so it has a wide range of socio-economic and attitudinal variables that are useful in explaining observed commuter patterns. It is also longitudinal, and provides some information on car ownership, so could be useful for assessing how commuting patterns evolve over time and relate to car ownership at the individual level. The National Travel Survey (NTS) is the other individual level dataset used. It is much more focussed on transport and provides detailed

information on trip distance, duration, mode and the reasons behind travel. Because this dataset is based on week-long travel diaries, and provides information collected over all seasons over the course of 7 years, it allows assessment of commuter habits over time, on weekly, seasonal and inter-annual time-scales. Additional datasets are geographical, with accurate co-ordinates allocated to physical features and elements in the transport network. Including these in the analysis is challenging, but provides useful insight into the possible underlying environmental reasons behind variation in commuting habits.

4.2 Energy use data

Energy use in transport is, in general, uncertain, due to the various system boundaries, conflicting sources and multiple definitions of what actually comprises energy (e.g. the distinction between direct and indirect energy use). Official data on the subject therefore provides a useful benchmark against which calculations of energy use can be compared. (Estimates of energy use by mode, as opposed to the official datasets presented in this chapter, are described and discussed in detail in chapter 5.) The uncertainty arises because energy costs of personal travel and hence commuting are not recorded in the same way as household energy use (available at MSOA level from Neighbourhood Statistics) or sub-regional fuel statistics (DECC, 2008a). Cars, for example, are mobile energy users that can refuel anywhere, so tracking their use of fuel is not currently feasible.⁴ Similar problems exist for public transport, where officially reported aggregate values are often the only source of data (see London Underground, 2007). Worse, the estimated energy costs of walking and cycling vary widely from study to study and are subject to a high level of uncertainty (Coley, 2002; Brand, 2006; Lovelace et al., 2011).

As indicated in chapter 1, the energy costs of commuting have not been previously analysed in detail. There is little direct evidence about the energy costs of transport to work, let alone its geographic variation: fuel use can be estimated for motorised transport vehicles, but regional statistics do not provide break-downs by trip reason, distance, socio-demographic category or low (sub Local Authority) levels geographic aggregation. One dataset (DECC, 2008b, 2013a) does provide direct estimates of transport energy use (table 4.1).

⁴This has the potential to change with the emergence of in-car fuel use monitoring. Technologies range from the simple and cheap (FuelLog is a smartphone app which costs under £2) to the expensive and complex (e.g. Scanguage — a retrofitted fuel monitor). Some models now come with fuel efficiency monitors pre-installed (e.g. all Nissan Micra models, since 2007). Despite these advancements and the acknowledged importance of fuel consumption Department for Transport currently has no plans to record fuel use alongside other data such as odometer readings which are routinely taken during the MOT (Rachel Moyce, DfT employee, personal communication).

TABLE 4.1: Sample of the regional transport energy consumption statistics released by DECC (2013a). 2010 data shown: available each year from 2002.

LAU1 Code	LAU1 Area	Energy consumption (Thousand tons of fuel)			
		Buses	Diesel Cars	Petrol Cars	Motor-cycles
UKL1605	Blaenau Gwent	0.9	5.6	9	0.1
UKL1705	Bridgend	3.1	21.2	30.6	0.3
UKL1604	Caerphilly	3.2	18	28.8	0.3
UKL2207	Cardiff	8.3	48.8	75.1	0.6

The data presented in table 4.1 is useful for providing an overall picture of the spatial variability of energy use within the UK. (The units are easily converted into Joules, the energy unit used here using the following conversion factor: $1\ Toe = 42\ GJ$ or $1\ MToe = 42\ PJ$). The dataset also includes estimates of the energy consumption by light and heavy goods vehicles (LGVs and HGVs respectively). This allows for personal travel to be placed in the wider context of overall travel: energy use for freight is just over half (55%) that of energy used for personal travel modes. This shows that energy in transport studies should not be limited to personal travel alone; moving goods uses over a third of the total energy use (35.3 *GToe*). In addition to these benefits, the data are temporal: it would allow changes in the geographical distribution of energy use in transport overall to be compared with shifting patterns of energy use for travel to work estimated from census data.

The data does have limitations, however. First, there is no breakdown of the data by reason for trip, so the fuel consumed by travel to work (as opposed to other types of trips such as leisure) must be estimated as a proportion of the total. A simple way of doing this is to simply multiply all fuel use values by 0.195, the proportion of total passenger kilometres attributable to commuting (NTS, 2012).⁵ The most obvious problem with this approach is that the proportion of distance travelled by each reason for trip varies greatly from place to place, so such a crude estimate will be highly inaccurate. More sophisticated methods of translating the total into commuter energy use only could be used, but these rely on datasets from which energy use estimates can be produced directly anyway. Therefore the main strength of the dataset is that allows commuter energy use to be compared with total energy use for personal travel at the LA level.

Another problem with the DECC (2008b) dataset is that it includes only road-based traffic. Walking, cycling, trains, trams and the underground, which make up almost 1/4 of trips to work in the UK, are omitted from the analysis. This is especially problematic for use of the dataset in what-if scenarios, as these are precisely the modes that would

⁵Commuting is jointly the greatest reason for person-kilometres in the UK (to the nearest percentage point) along with “visiting a friend” (19.7 %) and “other leisure” (20.4 %). This dataset is from 2010 and can be found in Table NTS0402 from NTS (2012).

need to grow fastest in a low energy future. In terms of distance travelled, the omission could be justified as the three main road-based modes (car drivers, car passengers and bus) accounted for 84% of passenger kilometres in 2010 (NTS, 2012). In terms of energy use, non-road modes are even less important, as they consume a fraction (specifically, less than one twentieth) of the energy per unit distance than cars and buses. The final problem with the dataset is its coarse geography: it would be of little use for local decision making processes. This coarseness is put in perspective table 4.2 and figure 4.3 below.

4.3 Social survey data

The best source of commuting data in terms of coverage in the UK is the national census, which must be answered by every household. The dataset is released a year or so after each census, which has taken place every 10 years (except 1941) since 1801. Dating back to at least 1971 (the earliest date for which travel to work data are available via the census data dissemination portal Casweb), there has been a question on mode of travel to work figure 4.2 (left). This dataset is provided for a 10% sample before 2001, which is problematic in small areas.⁶ Since 2001, the data has also provided breakdowns of travel to work by distance, crucial to constraining estimates of energy use for travel to work. (Distance is not reported directly by respondents, but calculated as the Euclidean distance between the area centroids of home and work postcodes — see figure 4.2 (right).) For all time periods, the data can be cross-tabulated by social class. This is important for understanding how commuting energy costs vary across social class and the likely distributional impacts of change.

These data are available at the individual level through the Sample of Anonymised Records (SARs) for 1 and 2% samples of the entire survey. For the purposes of this study, however, alternative sources of individual level commuting data were used, to provide additional variables. The main use of census data, therefore, was as a source of ‘small area constraints’ (described in section 3.1) for spatial microsimulation, at various levels of geographic aggregation. The main disadvantage of the census dataset is that it only provides information about a small number of variables compared with more specific surveys that have lower samples sizes. Only 57 questions were asked in the 2011 Census. By contrast, the number of variables in the NTS and the USd datasets runs into several hundred.

⁶The dataset is provided down to enumeration district (ED) level, each of which contained ~500 residents since 1971, and down to the output area level (~300 residents) since 2001.

33 What is the address of the place where you work in your *main* job?
 ♦ If you report to a depot, write in the depot address.

Grid for street name (10 columns)
 Grid for house number (10 columns)
 Grid for postcode (10 columns, with 'Postcode' label above the last 5 columns)

Mainly work at or from home Offshore installation
 No fixed place

34 How do you usually travel to work?
 ♦ *one box only.*
 ♦ *the box for the longest part, by distance, of your usual journey to work.*

Work mainly at or from home
 Underground, metro, light rail, tram
 Train
 Bus, minibus or coach
 Motor cycle, scooter or moped
 Driving a car or van
 Passenger in a car or van
 Taxi
 Bicycle
 On foot
 Other

FIGURE 4.2: Questions 33 and 34 of the 2001 UK Census, which provide information on mode (left) and distance (right) travelled to work, respectively.

4.3.1 Geographically aggregated data

Census data on commuting is disseminated by Casweb at a range of geographic scales (figure 4.3) and with a variety of cross-tabulations. Before forging ahead and describing how the datasets are used, it is worth taking stock of the scales of geographical aggregation at which they are available. Consideration of the range of options at the outset is especially important because research findings can depend on the size and shapes of geographic zones, the ‘areal units’ of analysis (Horner and Murray, 2002; Openshaw, 1983). Selecting zones that are too small relative to the study area can lead to long processing times, messy maps and over-complexity. Analyses based on overly large zones, on the other hand, can gloss over spatial variability by presenting space in extensive, homogeneous blocks. Regardless of the scale of analysis selected, it is important to remember that *all* analysis based on geographically aggregated data may be susceptible to the modifiable areal unit problem (MAUP) (Wong, 2009).

One of the advantages of spatial microsimulation is that it facilitates ‘frame-independent’ (scale independent) analysis (Horner and Murray, 2002). The results for any particular region — a table of geo-located individuals equal in population to the commuting population of the region — should be roughly the same in terms of the size of the output file and distributions of individual level variables, regardless of the scale of analysis. It is still important to choose an appropriate scale, as lower geographies will provide more localised information, yet be harder to analyse and visualise. Spatial datasets related to commuting in the UK, and their scales of dissemination, are outlined in Table 4.2.⁷

⁷The administrative acronyms OA, LSOA, MSOA, and LA refer to Output Areas (which contain ~300 people), Lower Super Output Areas (~1600 people), Medium Super Output Areas (~7000 people) and Local Authorities (more than 100,000 people) respectively.

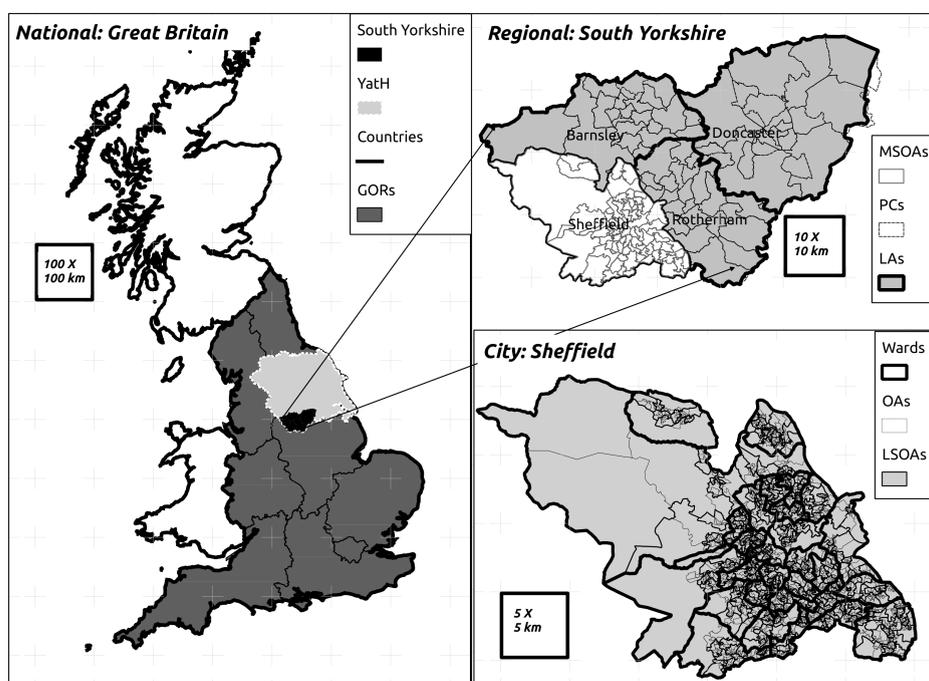


FIGURE 4.3: National, regional and city-wide scales of analysis, as illustrated by a range of administrative boundaries. Yorkshire and the Humber (left), South Yorkshire (top right) and Sheffield (bottom right) are the study areas used for this section.

TABLE 4.2: Aggregate data related to the energy costs of transport to work and the scales at which they are available for South Yorkshire. The slash symbol (e.g. in “Mode/distance”) represents cross-tabulation. Source: Casweb, unless otherwise stated.

Variable	OA	LSOA	MSOA	ST Ward	LA
N. zones in South Yorkshire	4278	845	173	59	4
Average population	296	1450	7320	21500	317000
Mode of transport to work	Y ^a	Y	Y	Y	Y
Average distance	N	Y	Y	Y	Y
Distance categories	Y ^a	Y ^c	Y ^c	Y	Y
Mode/Distance	N	N	N	Y	Y
Car access ^b	Y	Y	Y	Y	Y
Domestic energy use ^d	N	N	Y	N	Y
Transport energy use ^d	N	N	N	N	Y
Total energy use ^d	N	N	N	N	Y

^a Output area statistics are often unreliable because values less than 3 are randomly allocated the value of 0 or 3. This is problematic for sparsely populated categories such as those who travel 60 km or more to work.

^b ‘Car access’ refers to the census dataset ‘cars or vans’ which provides counts for the number of houses with access to no cars, one car etc, and total number of cars in each area. This is for estimating reliance on public transport.

^c Data provide by Nomis government data portal, providing various cross-tabulation options (<https://www.nomisweb.co.uk/Default.asp>).

^d Data provided by the Department of Energy and Climate Change (DECC, from http://www.decc.gov.uk/en/content/cms/statistics/energy_stats/regional/).

As well as being available at different administrative geographies, the datasets presented in Table 4.2 are variable in terms of reliability, their origin, and times of collection. Following the ‘confidentiality principle’ of census data release (Rees and Martin, 2002), small numbers (3 or below) are allocated as either 0 or 3 for census data. This makes cross-tabulated datasets of unusual categories such as ‘cycles to work’ unreliable at the smallest Output Areas (OA) level. Census data are the ‘gold standard’ in terms of accuracy and geographical coverage (Rees et al., 2002, p. 4). However, as mentioned earlier, the census lacks details covered by more specific surveys. Of relevance to energy use, there is no information about the type of car that car commuters used, or the route distance to work each of which can have a large impact on overall energy use. The fact that census datasets are only released every 10 years is a major disadvantage for dynamic analyses compared with rolling surveys such as the NTS and the USd. It should be noted that while the data provided by Casweb and Nomis are essentially the same, the DECC data on energy use was collected in a different way and at a different time, running from 2005 to 2010, as opposed to 2001.

Cross-tabulated counts

Cross-tabulated count data refers to categories which are split up into subsections. The cross-tabulation mode/distance, for example would contain the number of car drivers who travel 0-2 km to work, 2-5 km etc. and the same sub-categories for every mode of transport. The number of variables (and hence cells) multiplies with each additional cross-tabulation. To provide another example, CAS119 (from Nomis) presents mode of travel to work (car, bus etc.) as cross-tabulated by two other variables — age and sex. This provides the potential for more accurate microsimulation (by constraining by more, cross-tabulated, variables) and a foundation for validation. Disadvantages of Nomis include the increased likelihood of empty cells in cross-tabulated data and ‘information overload’ for the researcher: it is difficult to analyse and visualise a 3 way cross-tabulated dataset including more than 100 variables, such as CAS119, using standard methods of spatial data analysis.

Data size can be a problem: the selected variables presented in Fig. 4.4 represent 308,016 cells at the output area for South Yorkshire⁸ and takes up almost a megabyte of hard-disk space just for Yorkshire and the Humber. All variables, downloaded for the entirety of England (165,665 OA areas), would take up ~80 Mb of hard disk space and require a powerful computer for spatial analysis and mapping. Larger administrative boundaries within a smaller case study area such as South Yorkshire present no such problems, however, for cross-tabulated data.

⁸6 age categories multiplied by 12 mode categories multiplied by 4,278 output areas.

Table CAS119 Sex and age by method of travel to work												
Table population: All people aged 16 to 74 working in the week before the Census												
Use the links in the headings to select entire rows or columns <input type="button" value="tick all"/> <input type="button" value="un-tick all"/>	ALL PEOPLE	Work mainly at or from home	Underground, metro, light rail, tram	Train	Bus, minibus, coach	Motor cycle, scooter or moped	Driving a car or van	Passenger in a car or van	Taxi or minicab	Bicycle	On foot	Other
	ALL PEOPLE	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Aged 16 to 24	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Aged 25 to 34	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Aged 35 to 49	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
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Aged 65 to 74	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Males	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
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Females	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
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Aged 50 to 59	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
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Aged 65 to 74	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

FIGURE 4.4: Cross-tabulated dataset containing mode/age/sex variables from Nomis (dataset CAS119).

Additional cross-tabulated datasets of relevance to commuting are provided by Nomis and Casweb (the latter via ‘Census Area Statistics’) at each of the spatial scales presented in Table 4.2, and a few others.⁹ A selection of these cross-tabulated datasets, and an explanation of how they relate to commuter patterns, is presented below:

- CAS118: Number of employed persons in household/mode/numbers of cars or vans in household. Useful for investigating rates of intra-household car sharing, links between car ownership and employment, and household level microsimulation.
- CAS120: Sex/age/distance travelled to work. Investigation of the demographics of people who depend on long-distance commuting.
- CAS122: NS-Sec/mode of travel to work. Allows investigation of the interaction between class and mode of transport to work.
- CAS121 Sex/distance/mode of travel to work. Which modes are used for long and short distance trips in each area?

⁹The complete set of Geographies at which these data are available via Casweb is: Country, GOR, County, Unitary Authority, District, ST Ward, CAS Wards, OA.

4.3.2 The Understanding Society dataset

The aggregated census data described above form a solid foundation for analysing commuting patterns. However, they omit a number of relevant variables and mask intrazonal variability. To perform any kind of microsimulation study, a micro level dataset must always be found as a starting point: “Before any attempts can be made at simulation the first requirement is for a population sample to be obtained at the micro level” (Clarke and Holm, 1987, p. 147). This sample can be based on a pre-existing survey data-set, a bespoke survey tailored to the demands of the model, or, if these options are unavailable, from synthetic populations based on Monte Carlo sampling techniques. Data on commuting is collected by the government in surveys, so the first option is used here.

Table 4.3 illustrates some important individual level ‘target variables’ (defined in section 3.1) that are available through a single dataset: the Understanding Society dataset (USd).¹⁰ Many more variables, covering many aspects of life are also available in this dataset. The most important ones, from the perspective of spatial microsimulation are the most basic ones: age, sex, socio-economic class, number of cars in household, hours of work and house tenure. These provide a link to the aggregated census variables described above via constraint (or ‘linking’) variables.

Crucially for this research, the USd also contains data on travel to work. In the British Household Panel Survey (BHPS), that preceded the USd, mode of travel to work and time of travel were the only variables available, and contained nothing on distance.¹¹ However, from 2011 onwards the USd (which replaced the BHPS) contained a question on distance travelled, resulting in the variable “workdis” (ESDS, 2011), which is the route distance reported by the respondent, to the nearest mile. This is the first time distance has been included in any major British longitudinal survey (Buck, 2011, personal communication).¹² However, the variable has only a 47.2% completion rate among those who travel to work, meaning the sample size is reduced from 10,681 to 5,043. Including the dropping of respondents who do not travel to work (48.0%), the

¹⁰Understanding Society replaces the British Household Panel Survey (BHPS) as the UK’s largest national governmental survey (see www.understandingsociety.org.uk). The Department for Travel’s National Travel Survey and the Living Costs and Food Survey provide additional options for individual level variables related to commuting. The USd is the most comprehensive (with a longitudinal sample size of 50,000), so was the first option that was used.

¹¹These variables resulted from the following questions: “About how much time does it usually take for you to get to work each day, door to door?” and “And what usually is your main means of travel to work?” (www.iser.essex.ac.uk/bhps).

¹²Prof. Nick Buck, director of the UK Longitudinal Studies Centre, by telephone, 05/10/2011. The National Transport Survey (NTS, 2009) also contains some information on transport to work but is only available to the public in aggregate forms, and is not comprehensive because it provides little on non-transport characteristics.

cleaning process reduced the sample size of the Understanding Society dataset by 3/4 from its original value of 22,265 employed people.

TABLE 4.3: Selected individual level variables related to commuting, available from the Understanding Society dataset.

Attribute	Variable	Measurement	Comment
Type of car	Household variable 146	Engine size of cars: < 1.4 , $1.4 - 1.9$, or $\geq 2l$	Data on additional cars also available
Household income	Household variable 193	Net household income, £/month	Equivalised income must be calculated
point Telecommuting potential	Individual level variable 953	7 point scale from no access to everyday	Must be linked with type of work
Ease of moving home	Household variable 171	Number of children (aged 15 or under) in household	One indication of how settled household is

It should be noted that the USd variables described in Table 4.3 are *proxies* of the attributes assigned to them: therefore they should be interpreted with caution. The propensity of households to move (linked to commuting via job mobility), for example, does not just depend on the number of children:¹³ it also depends on other factors such as the ownership status of the house, years left on mortgage, time spent at current location and satisfaction with the local community (Mellander et al., 2011). Some of this information is in fact provided by the USd (in variables ‘hsownd’ and ‘mglife’, at the household level and ‘mvyr’ and ‘lkmov’ in the individual questionnaire): Table 4.3 represents only a snapshot of the available variables. For more detailed information about personal travel (but less more general data) the National Travel Survey was analysed.

4.3.3 The National Travel Survey

More detailed information on commuting behaviour is provided by the 2002-2008 National Travel Survey (NTS). This household and individual level survey was commissioned by the government to better understand transport issues. A stratified random sample of $\sim 8,000$ households each year took place, resulting in detailed travel diary data for 152,344 (un-weighted) individuals or $\sim 20,000$ in each of the 7 sample years.

The household level dataset is most useful at providing insight into people’s perceptions of their surroundings from a transport perspective. Issues probed within the 165 variables of the 63,952 row dataset include:

¹³To provide another example, the USd provides three categories of car engine size rather than describing the exact make and model, a substantial oversimplification from the perspective of energy use.

- The accessibility of public infrastructure nodes (e.g. variable H13, “Walk time to bus stop” or H15, “walk time to railway station”).
- Quality of the travel network (e.g. h122: “Rate the frequency of local buses” and h127: “Rate the provision of local cycle lane/paths [on a 5 point Likert scale]”).
- Ownership and availability of vehicles (e.g. Number of bicycles or cars/vans (h35a and h55) and h57: “Household vehicle availability”).
- Importance of travel in quality of life (e.g. variable H148, “Importance of public transport in choice of home”).
- Proximity of essential services: Journey time to nearest GP, hospital, shopping centre, school, post-office etc (variables h160 to h168).

These variables are not used directly in the spatial microsimulation model presented here. They could, however, be useful for evaluating the impact of environmental factors and household possessions on transport energy use and for comparing energy use for travel to work with energy use for other types of transport at the household level.

At the individual level, the NTS also provides a range of useful variables, many of which are not available in other surveys. These include basic social and demographic details: age, sex, employment status (self employed vs employee), economic status (full time, part time, unemployed etc.). In addition, via links to the household level dataset, tenancy, household income (in three bands), social class (of household representative) and car ownership can also be allocated at the individual level. These basic variables are also collected by the Census. This would enable the NTS to be used as an input micro-dataset for spatial microsimulation models.

The individual level dataset consists of 175 variables which contain more detailed information about travel habits than any other major British survey. These interrogate many aspects of individuals’ travel experiences, from expenditure on public transport to driving experience and from frequency of flights to where they cycle. A selection of the most relevant questions (which are not directly related to commuting) are summarised below.

- Variable i182A — Driving licence (yes, no or provisional): this may help separate those who do not drive because they *cannot* from those who do not drive out of choice (although some may choose not to own a driving licence).
- I203 — Access to car (with answers falling into the following 5 categories: company car, main driver, not main driver of household car, car available but non driver, driver but no car): enables use of car to be linked to car accessibility.

- I283 — Method of school travel (and many questions about the reasons for this): enables investigation of the links between mode of travel to work to be linked with mode of school commute, at different distances.
- Frequency of walking and cycling — would allow researchers to investigate the link between walking and cycling to work and for other reasons. If one replaces the other, the energy impact of shift to these modes may be more positive.

As with the household level variables, the main utility of these is adding subtleties, quantifying uncertainties and demonstrating the complexity of variables that interact with travel behaviour overall. None of the NTS variables mentioned so far deal with travel to work directly, however. Commuting data are provided by variable I180 (“usual means of travel to work”) and I92 (“work place”, which provides four categories about their work location: a single location, 2 places (visiting each at least twice per week consecutively), different places or mostly from home). The main drawback of the NTS dataset from a commuting perspective is that it does not provide information on the distance between home and work directly.¹⁴ An individual level “distance to work” variable can be calculated based on the trips database, which would enable the NTS dataset to be used as a complete replacement for the USd dataset in terms of constraint variables.

The main strength of the NTS dataset, that *is* directly related to commuting and provided directly at the individual level, is its provision of detail about travel behaviour. Used in addition to the more general USd, it allows complexities of travel to work to be examined quantitatively. Quantitative information about travel to work usually oversimplifies of reality — person X travels to work by mode of transport Y. Yet in the real world things are rarely that simple. The NTS tackles this issue at both individual and trip levels. At the individual level questions probe the extent to which the same trip to work is a regular event. Variable I309 provides a binary yes/no answer to the question: “Possible to work at home?”. Variable I310 adds subtly to this by providing seven categorical answers to the question: “How often work at home?” ranging from “3 or more times per week” to “less than once a year or never”. The prevalence of each answer (figure 4.5) becomes useful during attempts to improve the accuracy of relatively crude energy cost estimates and discussions of the reliability of the results. To provide

¹⁴Data on trip commuting trip distance is provided in a separate NTS database entitled ‘commuting-trips’, a small subset (38 Mb, in .sav format) of the larger (225 Mb) complete ‘trips’ file. Variable jd provides the most precise data on the responses to this question, to the nearest tenth of a mile and jdungross provides the rounded average. Variable j34 provides this data as relatively fine categorical data. 12 variables are provided: “under 1 mile”, “1 to under 2 miles” ... “200 miles and over”, with further bin breaks at 3, 5, 10, 20, 15, 25, 35, 50 and 100 miles. This trips provides 44 variables in total on the origin, destination duration time, distance and (for public transport) costs, with one row allocated per trip.

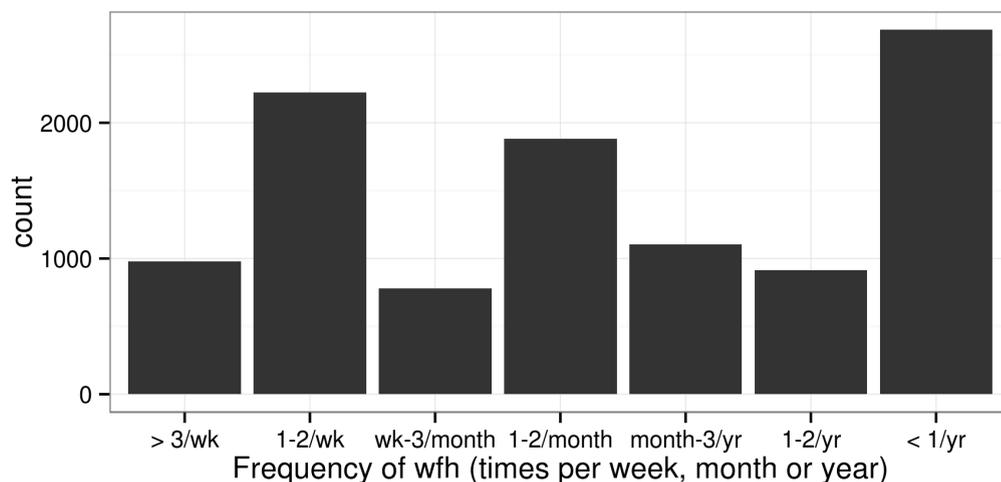


FIGURE 4.5: Bar-plot of frequency of working from home (wfh) in the NTS, 2002-2008. Note: only 7% of the individual level sample answered this question; around half of the non-respondents do not work.

another example, the extent to which mode of travel to work varies can be explored with the variable i316: “Journey to work another way”, which is rated on a 5 level scale from very easy to very difficult. Subsequent questions ask what the greatest problem with travelling to work by another mode is (e.g. cost of public transport) and main reason for using/not using the car for the daily commute. Each of these questions helps to understand the likelihood of modal shift away from the car and the factors impeding this shift in scenarios of the future.

At the trip level, the NTS contains the following data that can add subtlety and complexity to our understandings of travel to work. A selection of the variables that do this are:

- D1, J31 and J31A: Journey day and time. This can provide information about likely level of congestion of work trips on average, and compared with other trips.
- J23: Number of stages. This data mitigates against the simplistic idea, reinforced by many questionnaires, that all trips consist of only one stage and one form of transport. The prevalence of multi-stage trips can be investigated using this variable and, in even finer detail, using the ‘stages’ dataset which breaks every trip up into its constituent stages.
- JTOTCOST: Total cost of public transport trips. This variable provides an insight into the costs of public transport and, if the costs of alternative modes are estimated, the changes that would make more efficient modes more efficient than driving financially.

‘Zooming in’ in even further, data on the individual stages taken and vehicles used for each trip is provided by the NTS in separate files, linked by multiple (e.g. household, individual) IDs. The ‘stages’ file provides 2.2 million rows of data (only 5% more than the trips dataset, as 96.7% of trips taken consist of just a single stage) on occupancy, parking and even the cost of parking. Clearly, this dataset is invaluable for identifying the types of multi-stage trip in travel to work, and how these impact on the energy cost estimates calculated via the assumption that all trips to or from work consist of just one stage. The ‘vehicles’ dataset contains only 5 types of motorised vehicle, including cars, motorcycles/scooter/moped, “landrover/jeep”, “light van” or other. The type of bicycle used to travel to work is not included, making it impossible to accurately estimate the embodied energy costs of cycling to work based on the NTS dataset. Surprisingly, details on the engine size is not provided, although this is not an issue from an energy use perspective as the CO₂ band of the vehicle (which can be converted into energy efficiency estimates) is included (in variable V164b). Other relevant variables from the vehicle dataset include annual mileage (V46), annual commuting mileage (V140) — these could be used to determine the extent to which people are dependent on their cars for commuting, compared with other reasons for trips — and age of car (V91a).

The final feature of the NTS dataset to consider is its geographic coverage. It is a stratified sample within Great Britain. It does contain some geographic information at the household level, about the type of area in which the household is based (variable h154a).¹⁵ Also, the region of each respondent can be inferred by linking individual and household ids to variable J57G (GOR of trip origin) of the trips dataset. The NTS dataset has an impressive response rate to key question which tend to have a lot of NA values, and are very patchy. This would allow an additional constraint variable to be used for individual level NTS data as an input into a spatial microsimulation model.

4.3.4 Other commuting datasets

Internationally, the availability of commuting data varies greatly. This is important, because it can frustrate attempts to compare commuting patterns across nations. However, if the methods are to make a major contribution, it should be possible to implement them worldwide. This depends on access to appropriate data. Using the aforementioned UK data as a benchmark, Dutch and Colombian datasets will be evaluated in terms of their suitability for the spatial microsimulation methods set out below. These datasets were selected because they represent very different levels of detail, aggregation and availability.

¹⁵The following 6 categories are provided: Met built-up areas, Other urban over 250K, Urban over 25K to 250K, Urban over 10K to 25K, Urban over 3K to 10K, Rural.

The Dutch data (shown in section 6.5.1) is provided to the public¹⁶ at a very high level of aggregation. The following attributes are provided for each mode of transport for each area to two decimal places:

- the proportion of all commuters travelling by each mode
- average distance of trip
- average time per trip

The Netherlands data publication policy can be characterised as providing a very high level of accessibility, but for quite low quality data: it would not be possible to use this dataset as the basis of a spatial microsimulation model because, even if socio-demographic constraints were obtained, the information is provided as averages, telling us nothing about the distribution of trip distances in each area. For more detailed geographically aggregated, one would have to manually aggregate the Dutch equivalent of the National Travel Survey.¹⁷ However, the Dutch data does allow for calculation of energy costs, as both mode, distances and proportions are available (section 6.5).

On the other extreme, many geo-referenced micro level datasets on commuting behaviour have been collected. These are generally small in geographical coverage (at least relative to the nationwide aggregate level commuting datasets collected through national censuses) and sometimes in scope also (for example, it is very common for large organisations to conduct travel surveys of their staffs' travel patterns). In many cases, a precise geo-reference is allocated to each individual participating in the survey, although this dataset is generally not released due to its sensitivity.¹⁸ A very large and detailed example of a geo-referenced individual level dataset is the *Encuesta de Movilidad de Bogotá 2011* (Centro Nacional de Consultoría, 2012), in which 16,157 'valid' questionnaires were collected. In addition to questions about travel (mode, distance and frequency of travel to work and other places), a range of socio-economic details were collected, including type of housing, social class, income, 'motorisation' (access to cars, motorbikes and bicycles) and level of education. Unsurprisingly this dataset is not available publicly, but is available to Colombian researchers with international collaborators (Ana Moreno Monroy, personal communication). To some extent such a rich dataset would render the process of generating spatial microdata unnecessary (although such datasets could

¹⁶See <http://statline.cbs.nl>, (full link embedded in the pdf version of this thesis.)

¹⁷Piet Rietveld, personal communication. In fact, there is a plan to do precisely this to provide data to help explain the differences between English and Dutch energy use, described in section 6.5.

¹⁸A potential case study for this thesis was to take data from the Ordnance Survey's travel survey as the basis for assessing the energy impacts of organisation level change. This did not materialise in part due to time constraints and in part due to concern over access to the geo-referenced individual level data.

be very useful for validation and testing of these methods). However, the methods of analysis used to interpret the datasets presented in the latter sections of this chapter and in section 7.3 could well be applicable to these valuable micro level datasets.

4.4 Geographical data: infrastructure and environment

The datasets presented so far, on energy use of personal travel and commuting behaviour, are sufficient to calculate the energy costs of commuting at individual and aggregate levels. The scope of this work extends beyond mere description, however. Additional input information is required to explain *why* commuting costs are as they are and to determine the factors likely to influence the energy costs of commuting beyond those considered so far. These additional data are classified into infrastructure and topography, and remoteness.

4.4.1 Infrastructure

As discussed further in section 5.4.4, the Euclidean distances reported in the census constraint variable categories (0 - 2 km; 2 - 5 km etc.) are often not the same as the actual distance travelled to work. This is due to many reasons, many of them behavioural. Trip chaining (e.g. taking a detour on the return journey from work to do the shopping or on the way there to ‘drop off the kids’), habitual use of a certain non-optimum route to work or even preference for certain parking spaces can all affect circuitry. However, infrastructure also has a large, probably dominant, role to play in determining how far people *actually* travel to work relative to the linear distance between home and work. In most cases it is physically impossible to travel from A to B in a straight line across an urban area due to various impassible objects that lie in the way, such as building, fences and rivers (for all modes of transport) and one-way streets, pedestrianised zones, prohibitive congestion charges and bollards (for cars). Public transport is the most constrained geographically, as buses and railed vehicles can only follow pre-defined paths. Thus, although trains (and to a limited extent buses, when dedicated bus lanes are present) tend to take more direct routes into the centre of cities, this does not guarantee that trips by these modes will be less circuitous than car travel.

Theoretically, the infrastructure on which every mode of transport can usefully be thought of as a set of points and one-dimensional lines that overlay the 2D geographical surface. This is reflected in available data on transport networks: they are a complex interacting masses of lines (representing the guideways) and points (intersections between these lines, places to enter the network such as train and bus stations and motorway

link roads). In order to differentiate between the different transport systems, they can be represented as completely separate (implicitly non-interacting) layers (figure 4.6). Alternatively, attributes can be assigned to each line and point on the entire transport network that includes all nodes and lines from all networks. These attributes (when present) can be used to determine the modes that are able to travel on each, the size of the pathway, information about speed of travel and, in some cases, direction of travel and other qualities. With the growth of internet-connected monitoring systems, ‘live’ attributes are increasingly feasible (although not yet available in any dataset the author knows of), such as frequency and destination of departures and congestion.

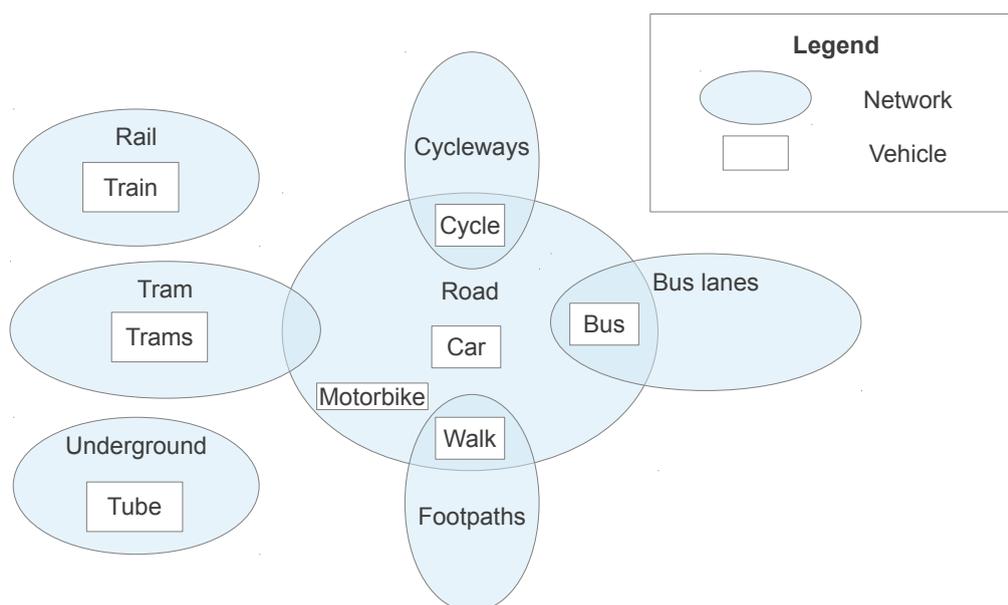


FIGURE 4.6: Schematic of main transport networks used for personal travel and the vehicles that can use them. Diagram based on Bolbol and Cheng (2013).

Clearly, this is a complex body of information, and different datasets deal with it differently (table 4.4). Only the top three data sources in table 4.4 are available free for academic purposes; these are illustrated in figure 4.7 to figure 4.9. Each of these data sources has its advantages and disadvantages, the most relevant of which (for the purposes of analysing energy use in personal travel) will be briefly discussed.

The Open Street Map dataset is the most suitable ‘on paper’ due to its coverage of all transport systems in a single file, its level of detail (between the two free Ordnance Survey offerings: not so large as to make it unwieldy; not too small to lack detail) and frequent

TABLE 4.4: Comparison of data sources for travel networks

Network data source	Networks covered	Key attributes	Availability
Open Street Map	All	Frequent updated, routing-compatible, official and unofficial	Free
Meridian 2	Road, rail	Lightweight (< 1 Gb for all UK), national coverage	Via Edina
Mastermap ITN	Road, pedestrian	Large (~100 Gb for all UK), detailed with routing	Via Edina
ITN Urban Paths	Pedestrian, cycle	Large, detailed map of UK's urban paths and cycleways	Priced

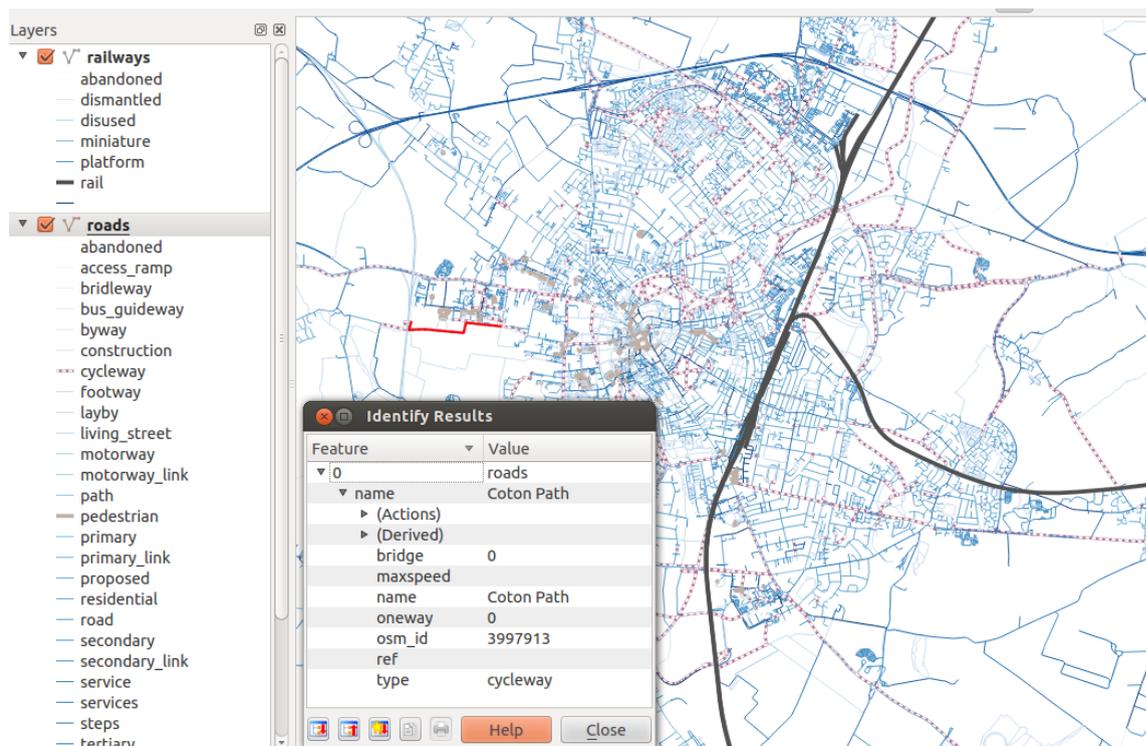


FIGURE 4.7: Visualisation of the OSM data source of the transport network.

rate of update. Another major advantage of the OSM dataset is its global coverage: this means that analyses conducted on it for one country can easily be replicated anywhere in the world. This is not the case with the Ordnance Survey datasets, as they are proprietary (not available to non-academic or foreign users) and unique to the UK.

The Ordnance Survey datasets do offer some advantages, however. These can be summarised as reliability, stability and links to policy makers. All data entries into the Ordnance Survey system are conducted by professionals who have been formally trained, and operate to carefully defined standards. OSM data, by contrast, can be added by

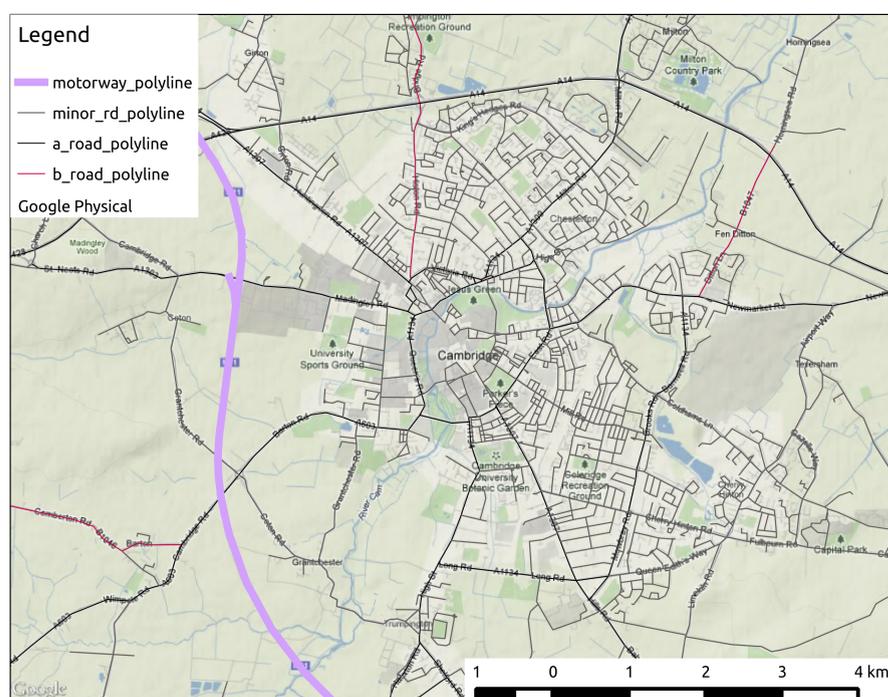


FIGURE 4.8: The Meridian 2 transport network dataset.

anyone with an internet connection. This ‘democratisation’ of data offers various auxiliary benefits to its participants (Foresman, 2008) but also raises issues of data quality. How can one trust the location and attributes of pathways on a map if they were entered by amateurs? This is not a question that will be tackled here, but the interested reader is directed towards the University of Nottingham’s OSM-GB (Open Street Map Great Britain) project¹⁹ and an academic paper on the subject (Haklay, 2010). Haklay (2010) notes the lack of systematic studies comparing the quality of traditional and open source (referred to as ‘volunteered geographic information’) approaches to maps, and sets-out to fill the research gap. It was found that datasets derived from OSM are generally accurate, especially for large infrastructures such as motorways, which had an 80% overlap with the Ordnance Survey data for 2008 data. However, inconsistencies in the quality of OSM data were also noted, with rural and deprived areas tending to be more poorly represented in terms of the existence of objects and the accuracy of their attributes. Quality of digitisation ranged from “fairly sloppy in the area of Highgate” to “consistent and careful in South Norwood” (Haklay, 2010, p. 699). Large errors were far rarer than small ones and overall the OSM dataset was evaluated as being of ‘very good’ quality.

¹⁹This project combines OSM data with information from official sources aims to measure and improve the quality of the OSM database. See <http://www.osmgb.org.uk/> for more detail and to see their map.

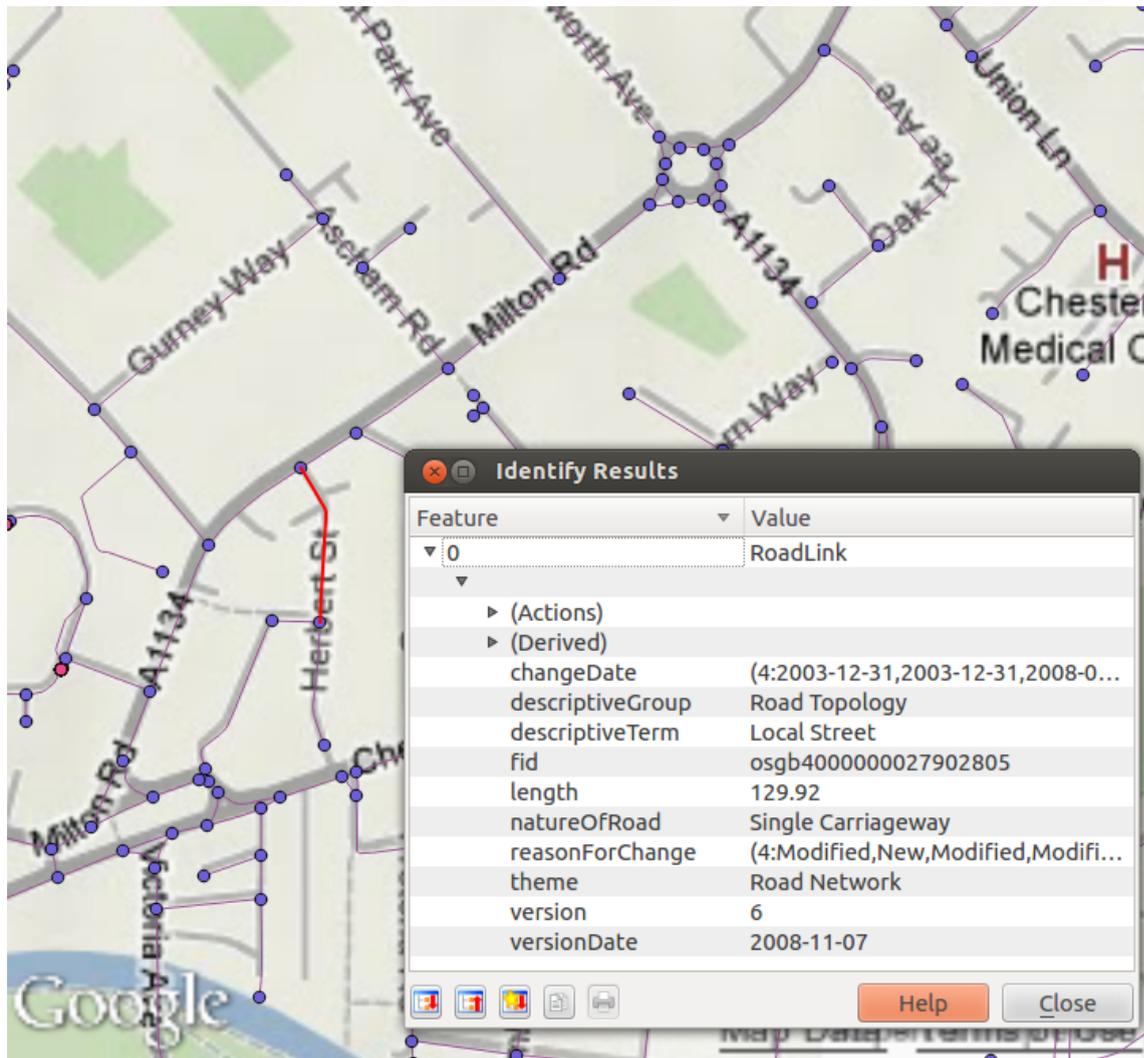


FIGURE 4.9: The Ordnance Survey's Integrated Travel Network dataset.

The second major concern is stability: because the OSM dataset is continually being updated, it is in constant flux. While most of these changes are small, and unlikely to alter the results of a particular routing operation, larger changes do sometimes occur. This is because every aspect of OSM is open to debate and change. There are, for example, around 5,000 object categories and growing for OSM objects and users are continuously adding new ones and debating the structure of the database.²⁰ The same issue also applies to the centralised Ordnance Survey datasets, although these update in a more systematic manner.

The final point to consider is usability. While OSM datasets are available worldwide, it is not the standard dataset in use by local planning departments, which generally have institutional access to Ordnance Survey data. The OSM data source is generally

²⁰See <http://wiki.openstreetmap.org/>.

also more difficult for non-expert users to find and download.²¹ Therefore, one could argue, analyses conducted using the official datasets will be more likely to be used officially. Of course, this point will vary from organisation to organisation and methods applicable to one network dataset are generally applicable to others. In OSM’s favour, public administrations in the UK have recently been recommended to use open source alternatives wherever possible, so the perception that only official sources are valid may fade.²²

Consideration of these points led OSM to be the favoured source for most applications due to its comprehensive coverage of transport networks in a single file and wide range of attributes for every transport path and node. The Meridian 2 dataset seems to be best suited for road coverage over large areas and is ideal for investigating road accessibility of different locations and network distances by car, as it is available in a handful of polygons for the entire country. Finally, Ordnance Survey’s ITN and Urban Paths layers should be useful for low level analysis of likely routes of non-motorised modes. However, the former was found to be difficult to use and the latter appears to be unavailable under an academic licence.

4.4.2 Topographic data

Topography is potentially useful both as an explanatory variable of non-motorised travel and an input into calculations of energy use, due the addition energy use of driving uphill compared with driving on the flat.²³ The extra mechanical energy use of vertical displacement is the same as the potential energy (PE, measured in Joules) gained by climbing:

$$PE = mgh \quad (4.1)$$

which is determined by the mass of the vehicle (m , in kg), the gravitational constant (g — $\sim 10 \text{ m/s}^2$ on Earth) and height gained (h , in meters).

²¹The OSM transport dataset presented in figure 4.7, for example, was not accessed directly as the .osm file in which the dataset is typically stored due to problems with downloading, extracting and loading the files in QGIS. Instead, pre-processed shapefiles, derived from the original OSM data were downloaded from download.bbbike.org <http://download.bbbike.org/osm/bbbike/Cambridge/>. Geofabrik.de, and cloudmade also offer OSM data in forms that are more user friendly for desktop GIS users. (OSM is well suited to use in geo-databases such as PostGIS.)

²²These recommendations were published in the Government Service Design Manual, as reported in the story “New UK government manual for public administrations promotes open source” by <https://joinup.ec.europa.eu/news/new-uk-government-manual-public-administrations-promotes-open-source>.

²³This energy could theoretically be regained via regenerative braking. This technology is currently available in only a handful of models, and their “charge/discharge capabilities are limited” (Clarke et al., 2010). Due to the added cost and complexity of regenerative braking systems, their commercialisation for cars and other vehicles is deemed to be long-way off (if it ever takes off).

Topographic datasets for the UK are available from the following sources, ranging from the coarsest to the finest:

- The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor mounted on the Space Shuttle has produced a dataset that has been analysed by the Japanese and US space agencies. This has resulted in the Global Digital Elevation Model Version 2 (GDEM V2). The GDEM has global coverage, a 30 meter resolution, and is free to download from a handful of websites, providing a user account and reason for download are provided.²⁴ The dataset forms the basis of digital elevation model used by Google Earth and other Google products.
- The Ordnance Survey provides height data, either as contour lines or as interpolated points, for the entirety of the UK and Ireland. The former has a 5 m vertical resolution with an error margin of 2.5 m; the latter has a spatial resolution of 10 m and an accuracy that depends on the complexity of the terrain from which points are interpolated.
- To improve its flood analysis capabilities, the Environment Agency paid for a private company to produce high quality LIDAR (light detection and ranging) data for the majority of the island of Great Britain. The data can be ordered from the Geomatics website at 25 cm, 50 cm, 1 m, and 2 m resolution, as either a digital terrain model (DTM, with buildings and vegetation included) or as a surface model (DSM, representing the 'bare' surface). The coverage increases from less than 1% for the 25 cm data (for areas most at risk from flooding) to around 95% for the 2 m data. The data can be downloaded commercially for £100 per square kilometre, or free for non-commercial purposes.

These datasets were not used directly in the thesis. Their inclusion could, however, provide background and interesting avenues for further research for example as a predictor of the rate of cycling and walking or as a local modifier of energy economy estimates.

4.4.3 Remoteness

In addition to the transport infrastructure of each area, remoteness was expected to influence commuter energy use, primarily via distance travelled and car dependence. Intuitively, remote areas are likely to have high energy costs simply by virtue of the average distance to jobs. Distance to nearest urban centre is a potentially useful proxy to

²⁴See the following hyperlinks: cdex.cr.usgs.gov, <http://reverb.echo.nasa.gov> and <http://www.jspacesystems.or.jp>. A digital elevation dataset was successfully downloaded from the first site.

measure this type of remoteness. This, and related classification of areas, form the basis of this section. The example described applies to medium super output areas (MSOAs) in Yorkshire and the Humber; the same method could just as easily be applied other geographies or regions.

The starting point for this analysis is to consider the opposite of remoteness: living within a city centre. City inhabitants are clearly not isolated in terms of amenities and social connection, but living in a city does not actually guarantee proximity to good jobs.²⁵ To tackle this issue the concept of ‘employment centre’, meaning an area with a high concentration of jobs, was used against which to measure remoteness. In order to calculate the remoteness of each MSOA area from employment centres, it was first necessary to define what constitutes an employment centre and what does not. Of course, the availability of jobs is not determined by the Euclidean distance to one dimensional points on the map: employment density varies continuously over space depending on the location of businesses, schools and other major employers (figure 4.10). However, employment centres can provide a neat simplification of reality, a model to simplify and help understand the complexity of the labour-market commuting interaction.

Initially, settlements were selected based on their populations. However, the selection of a threshold population will inevitably be arbitrary and would not necessarily reflect the employment opportunities of the area. (On the contrary, one could argue that jobs in some high population areas would be harder to get and more fought-over than in prosperous countryside areas.) To overcome this problem, the government’s official travel to work areas (TTWAs) were used. These are defined as geographically contiguous areas within which 75% of the population both lives and works (ONS, 2011). They are named according to the main economic centre(s) within each. In some cases the TTWAs two main employment centres, as reflected in their name, for example Malton & Pickering.

To use these TTWA centres as the basis for distance to work calculations, points were allocated to the named employment centre(s) within each TTWA (see the white stars in figure 4.11) using Ordnance Survey’s Strategic vector layer of place names. The next stage was to convert the MSOA areas into points. Care was taken to use the population-weighted centres of each area, rather than the more commonly used area-weighted centroids, to reflect distances for typical commuters in each MSOA. The use of population-weighted centroids reduced the average distance to employment centres. This is illustrated clearly in the case of “Ryedale 002” in North Yorkshire, which extends more than 10 km North of Pickering town centre (located above the “i” in “Malton and

²⁵A good example of this is Hull, which has the highest unemployment rate of any UK city: 8.7% of the adult population was receiving unemployment benefit as of March 2013 (Rogers, 2013).

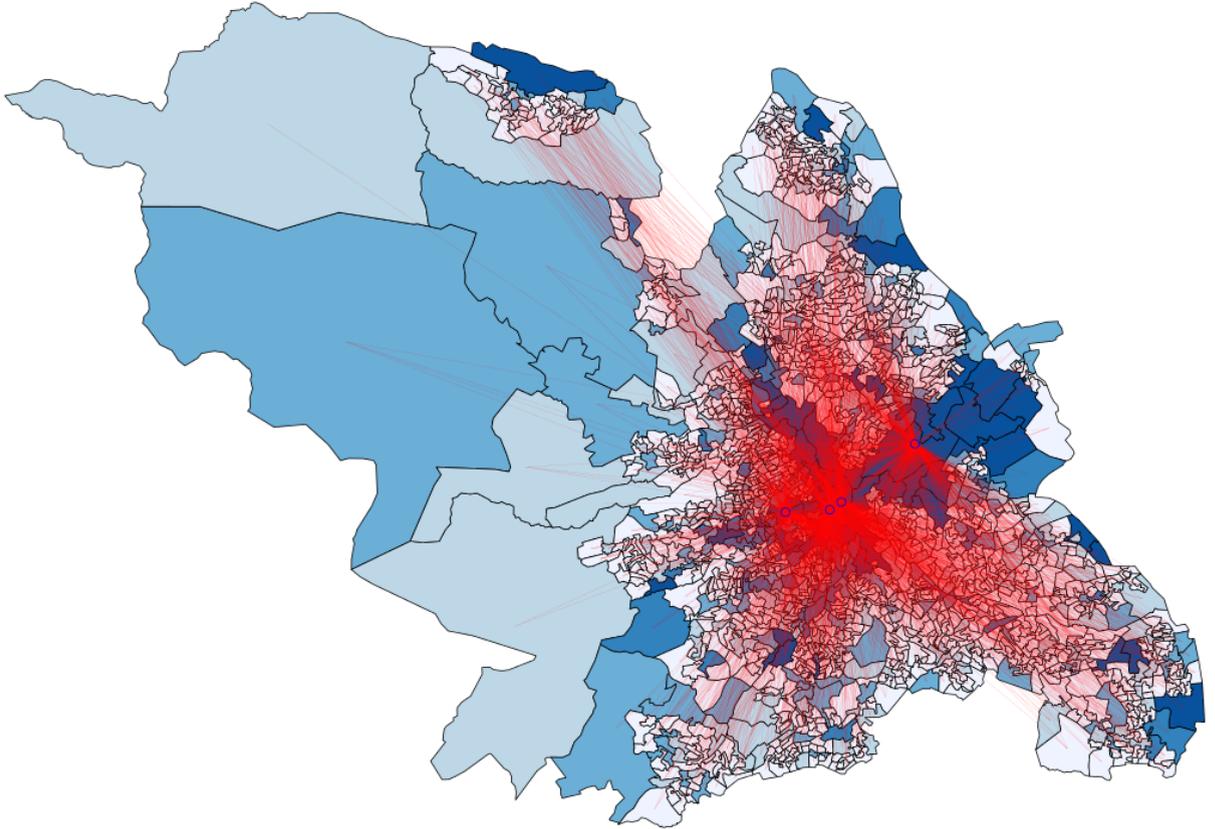


FIGURE 4.10: Distribution of employment in Sheffield, based on flow data from Nomis. Blueness is proportional to the number of jobs; red lines represent the home-work trips of people who work in the four Output Areas that employ the most.

Pickering”) while its population centre is located less than 2 km from the employment centre, hence the blue colour.

The algorithm to calculate the distance to the nearest neighbour in a separate layer is available in QGIS using the Ftools plugin. However, this produced erroneous results, so the analysis was transferred to R where the function `mncross` from the package `spatstat` was used to produce the correct output. These results were converted back into the vector geographic file format of shapefiles using QGIS for plotting. The resulting Euclidean distances are depicted in figure 4.11. The variable is interpreted as ‘distance from employment centre’ and a proxy for remoteness.

4.5 Building a spatial microsimulation model in R

The previous sections have established the availability of high quality data on commuting behaviour at geographic and individual levels. Associated variables such as remoteness and proximity to key transport networks and nodes can also be inferred based on good

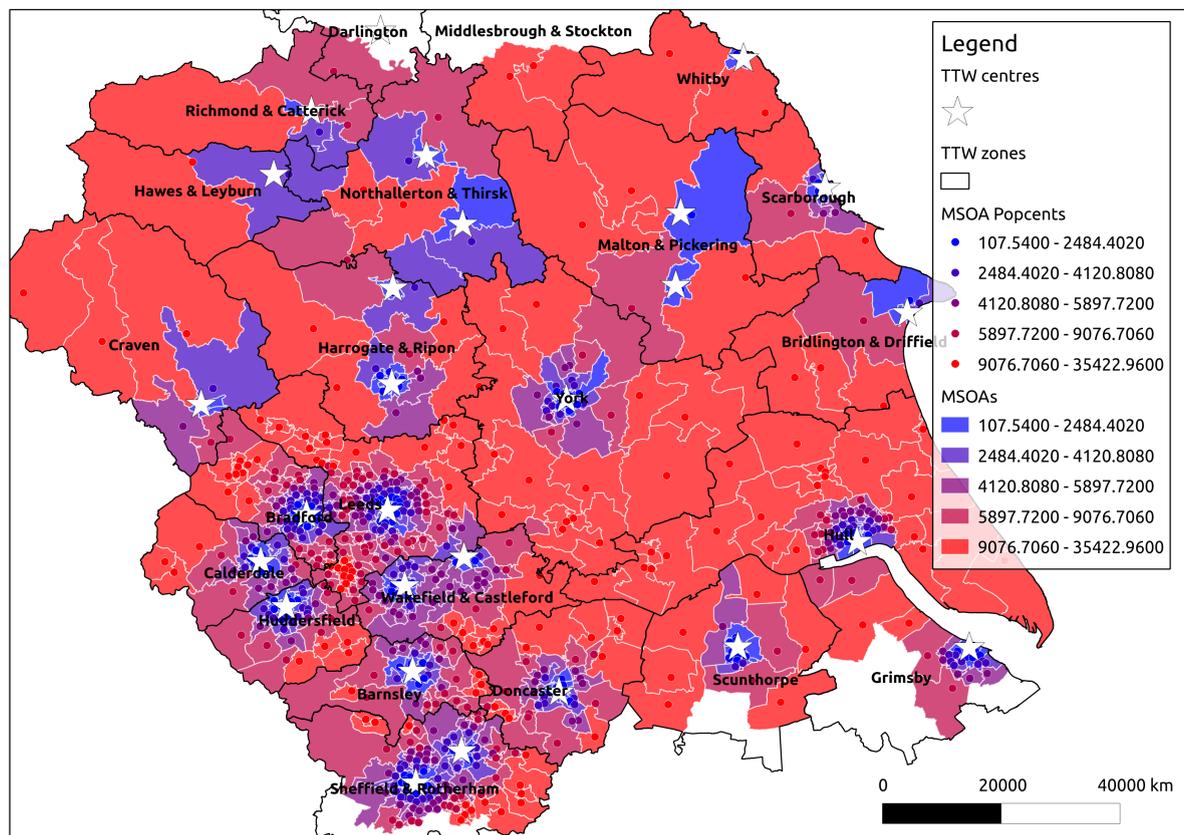


FIGURE 4.11: Illustration of how distance to employment centre was calculated.

geographic data. The challenge now from a modelling perspective is to join all these elements together. Travel to work is clearly an activity that occurs at the individual level. Overall patterns of commuting can be expected to be closely related to larger scale processes — such as the nature of labour and housing markets, cultural norms and the main sectors of local economic activity. However, commuting *behaviour* is always undertaken by individuals making decisions over which they have some degree of control. From short-term choices about at what time to get into work (increasingly common due to ‘flexi-time’) to strategic decisions about where to live and work, individuals influence their commuting patterns.

The critical next step, therefore, is to generate spatial microdata on commuting: individual level data allocated to spatial areas. This is where spatial microsimulation comes in, to combine the aggregate level commuting data with the individual level data presented in the previous section. The technique used in this thesis is Iterative Proportional Fitting (IPF), which is described in chapter 3. The IPF algorithm allocates a weight to each individual for each area under consideration. If the individual is highly representative of the area (relative to the individual level dataset) the weight will increase; if the

individual is not representative of the area in question (or is not present), the weight will decrease.

As discussed in chapter 3, computer hardware has long influenced, and even *determined* the types of analysis that can be conducted at the individual level. Hardware limitations are far less of a constraint than they used to be, elevating the importance of software. As Clarke and Holm (1987) made clear more than 20 years ago, the choice of software also has a major impact on the model's flexibility, efficiency, reproducibility and ease of coding. It was noted that "little attention is paid to the choice of programming language used" (Clarke and Holm, 1987, p. 153), an observation that appears to be as true now as it was then. For this research, a conscious decision was made early on to use R, and this has had an impact on the model construction, features, analysis and even design philosophy. It is at this stage, therefore, that R as a platform for undertaking spatial microsimulation is discussed in some detail. The theory is discussed in section 4.5.2

4.5.1 Why R?

The majority of the quantitative analysis conducted for this thesis, and the entirety of the spatial microsimulation model used, was written in R. This was a deliberate choice made at the outset rather than an arbitrary decision based on predecessors. This section briefly explains the importance of choosing appropriate computer software in academic research in general, with respect to reproducibility, a cornerstone of science. The choice of R in particular is then described. R was chosen for its virtues, which are summarised well in Matloff (2011):

- "a public-domain implementation of the widely-regarded S statistical language; R/S is the de facto standard among professional statisticians
- comparable, and often superior, in power to commercial products in most senses
- available for Windows, Macs, Linux
- in addition to enabling statistical operations, it's a general programming language, so that you can automate your analyses and create new functions
- object-oriented and functional programming structure
- your data sets are saved between sessions, so you don't have to reload each time
- open-software nature means its easy to get help from the user community"

Matloff (2011) also provides five examples of the type of people who would be interested in programming in R, rather than using it as a quick and easy tool for graphing and numerical analysis. Of particular relevance to this thesis is the second of Matloff's categories of people for whom R is recommended: "Academic researchers developing statistical methodology that is either new or combines existing methods into an integrated procedure that needs to be codified for usage by the general research community" (Matloff, 2011, p. xiii).

The quote also suggests some of the potential advantages of writing multi-use scripts in R rather than a collection of unrelated functions: by its very nature modelling is an iterative exercise, so it is important to be able to invoke specific chunks of code (e.g. using the `source()` command) that are modular. While this capability is not unique to R, the range of statistical functions that can be performed within a unified environment is. The rapidly growing use of R for spatial data analysis was another factor that makes it well-suited to spatial-microsimulation and other types of geographic modelling (e.g. Singleton and Stephenson, 2013). R overcomes the need to switch between several different programs (e.g. one for analysis, one for graphing, one for mapping), increasing simplicity and (eventually) productivity.

Despite all these advantages, R has a number of weaknesses itemised below along with techniques and projects which mitigate them:

- R loads everything into RAM. This can be problematic when querying large datasets, of which only one part needs to be accessed at a time.²⁶ There are numerous tools that overcome this constraint by querying databases (stored on the hard-disk) from within R, including RMySQL (James and DeRoy, 2012) and Rattle (Williams, 2009). Singleton and Stephenson (2013) queried a PostGIS database from within R to estimate the route taken by school commuters, for the estimation of associated CO₂ emissions.
- R can be slow, for example running for loops and when used as a general programming language which is not R's main purpose. R being an interpreted language there are times when the performance advantages of a compiled language such as C/C++ are needed. To this end the RCPP package was developed, which provides "Seamless R and C++ integration" (Eddelbuettel and François, 2011). Packages are also available to integrate R with Java (rJava), Python (rpy2) and text markup languages such as Markdown and L^AT_EX(knitr). Also, the base installation of R provides an inbuilt C compiler for doing the 'heavy lifting' tasks such as kernel density estimation (Peng and de Leeuw, 2002). These links to other languages

²⁶ This is especially common with geographical analysis, which often focus on a small area of a large map at a time (Obe and Hsu, 2011).

could be useful for porting pre-existing algorithms for spatial microsimulation into R (e.g. Williamson, 2007; Ballas et al., 2007).

- R's base graphics are unattractive and unintuitive. This problem has been tackled most comprehensively in a PhD thesis by Hadley Wickham (Wickham, 2008). The aim was to implement the 'grammar of graphics' (Wilkinson and Wills, 2005), a comprehensive and coherent approach to data visualisation, into an existing open-source statistical programming language. The result is `ggplot2`, which has a very active user and developer community (Wickham, 2011). `ggplot2` has been used throughout this thesis for plotting with help from key references (Wickham, 2011; Chang, 2012).
- R's visualisations are not dynamic. This problem has been partly overcome in the realm of GIS with two QGIS plugins: `ManageR` and `Home range`. For dynamic web applications, the R package `Shiny` provides similar interactive functionality as Google's Fusion tables project. There is also a nascent interface between R and Processing (`rprocessing`), an abstraction of Java ideal for dynamic visualisations of geographic data (e.g. Wood et al., 2010).

4.5.2 IPF theory: a worked example

In most modelling texts there is a strong precedence of theory over application: the latter usually flows from the former. The location of this section after a description of the programming language R is therefore a little unconventional but there is a logic to this order. Having demonstrated the power and flexibility of the programming language in which the model is written, the next stage is to analyse the task to which it is to be set. More importantly for reproducible research, this theory section is illustrated with a simple worked example that culminates in a question to the reader, to test his or her understanding.

IPF is a simple statistical procedure, "in which cell counts in a contingency table containing the sample observations are scaled to be consistent with various externally given population marginals" (McFadden et al., 2006). In other words, and in the context of *spatial* microsimulation, IPF produces maximum likelihood estimates for the frequency with which people appear in different areas. The method is also known as 'matrix raking' or the RAS algorithm, (Birkin and Clarke, 1988; Axhausen and Müller, 2010; Simpson and Tranmer, 2005; Kalantari et al., 2008; Jiroušek and Peučil, 1995) and has been described as one particular instance of a more general procedure of 'entropy maximisation' (Johnston and Pattie, 1993; Blien and Graef, 1998). The mathematical properties of IPF have been described in several papers (Bishop et al., 1975; Fienberg, 1970; Birkin

and Clarke, 1988). Illustrative examples of the procedure can be found in Saito (1992), Wong (1992) and Norman (1999). Wong (1992) investigated the reliability of IPF and evaluated the importance of different factors influencing the its performance. Similar methodologies have since been employed by Mitchell et al. (2000), Williamson et al. (2002) and Ballas et al. (2005a; 2005b) to investigate a wide range of phenomena.

To illustrate how IPF works in practice, a simplified example is described below. This is a modified version of a simpler demonstration from Ballas et al. (2005b).²⁷ Table 4.5 describes a hypothetical microdataset comprising 5 individuals, who are defined by two constraint variables, age and sex. Each has two categories. Table 4.6 contains aggregated data for a hypothetical area, as it would be downloaded from census dissemination portal Casweb. Table 4.7 illustrates this table in a different form, which shows our ignorance of interaction between age and sex.

TABLE 4.5: A hypothetical input microdata set (the original weights set to one). The bold value is used subsequently for illustrative purposes.

Individual	Sex	Age-group	Weight
1	Male	Over-50	1
2	Male	Over-50	1
3	Male	Under-50	1
4	Female	Over-50	1
5	Female	Under-50	1

TABLE 4.6: Hypothetical small area constraints data (s).

Constraint \Rightarrow	i		j	
Category \Rightarrow	i_1	i_2	j_1	j_2
Area \Downarrow	Under-50	Over-50	Male	Female
1	8	4	6	6

Table 4.8 presents the hypothetical microdata in aggregated form, that can be compared directly to Table 4.7.

Using these data it is possible to readjust the weights of the hypothetical individuals, so that their sum would add up to the totals given in Table 4.7 (12). In particular, the

²⁷In Ballas et al. (2005b) the interaction between the age and sex constraints are assumed to be known. (Their equivalent of table 4.7 contains data for every cell, not question marks.) This results in IPF converging instantly. However, in Census data, such cross-tabulation is often absent, and IPF must converge over multiple constraints and iterations. This latter scenario is assumed in the worked example below. Other worked examples of the principles are provided in Johnston (1985, Appendix 3) (for entropy maximisation), Norman (1999) and Simpson and Tranmer (2005) (using the proprietary statistical software SPSS).

TABLE 4.7: Small area constraints expressed as marginal totals, and the cell values to be estimated.

Marginal totals	Age/sex	<i>j</i>		T
		Male	Female	
<i>i</i>	Under-50	?	?	8
	Over-50	?	?	4
	T	6	6	12

TABLE 4.8: The aggregated results of the weighted microdata set ($m(1)$). Note, these values depend on the weights allocated in Table 4.5 and therefore change after each iteration

Marginal totals	Age/sex	<i>j</i>		T
		Male	Female	
<i>i</i>	Under-50	1	1	2
	Over-50	2	1	3
	T	3	2	5

weights can be readjusted by multiplying them by the marginal totals, originally taken from Table 4.6 and then divided by the respective marginal total in 4.8. Because the total for each small-area constraint is 12, this must be done one constraint at a time. This can be expressed, for a given area and a given constraint (i or age in this case), as follows:

$$w(n+1)_{ij} = \frac{w(n)_{ij} \times sT_i}{mT(n)_i} \quad (4.2)$$

where $w(n+1)_{ij}$ is the new weight for individuals with characteristics i (age, in this case), and j (sex), $w(n)_{ij}$ is the original weight for individuals with these characteristics, sT_i is element marginal total of the small area constraint, s (Table 4.6) and $mT(n)_i$ is the marginal total of category j of the aggregated results of the weighted microdata, m (Table 4.8). n represents the iteration number. Although the marginal totals of s are known, its cell values are unknown. Thus, IPF estimates the interaction (or cross-tabulation) between constraint variables. (Follow the emboldened values in the tables to see how the new weight of individual 3 is calculated for the sex constraint.) Table 4.9 illustrates the weights that result. Notice that the sum of the weights is equal to the total population, from the constraint variables.

After the individual level data have been re-aggregated (table 4.10), the next stage is to repeat equation (4.2) for the age constraint to generate a third set of weights, by replacing the i in sT_i and $mT(n)_i$ with j and incrementing the value of n :

TABLE 4.9: Reweighting the hypothetical microdataset in order to fit Table 4.6.

Individual	Sex	age-group	Weight	New weight, $w(2)$
1	Male	Over-50	1	$1 \times 4/3 = \frac{4}{3}$
2	Male	Over-50	1	$1 \times 4/3 = \frac{4}{3}$
3	Male	Under-50	1	$1 \times 8/2 = 4$
4	Female	Over-50	1	$1 \times 4/3 = \frac{4}{3}$
5	Female	Under-50	1	$1 \times 8/2 = 4$

$$w(3)_{ij} = \frac{w(2)_{ij} \times sT_j}{mT(2)_j} \quad (4.3)$$

To test your understanding of IPF, apply equation (4.3) to the information above and that presented in table 4.10. This should result in the following vector of new weights, for individuals 1 to 5:

$$w(3) = \left(\frac{6}{5}, \frac{6}{5}, \frac{18}{5}, \frac{3}{2}, \frac{9}{2} \right) \quad (4.4)$$

As before, the sum of the weights is equal to the population of the area (12). Notice also that after each iteration the fit between the marginal totals of m and s improves. The total absolute error (TAE, see equation (4.6) below) from $m(1)$ to $m(2)$ improves from 14 to 6 in table 4.8 and table 4.10 above. TAE for $m(3)$ (not shown, but calculated by aggregating $w(3)$) improves even more, to 1.3. This number would eventually converge to 0 through subsequent iterations, as there are no empty cells in the input microdataset; a defining feature of IPF.

TABLE 4.10: The aggregated results of the weighted microdata set after constraining for age ($m(2)$).

Marginal totals	Age/sex	i		
		Male	Female	T
j	Under-50	4	4	8
	Over-50	$\frac{8}{3}$	$\frac{4}{3}$	4
	T	$6\frac{2}{3}$	$5\frac{1}{3}$	12

The above process, when applied to more categories (e.g. socio-economic class) and repeated iteratively until a satisfactory convergence occurs, results in a series of weighted microdatasets, one for each of the small areas being simulated. This allows for the estimation of variables whose values are not known at the local level (e.g. income) (Ballas et al., 2005b). An issue with the results of IPF (absent from combinatorial optimisation methods), however, is that it results in non-integer weights: fractions of individuals appear in simulated areas. As described in the introduction, this is not ideal for certain applications. Integer weights allow the results of spatial microsimulation to be

further processed using dynamic microsimulation and agent based modelling techniques (Pritchard and Miller, 2012).

Spatial microsimulation can also provide insight into the likely distribution of individual level variables about which only geographically aggregated statistics have been made available. An issue with the results of IPF (absent from combinatorial optimisation methods), however, is that it results in non-integer weights: fractions of individuals appear in simulated areas.

4.5.3 Implementing IPF in R

The above example is best undertaken by hand, probably with a pen and paper to gain an understanding of IPF, before the process is automated for larger datasets. This section explains how the IPF algorithm described above was implemented in R, using a slightly more complex example. (Lovell and Ballas, 2013).²⁸

Loading in the data

In the full model the input datasets are stored as .csv files, one for each constraint and one for the input microdata, and read in with the command `read.csv`. For the purposes of understanding how the model works, the dataset is read line by line, following the example above. The following code creates example datasets, based on the same hypothetical survey of 5 individuals described above, and 5 small areas. The spatial microsimulation model will select individuals based on age and sex and mode of transport (mode of transport is also used on the larger online example described in footnote 28). For consistency with the (larger) model used for the paper, the individual level data will be referred to as USd (Understanding Society dataset) and the geographic data as all.msim (for all constraint variables). The code to read-in the individual level data are presented in code sample 4.1. When called, the data are then displayed as a table (see listing 4.2). The same procedure applies to the geographical data (listing 4.3).

IPF relies on the assumption that all constraint variables will contain the same number of people. This is logical (how can there be more people classified by age than by sex?) but can cause problems for constraint variables that use only a subset of the total population, such as those who responded to questions on travel to work. To overcome this problem, it is possible to normalise the constraint variables, setting the total for each to the one that has the most reliable total population. This worked example simply checks whether or not they are (listing 4.4).

²⁸This tutorial is available from Rpubs, a site dedicated to publishing R analyses that are reproducible. It uses the RMarkdown mark-up language, which enables R code to be run and presented within documents. See <http://rpubs.com/RobinLovell/5089>.

```

# Read in the data in long form (normally read.table() used)
c.names <- c("id", "age", "sex")
USd <- c(
  1, 59, "m",
  2, 54, "m",
  3, 35, "m",
  4, 73, "f",
  5, 49, "f")
USd <- matrix(USd, nrow = 5, byrow = T) # Long data into matrix
USd <- data.frame(USd) # Convert this into a dataframe
names(USd) <- c.names # Add correct column names
USd$age <- as.numeric(levels(USd$age)[USd$age]) # Age is a numeric

```

LISTING 4.1: Manual input of individual level data in R

```

USd # Show the data frame in R
##   id age sex
## 1  1  59  m
## 2  2  54  m
## 3  3  35  m
## 4  4  73  f
## 5  5  49  f

```

LISTING 4.2: Output of the USd data frame

```

category.labels <- c("16-49", "50+" # Age constraint
, "m", "f" # Sex constraint
# more constraints could go here
)
all.msim <- c( 8, 4, 6, 6, # Original aggregate data
2, 8, 4, 6, # Elderly
7, 4, 3, 8, # Female dominated
5, 4, 7, 2, # Male dominated
7, 3, 6, 4 # Young
)
all.msim <- matrix(all.msim, nrow = 5, byrow = T)
all.msim <- data.frame(all.msim) # Convert to dataframe
names(all.msim) <- category.labels # Add correct column names

```

LISTING 4.3: Geographic data input

Reweighting the survey dataset

Iterative proportional fitting determines the weight allocated to each individual for each zone to best match the geographically aggregated data. A weight matrix is therefore created, with rows corresponding to individuals and columns to zones, as described in section 4.5.2. In R, this, and the creation of the aggregated results matrix, is done with

```

# Check totals for each constraint match
rowSums(all.msim[,1:2]) # Age constraint
## [1] 12 10 11 9 10
rowSums(all.msim[,3:4]) # Sex constraint
## [1] 12 10 11 9 10

rowSums(all.msim[,1:2]) == rowSums(all.msim[,3:4])
## [1] TRUE TRUE TRUE TRUE TRUE

```

LISTING 4.4: R code to check the constrain populations match

code presented in listing 4.5).²⁹

```

weights0 <- array(dim=c(nrow(USd),nrow(all.msim)))
weights1 <- array(dim=c(nrow(USd),nrow(all.msim)))
weights2 <- array(dim=c(nrow(USd),nrow(all.msim)))

weights0[,] <- 1 # sets initial weights to 1

USd.agg <- array(dim=c(nrow(all.msim),ncol(all.msim)))
USd.agg1 <- array(dim=c(nrow(all.msim),ncol(all.msim)))
USd.agg2 <- array(dim=c(nrow(all.msim),ncol(all.msim)))
colnames(USd.agg1) <- category.labels

```

LISTING 4.5: Creating arrays of weights in R

It is important to note that in real survey data, the variables are not always neatly categorised into the same bins as the levels of the aggregate data. Age, for example can be classified in many different ways. Also, a wide form is useful for subsequent steps. Therefore, it is necessary to convert the ‘thin’ survey dataset into a wider form, by converting a single column such as age or sex into multiple columns corresponding to the number of categories. Sometimes the cut-off points of the categories can be decided (as with age), or categories can be merged (when many different NA options are available, for example). The code that performs this important process for our example dataset is presented in listing 4.6.

Another important step shown in section 4.5.2 was that of converting the ‘long’ survey dataset into a form that can be compared directly with the aggregated constraint variables. Listing 4.7 shows how this is done in R, and the code needed to view the results. (Notice that the first row of all.msim is the same as those displayed in table 4.6)

With the data loaded and processed into comparable formats, one is in a position to start comparing how well our individual level survey dataset fits with the aggregate

²⁹In subsequent versions of the model, single, multi-dimensional weight and aggregated result matrices are used, to reduce the length of the scripts.

```

USd.cat <- array(rep(0), dim=c(nrow(USd),
                             length(category.labels !=0)))

USd.cat[which(USd$age < 50),1] <- 1 # Age, "< 50"
USd.cat[which(USd$age >= 50),2] <- 1 # "50+"
USd.cat[which(USd$sex == "m"),3] <- 1 # Sex constraint: "m"
USd.cat[which(USd$sex == "f"),4] <- 1 # "f"
sum(USd.cat) # Should be 10

```

LISTING 4.6: R code to convert the survey dataset into binary form

```

for (i in 1:nrow(all.msim)){ # Loop creating aggregate values
  USd.agg[i,] <- colSums(USd.cat * weights0[,i])
}

# Test results
USd.agg

##      [,1] [,2] [,3] [,4]
## [1,]    2    3    3    2
## [2,]    2    3    3    2
## [3,]    2    3    3    2
## [4,]    2    3    3    2
## [5,]    2    3    3    2

all.msim

##    16-49 50+ m f
## 1     8   4 6 6
## 2     2   8 4 6
## 3     7   4 3 8
## 4     5   4 7 2
## 5     7   3 6 4

plot(as.vector(as.matrix(all.msim)),
     as.vector(as.matrix(USd.agg)), xlab = "Constraints",
     ylab = "Model output")
abline(a = 0, b = 1)

```

LISTING 4.7: R code to aggregate the survey dataset

constraints (see listing 4.7). Note that for `USd.agg`, the results are the same for every zone, as each individual has a weight of 1 for every zone. Note also the very poor fit between the variables at the aggregate level, as illustrated by poor correlation between the constraint and microdata variables ($r = 0.05$), and a plot of the fit presented in figure 4.12. The next stage is to apply the first constraint, to adjust the weights of each individual so they match the age constraints (listing 4.8 — note that the top row

USd.agg1 is the same as table 4.10). After this operation, the fit between the constraint variables and the aggregated microdata are far better ($r = 0.67$), but there is still a large degree of error (figure 4.13).

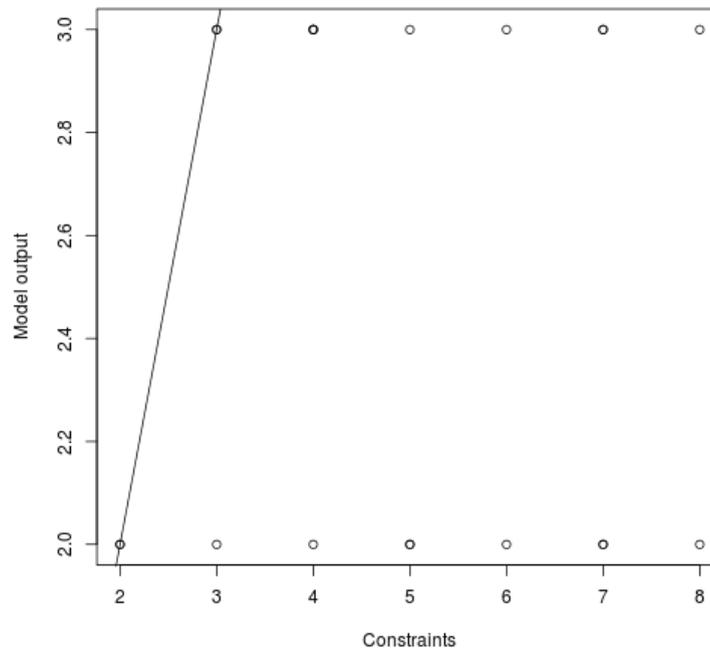


FIGURE 4.12: Scatter plot of the fit between census and survey data. This plot can be re-created using the plot command in listing 4.7.

We will perform the same checks after each constraint to ensure our model is improving. To see how the weights change for each individual for each area, one simply types `weights1`, for constraint 1 (listing 4.9). Note that the first column of weights 1 is the same as table 4.6.

```
##      [,1] [,2] [,3] [,4] [,5]
## [1,] 1.333 2.667 1.333 1.333 1.0
## [2,] 1.333 2.667 1.333 1.333 1.0
## [3,] 4.000 1.000 3.500 2.500 3.5
## [4,] 1.333 2.667 1.333 1.333 1.0
## [5,] 4.000 1.000 3.500 2.500 3.5
```

LISTING 4.9: The new weight matrix. Previously all weights were set to one.

To further improve the fit, one next constrains by the second aggregate constraint: sex (listing 4.10). To check that our implementation in R produces the same results

```

for (j in 1:nrow(all.msim)) {
  weights1[which(USd$age < 50),j] <- all.msim[j,1]/USd.agg[j,1]
  weights1[which(USd$age >= 50),j] <- all.msim[j,2]/USd.agg[j,2]
}
# Aggregate the results for each zone
for (i in 1:nrow(all.msim)) {
  USd.agg1[i,] <- colSums(USd.cat * weights0[,i] * weights1[,i])
}
# Test results
USd.agg1
##      16-49 50+      m      f
## [1,]      8   4 6.667 5.333
## [2,]      2   8 6.333 3.667
## [3,]      7   4 6.167 4.833
## [4,]      5   4 5.167 3.833
## [5,]      7   3 5.500 4.500

plot(as.vector(as.matrix(all.msim)),
     as.vector(as.matrix(USd.agg1)), xlab = "Constraints",
     ylab = "Model output")
abline(a = 0, b = 1)

```

LISTING 4.8: Reweighting of first constraint and testing of results

as the hand-calculated example, the resulting weights were queried. As shown by `weights3[,1]`, these are the same as those calculated for $w(3)$ above.

```

for (j in 1:nrow(all.msim)) {
  weights2[which(USd$sex == "m"),j] <-
    all.msim[j,3]/USd.agg1[j,3]
  weights2[which(USd$sex == "f"),j] <-
    all.msim[j,4]/USd.agg1[j,4]
}

weights3 <- weights0 * weights1 * weights2
for (i in 1:nrow(all.msim)) {
  USd.agg2[i,] <- colSums(USd.cat * weights3[,i])
}

weights3[,1]
## [1] 1.2 1.2 3.6 1.5 4.5

```

LISTING 4.10: Code to constrain the weights by sex

The model fit improves greatly after constraining for sex ($r = 0.992$). However, to ensure perfect fit more iterations are needed. Iterating just once more, as done on the online

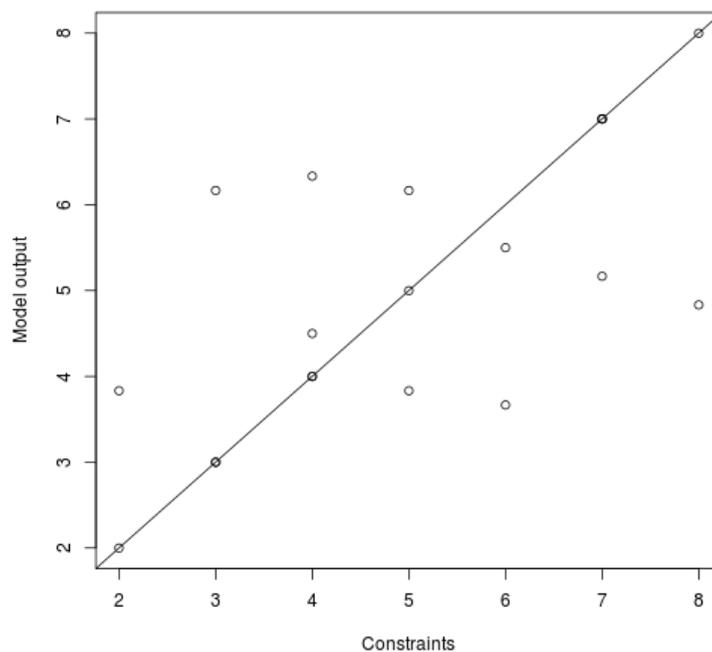


FIGURE 4.13: Scatter plot showing the fit after constraining by age.

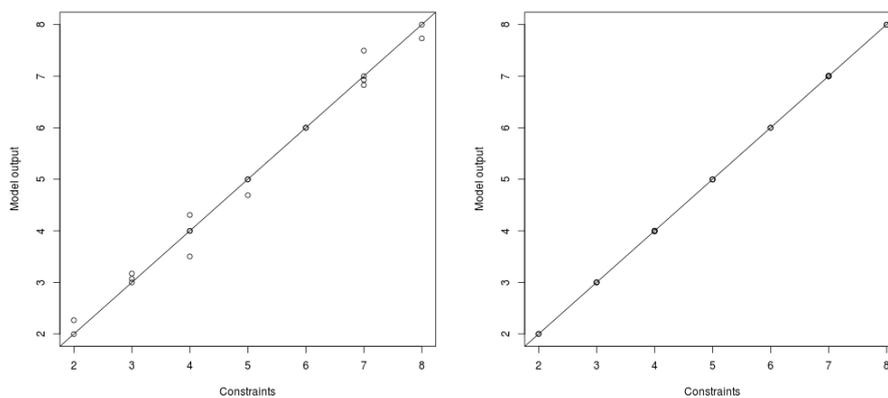


FIGURE 4.14: Improvement of model fit after constraining by sex (left) and after two complete iterations (right).

version of this section³⁰ results in a fit that is virtually perfect (figure 4.14). More iterations are needed for larger datasets with more constraints to converge.

The worked code example in this section is replicable. If all the code snippets are entered, in order, the results should be the same on any computer running R. There is great scope for taking the analysis further: some further tests and plots are presented on

³⁰See rpubs.com/RobinLovelace/6193

the on-line versions of this section. The simplest case is contained in Rpubs document 6193 and a more complex case (with three constraints) can be found in Rpubs document 5089. The preliminary checks done on this code are important to ensure the model is understood at all times and is working correctly. More systematic methods for model checking are the topic of the following section.

4.6 Model checking and validation

The R scripts that implement the methods described in section 4.5 and section 4.7 contain over 1000 lines of code. This means that making mistakes while writing the code was almost inevitable, from time to time.³¹ The large size of the output files (approximately 250 Mb for 10 iterations of the spatial microsimulation model for Yorkshire and the Humber) means that it would be easy to miss fundamental errors. Hence the need for a systematic strategy of checking the output. Beyond checking the model's internal validity, it is necessary to test its external validity. This process, validation, is inherently limited by lack of real spatial microdata. Validation is a crucial step to take before the results are presented, discussed and used as the basis of policy guidance. To make an analogy with corporate food safety standards, it is important be open about and highlight times when things do go wrong, in order to achieve high standards (Powell et al., 2011). Transparency is needed in modelling for similar reasons (Tamminga et al., 2012). This section is therefore an overview of the methods used to find fault in the model, rather than assuming that everything is working perfectly as the rest of the thesis does. It is divided into two halves: first the process of comparing the model results with knowledge of how it *should* perform *a-priori* (model checking). Second, the internally consistent model results are compared with external empirical data (validation). Validation is also discussed in the context of a single case study in section 7.4.

4.6.1 Model checking

A proven method of checking that data analysis and processing is working is wide ranging and continual visual exploration of its output (Janert, 2010). This strategy has been employed throughout the modelling process, both to gain a better understanding of the

³¹ A couple of examples serve to illustrate this point: during the construction of vulnerability metrics based on the individual level output from the spatial microsimulation model, the estimated expenditure on commuting was divided by equalised household income (a proxy of disposable income). One issue was that trip cost estimates are per year while the income estimates are supplied per month in the USd. It took several more alterations and runs of the model before the cause of the high proportion of income spent on commuting (sometimes over 100%) was realised. Another example is simple typing errors while writing the code. The results are presented in figure 4.16, and are described below.

behaviour of the underlying R code, and to search for unexpected results. These were often precursors to error identification.

An example of this, that illustrates the utility of ad-hock checks, is the continual plotting of model inputs and outputs to ensure that they make sense. The R commands `summary()` and `plot()` are ideal for this purpose. The former provides basic descriptive statistics; the latter produces a graphical display of the object. Both are *polymorphic*, meaning that command adapts depending on the type of object it has been asked to process (Matloff, 2011). Thus, to check that the number of people in each age and sex category in the input and output dataset made sense overall, the following command was issued, resulting in the plot illustrated in figure 4.15:

```
plot(cut(USd$age, breaks=(seq(0,100,20))), USd$sex)
```

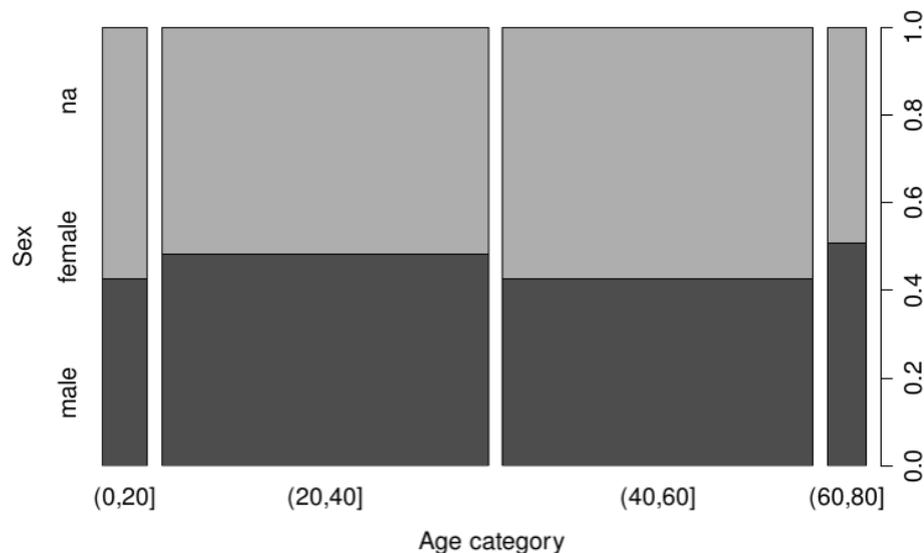


FIGURE 4.15: Diagnostic plot to check the sanity of age and sex inputs. (Square brackets indicate that the endpoint is not included in the set — see International Organization for Standardization (ISO) 80000-2:2009, formerly ISO 31-11 on “mathematical signs and symbols for use in physical sciences and technology”).

These common-sense methods of data checking may seem overly simplistic to warrant mention. Yet such basic sanity tests are the ‘bread-and-butter’ of quantitative analysis. They ensure that the data are properly understood (Wickham, 2008). Had the input data represented in figure 4.15 contained an equal proportion of people under 20 as over 20, for example, one would know that the input data for commuters was faulty. This approach, whereby major problems are revealed early on in frequent tests, is preferable

to waiting until the results of the full spatial microsimulation are analysed. Hours were saved, and understanding of the input datasets was improved.³²

The basic tenet of spatial microsimulation is that simulated and actual data should match at the aggregate level (Ballas et al., 2007). This knowledge led to the continual plotting of census vs simulated results in the early stages of the model construction, and the development of more sophisticated plots (see figure 4.25). Still, the humble scatter plot was used frequently for preliminary analysis. To provide an example, after the model was run for Yorkshire and the Humber region for 20 iterations, I was confident the results were correct: the results had been tested for Sheffield, and everything *seemed* to be working as expected.

Knowledge of how model-census fit should look started alarm bells ringing when an imperfect plot was discovered: figure 4.16 (A) was cause for concern, not only for the low correlation between the two variables (which was still greater than 0.8), but because the direction of the error: the model had *always* overestimated the number of people travelling short distances to work in past runs. This seemed suspicious, and the relationship was plotted for earlier constraints to identify where the problem was variables were plotted. figure 4.16 (B) was the result of this, after constraining by distance. Something had clearly gone wrong because no people who work from home had been registered in the aggregate output. These issues led to a re-examination of the code contained within the file `cats.r`. It was found that a faulty placement of an equals sign (such that values “greater than or equal” to 0 were accepted as 0 - 2 km travel to work). The problem was solved, and the model correlation improved as a result (figure 4.16 (C)).

The two examples described above provided insight into how the model was performing by its own standards. The more challenging stage is to validate the model against factors external to it.

4.6.2 Model validation

Beyond ‘typos’ or simple conceptual errors in model code, more fundamental questions should be asked of spatial microsimulation models. The validity of the assumptions on which they are built, and the confidence one should have in the results are important. This is especially true of models designed to inform policies which have the potential to influence quality of life. Yet evaluation and ‘validation’ are problematic for any models that attempt to explain extensive, complex systems such as cities or ecosystems. The

³²The use of the same command to check model output was crucial to the identification of important errors, including a small mistake in the code which led to large errors in the synthetic microdata output for the distance constraint variables.

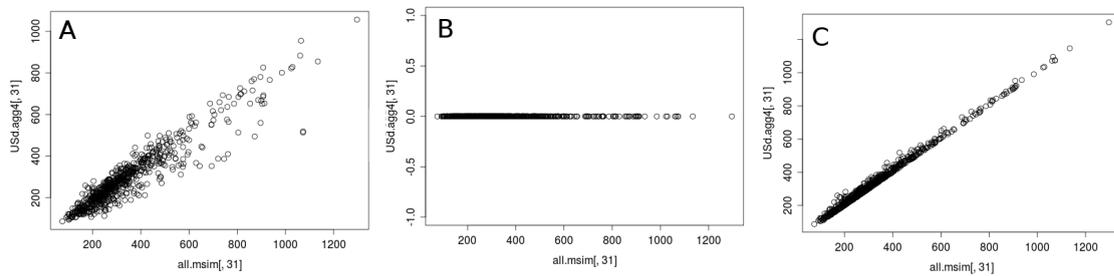


FIGURE 4.16: Three diagnostic plots used to identify a code error in the spatial microsimulation model (for the distance category ‘travels 0–2 km to work’). The x-axis is census data, the y-axis is the simulated result. A) First plot analysed (for iteration 20); B) second plot, which illustrated the source of the problem, in the distance constraint; C) satisfactory diagnostic plot, after the problem had been resolved.

urban modelling approach, of which spatial microsimulation of commuters is a subset, has been grappling with this problem since its infancy. Lacking a crystal ball, time-machine or settlements on which controlled experiments can be performed, the difficulty of model evaluation can seem intractable: “only through time can a model be verified in any conventional sense of the word”, by comparing the range of projected futures with the reality of future change in hindsight (Batty, 1976, p. 15).

Why do urban models pose such a problem? Previously unknown knock-on impacts cannot be ruled out due to the vast number of links between system elements.³³ Rigorous real-world testing is usually impossible due to the scale of the system and ethics involved with intervening in peoples’ lives for the sake of research. Controlled experiments cannot be performed on real settlements in the same way that experiments can be performed in the physical sciences and, even if two similar settlements could be found on which to apply different interventions, there is no guarantee that all other factors will be held constant throughout the duration of the experiment.

Additional evaluation problems apply to spatial microsimulation models in particular for a number of reasons, including:

- The aggregate values of categorical ‘small area’ constraint variables are already known from the Census, so should be accurate. Checking the distribution of continuous variables such as age and distance travelled to work against these crude categories is problematic.³⁴

³³It is, of course, impossible to know how every resident of an area interacts with every other, let alone predict the future impacts of this interaction, even in the era of ubiquitous digital communications.

³⁴For example, if 50% of commuters in a particular area travel 2–5 km to work according to the Census, does that mean that there is a normal distribution of trip distances with the mean focussed on 3.5? Or is it more likely that there is a single large employer located somewhere between 2 and 5 km from the bulk of houses in the area, which accounts for the majority of these jobs and leads to a skewed

- Target variables are not generally known as geographic aggregates. Therefore checking their validity for small areas is difficult: new surveys may be needed.
- Spatial microsimulation results in long lists of individuals for each zone. With thousands of individuals in each zone and hundreds of zones, the datasets can become large and unwieldy.

Regarding the target variables, inaccuracies can be expected because they are determined entirely by their relationships with constraint variables. Also it can be expected these relationships will not remain constant for all places: perhaps in one area the number of female drivers is positively correlated to distance travelled to work, yet there may be a different strength of correlation, or the variables may be unrelated in another.

As mentioned above, validation of target variables is especially problematic due to lack of data. To overcome this problem, two techniques were employed. First, the interaction between constrained variables and unconstrained variables was tested using data from the Census. Second, an additional dataset from the UK's National On-line Manpower Information System (Nomis) was harnessed to investigate the correlation between unconstrained 'interaction' variables — those composed of two or more constraint variables such as 'female driver'.

The first approach tested the model's ability to simulate income. Although income data are lacking for small areas, Neighbourhood Statistics provides estimates of net and gross household incomes at the MSOA level. For the purposes of this study, equivalised net income was used. The fit between the Neighbourhood Statistics and simulated values are displayed in figure 4.17.

The results show the microsimulation model could be used to predict income (modelled income), accounting for almost 80% of the variation in the Neighbourhood Statistics data using an ordinary least squares (OLS) regression model. This is impressive, given that the aim of the model is not to simulate income but energy costs of work travel, based on mode, distance, age/sex and class. Of these socio-economic class is the only constraint variable traditionally thought to be closely associated with income. The main problem with the income estimates generated through spatial microsimulation is the small range of estimates simulated: the standard deviation was £1,194 and £3,596 for the simulated and National Statistics data respectively. (Note the differences in the x and y axis scales in figure 4.17.) This underestimation of variance can be explained because social class, distance and modes of transport are not sufficient to determine the true variability in

distribution of home-work distances. In every event, spatial microsimulation will ignore such subtleties and smooth out extreme skewness by approximating the national distance trends within each distance bin.

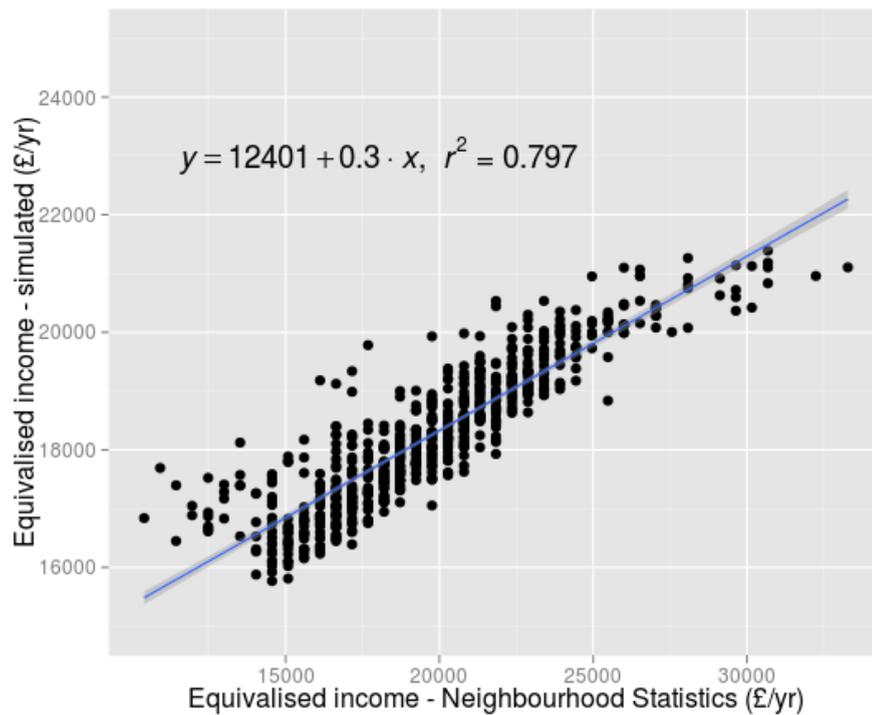


FIGURE 4.17: Scatter plot illustrating the correlation between mean income simulated from the model and official estimates at the MSOA level.

household incomes. Constraining by car ownership and tenure variables would be likely to improve the fit.

The purpose of this fitting exercise is not so much to provide accurate income estimates at the local level but to evaluate the performance of the spatial microsimulation model. In terms of income, a variable that is unconstrained in the model yet available from the survey data, the spatial microsimulation model has worked well. The results suggest that the values of unconstrained variables will not simply repeat the national average for every small area, but will vary based on how their variation at the national level is related to the constraint variables. In this case, the assumption that the relationships between the target variable (income) and constraint variables at the local level (in Yorkshire and the Humber) are similar to the relationships between these variables at the national level, receives support. How well does the model simulate other target variables such as environmental habits, domestic energy use and levels of deprivation? These are interesting questions that merit further attention based on available data.

The second approach relies on Nomis, which provides cross-tabulations of census variables, for example transport mode by class. The downside is that the data are randomised, as stated at the bottom of each of their small-area census tables: “Figures have been randomly adjusted to avoid the release of confidential data” (this phrase appears in many of Nomis’s tables. One example can be found here: <http://www.nomisweb.co.uk/livelinks/4652.xls>

In order to harness Nomis data to test the accuracy of the microsimulation model for calculating, it was first necessary to establish how accurate Nomis data are. How much have Nomis data been randomised, and in what way? This question is relatively easy to answer because of the census variables shared between those published by Nomis and by Casweb at the MSOA level. Scatter plots suggest Nomis data are faithful to the original census results:

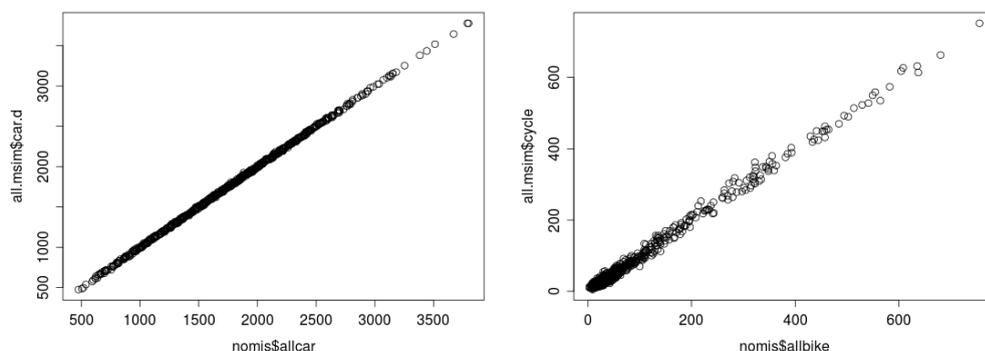


FIGURE 4.18: Scatter graphs illustrating the fit between Nomis and Casweb versions of the same census variables. The correlation (Pearson's r) is 0.9998 and 0.9969, for the number of car drivers and number of cyclists in each MSOA respectively.

From figure 4.18 it is interesting to note that the correlation decreases for cyclists. This, it was inferred, could represent an increase in the signal-to-noise ratio for variables with small values to a fixed randomising factor. To test this, the errors were plotted for variables with large (car drivers) and small (cyclists) totals. The results indicate that the noise added by randomisation is equal for each variable, regardless of the cell count (figure 4.19).

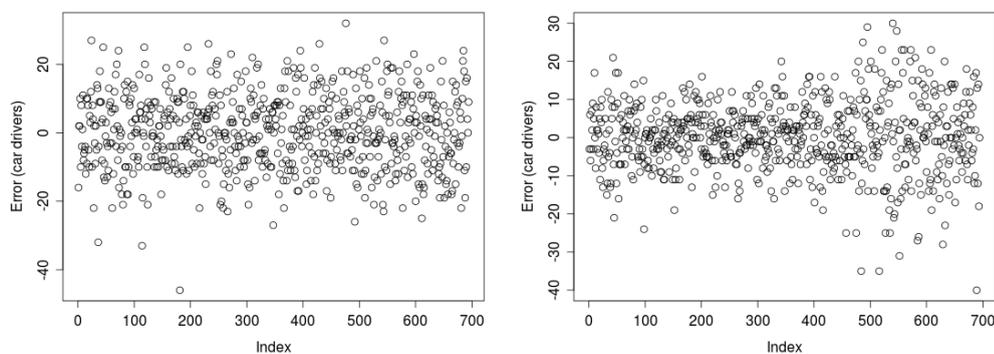


FIGURE 4.19: Errors (Casweb values – Nomis values) associated with car driver (right) and bicycle commuter (left) census variables.

The errors seem to be similar, with a range of approximately 70 and a mean of zero. This observation is confirmed by descriptive statistics for each set of errors (standard deviation

= 11.01, 9.47; mean = 0.15, 0.23) for car driver and cyclist variables respectively. We can therefore conclude that the error added by randomisation is constant for each variable and this was confirmed by plotting the errors for additional census variables. Q-Q plots — which compare the quantile values of one distribution against another, in this case those of the errors against those of the normal distribution — suggest that the distribution of error is approximately normal.

These exploratory methods provide confidence in the Nomis data, but only for relatively large cell counts (the signal-noise ratio approaches 1:1 as the cell count approaches 20): therefore evaluations based on Nomis data are better suited to cross tabulated categories that have high cell counts, for example car drivers. In our microsimulation model, both gender and mode of transport are constrained, but not simultaneously, so the fit between the Nomis cross-tabulation and the cross-tabulation resulting from our model provides some indication of accuracy. The results are presented in figure 4.20. Interestingly, the accuracy of this ‘partially constrained’ simulated target variable appears to be worse than that of the completely unconstrained income variable (compare figure 4.20 and figure 4.17). In both cases, the correlation is reasonably strong and positive (0.47 and 0.80 respectively). However, as with the income estimates, the *distribution* of estimates arising from the model is less dispersed than actual data: the standard deviation for the former (0.30) is substantially less than for the latter (0.44). This illustrates the tendency of spatial microsimulation models to underestimate the extent of spatial variation.

4.6.3 Additional validation methods

The methods described above illustrate the techniques used to prevent model errors and ensure that the results were compatible with external data sources. But they only scratch the surface of what is possible in terms of model validation. This section will not go into detail. Its purpose is to draw attention to additional methods that could be conducted as lines of future research and discuss the merits of each. Specifically, the following additional validation methods could (given sufficient resources) be implemented:

- Primary data collection of target variables at the individual level in specific areas to validate the spatial microdata locally.
- Comparing of the spatial microdata over entire region with a survey data that specifies home region of resident.
- Aggregating local model outputs to coarser geographical levels at which cross-tabulated data are available.

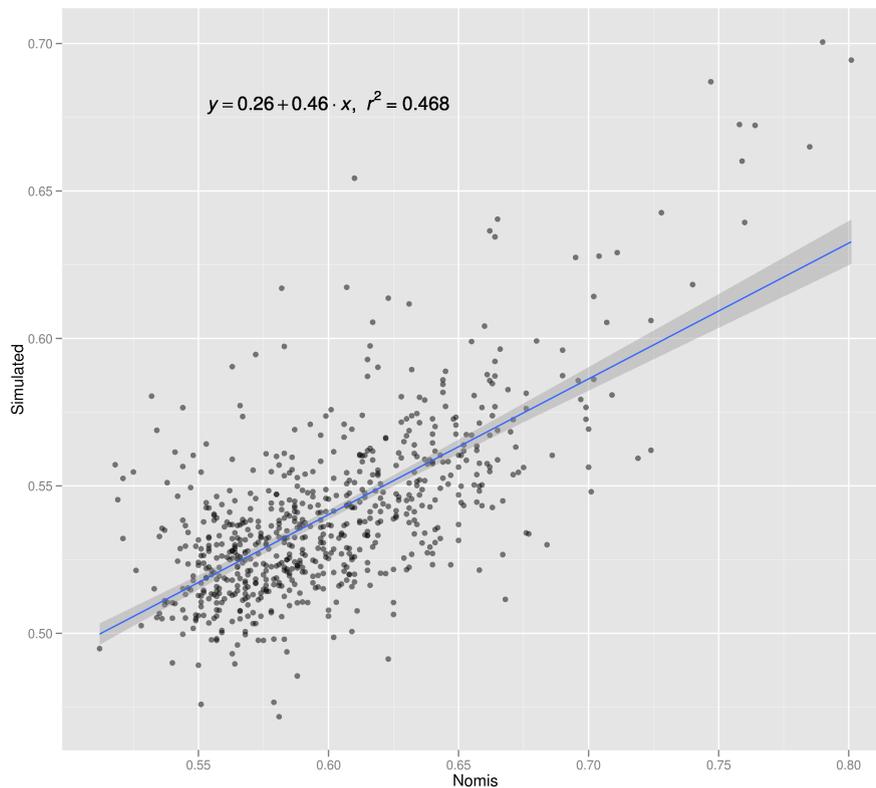


FIGURE 4.20: Scatter plot of the proportion of male drivers in each MSOA area in Yorkshire and the Humber according to simulated and Nomis data.

- Comparison of mode and distance data with external correlates of personal travel (e.g. MOT data on distance travelled and bus usage data).

Other than the sanity check of age-sex ratios presented in figure 4.15, the evaluation methods considered above operate at the level of geographically aggregated counts. However, the unique feature of spatial microsimulation is its simulation of individuals. Evaluation techniques should therefore operate at the individual level as well. Because simulation, almost by definition, estimates something that is not otherwise known, it is hard to find reliable individual level data against which the estimates can be evaluated. For this reason individual level surveys could be conducted in a specific area where spatial microdata have been generated. To take one example, a randomised sample of households could be taken in a single ward. Respondents would be asked the mode of travel to work, distance and frequency of trip and other variables. This would allow the model to be evaluated not only in terms of the correlations that it outputs between different categories, but also for the evaluation of the assumptions on which the energy calculations are based.

One of the main advantages of spatial microsimulation over just using aggregated data is that it provides insight into the *distribution* of continuous variables within each zone,

rather than just counts of categories which are often rather coarse. T-tests and Analysis of Variance (ANOVA) tests could then be used to check if the mean and variance of the simulated and survey data are statistically likely to be from the same population. However, the raw results of IPF are not conducive to such tests at the individual level because they do not contain whole individuals. Integerisation of the weight matrices is needed.

4.7 Integerisation

An important advantage of spatial microsimulation models is their ability to model individuals. Yet, as shown in the previous section, the IPF procedure does not result in whole individuals, but fractions of individuals. This is not a problem if the aim of spatial microsimulation is *small area estimation* (Ballas et al., 2005d). However, the potential to model individual people using agent-based modelling techniques can make spatial microsimulation much more powerful. One way to tackle this issue is by using a different reweighting strategy to select representative individuals for each area. An alternative is to convert the results of IPF into integer results. Lovelace and Ballas (2013) tackled this issue in detail and developed a new method of integerisation. The following section is therefore based on Lovelace and Ballas (2013) and repeats much of the content.

The aim of IPF, as with all spatial microsimulation methods, is to match individual level data from one source to aggregated data from another. IPF does this repeatedly, using one constraint variable at a time: each brings the column and row totals of the simulated dataset closer to those of the area in question (see Ballas et al., 2005d and Fig. 4.25 below).

Unlike combinatorial optimisation algorithms, IPF results in non-integer weights. As mentioned above, this is problematic for certain applications. In their overview of methods for spatial microsimulation Williamson et al. (1998) favoured combinatorial optimisation approaches, precisely for this reason: “as non-integer weights lead, upon tabulation of results, to fractions of households or individuals” (p. 791). There are two options available for dealing with this problem with IPF:

- Use combinatorial optimisation microsimulation methods instead (Williamson et al., 1998). However, this can be computationally intensive (Pritchard and Miller, 2012).

- Integerise the weights: Translate the non-integer weights obtained through IPF into discrete counts of individuals selected from the original survey dataset (Ballas et al., 2005a).

We revisit the second option, which arguably provides the ‘best of both worlds’: the simplicity and computational speed of deterministic reweighting and the benefits of using whole individuals rather than fractions.

IPF is an established method for combining microdata with spatially aggregated constraints to simulate target variables whose characteristics are not recorded at the local level. Integerisation translates the real number weights obtained by IPF into samples from the original microdata, a list of ‘cloned’ individuals for each simulated area. Integerisation may also be useful conceptually, as it allows researchers to deal with entire individuals. The next section reviews existing strategies for integerisation.

4.7.1 Method

Despite the importance of integer weights for dynamic spatial microsimulation, and the continued use of IPF, there has been little work directed towards integerisation. It has been noted that “the integerization and the selection tasks may introduce a bias in the synthesized population” (Axhausen and Müller, 2010, 10), yet little work has been done to find out *how much* error is introduced.

To test each integerisation method, IPF was used to generate an array of weights that fit individual level survey data to geographically aggregated census data (see Section 4.7.1.7). Five methods for integerising the results are described, three deterministic and two probabilistic. These are: ‘simple rounding’, its evolution into the ‘threshold approach’ and the ‘counter-weight’ method and the probabilistic methods: ‘proportional probabilities’ and ‘truncate, replicate, sample’. TRS builds on the strengths of the other methods, hence the order in which they are presented.

The application of these methods to the same dataset and their implementation in R allows their respective performance characteristics to be quantified and compared. Before proceeding to describe the mechanisms by which these integerisation methods work, it is worth taking a step back, to consider the nature and meaning of IPF weights.

4.7.1.1 Interpreting IPF weights: replication and probability

It is important to clarify what is meant by ‘weights’ before proceeding to implement methods of integerisation: this understanding was central to the development of the

integerisation method presented in this section. The weights obtained through IPF are real numbers ranging from 0 to hundreds (the largest weight in the case study dataset is 311.8). This range makes integerisation problematic: if the probability of selection is proportional to the IPF weights, as is the case with the ‘proportional probabilities’ method, the majority of resulting selection probabilities can be very low. This is why the simple rounding method rounds weights up or down to the nearest integer weight to determine how many times each individual should be replicated (Ballas et al., 2005a). This ensures that replication weights do not differ greatly from non-integer IPF weights. However, some of the information contained in the weight is lost during rounding: a weight remainder of 0.501 is treated the same as 0.999.

This raises the following question: Do the weights refer to the number of times a particular individual should be replicated, or is it related to the probability of being selected? The following sections consider different approaches to addressing this question, and the integerisation methods that result.

IPF weights do not merely represent the probability of a single case being selected. They also (when above one) contain information about repetition: the two types of weight are bound up in a single number. An IPF weight of 9, for example, means that the individual should be replicated 9 times in the synthetic microdataset. A weight of 0.2, by contrast, means that the characteristics of this individual should count for only 1/5 of their whole value in the microsimulated dataset and that, in a representative sampling strategy, the individual would have a probability of 0.2 of being selected. Clearly, these are very different concepts. As such, the TRS approach to integerisation isolates the replication and probability components of IPF weights at the outset, and then deals with each separately. Simple rounding, by contrast, interprets IPF weights as inaccurate count data.

4.7.1.2 Simple rounding

The simplest approach to integerisation is to convert the non-integer weights into an integer by rounding up if the decimal is 0.5 or above or down otherwise. Rounding alone is inadequate for accurate results, however. As illustrated in Fig. 4.22 below, the distribution of weights obtained by IPF is likely to be skewed, and the majority of weights may fall below the critical 0.5 value and be excluded. As reported by Ballas et al. (2005a, 25), this results in inaccurate total populations. To overcome this problem Ballas et al. (2005a) developed algorithms to ‘top up’ the simulated spatial microdata with representative individuals: the ‘threshold’ and ‘counter-weight’ approaches.

4.7.1.3 The threshold approach

Ballas et al. (2005a) tackled the need to ‘top up’ the simulated area populations such that $Pop_{sim} \geq Pop_{cens}$. This is done by creating an inclusion threshold (IT) set to 1 which iteratively reduced. This samples additional individuals with incrementally lower weights.³⁵ Below the exit value of IT for each zone, no individuals can be included (hence the clear cut-off point around 0.4 in Fig. 4.21). In its original form, based on rounded weights, this approach over-replicates individuals with high decimal weights. To overcome this problem, the truncated weights were taken as the starting population, rather than the rounded weights. This modified approach improved the accuracy of the integer results and is therefore the meaning of the ‘threshold approach’ henceforth.³⁶

The technique successfully tops up integer populations yet has a tendency to generate too many individuals for each zone. This oversampling is due to duplicate weights — each unique weight was repeated on average 3 times in our model — and the presence of weights that *are* different, but separated by less than 0.001. (In our test, the mean number of unique weights falling into non-empty bins between 0.3 and 0.48 in each area — the range of values reached by IT before $Pop_{sim} \geq Pop_{cens}$ — is almost two.)

4.7.1.4 The counter-weight approach

An alternative method for topping-up integer results arrived at by simple rounding was also described by Ballas et al. (2005a). The approach was labelled to emphasise its reliance on both counter and a weight variables. Each individual is first allocated a counter in ascending order of its IPF weight. The algorithm then tops-up the integer results of simple rounding by iterating over all individuals in the order of their count. With each iteration the new integer weight is set as the rounded weight plus the rounded sum of its decimal weight plus the decimal weight of the next individual, until the desired total population is reached.³⁷

There are two theoretical advantages of this approach: its more accurate final populations (it does not automatically duplicate individuals with equal weights as the threshold approach does) and the fact that individuals with decimal weights down to 0.25 may

³⁵A more detailed description of the steps taken and the R code needed to perform them iteratively can be found in the Supplementary Information, Section 3.2.

³⁶An explanation of this improvement can be illustrated by considering an individual with a weight of 2.99. Under the original threshold approach described by Ballas et al. (2005a), this person would be replicated 4 times: three times after rounding, and then a fourth time after IT drops below 0.99. With our modified approach they would be replicated three times: twice after truncation, and again after IT drops below 0.99. The improvement in accuracy in our tests was substantial, from a TAE (total absolute error, described below) of 96,670 to 66,762. Because both methods are equally easy to implement, only to the superior version of the threshold integerisation method is used.

³⁷This process is described in more detail in the Supplementary Information.

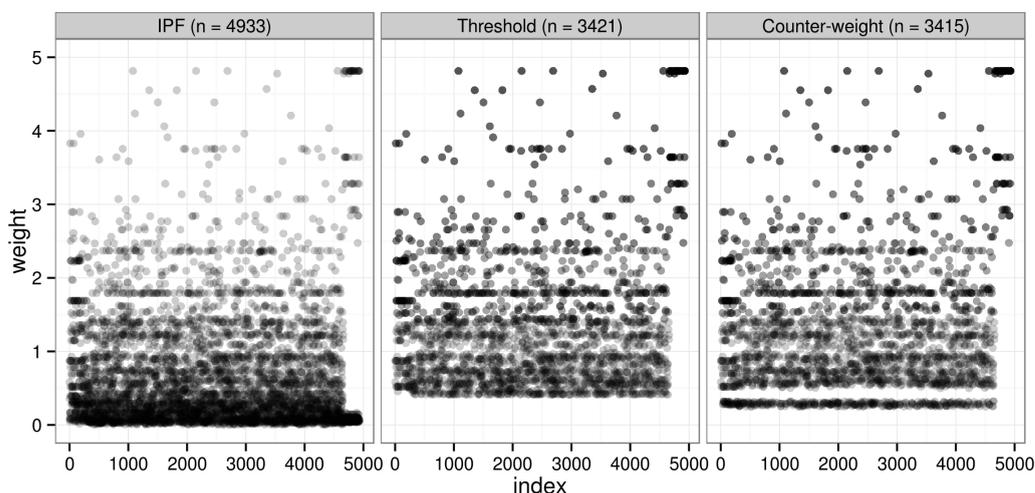


FIGURE 4.21: Overplotted scatter graph showing the distribution of weights and replications after IPF in the original survey (left), those selected by inclusion thresholds for a single area (middle), and those selected by the counter-weight method (right) for zone 71 in the example dataset. The lightest points represent individuals who have been replicated once, the darkest 5 times.

be selected. This latter advantage is minor, as IT reached below 0.4 in many cases (Supplementary Information, Fig. 2) — not far off. A band of low weights (just above 0.25) selected by the counter-weight method can be seen in Fig. 4.21.

The total omission of weights below some threshold is problematic for all deterministic algorithms tested here: they imply that someone with a weight below this threshold, for example 0.199 in our tests, has the same sampling probability as someone with a weight of 0.001: zero! The complete omission of low weights fails to make use of all the information stored in IPF weights: in fact, the individual with an IPF weight of 0.199 is 199 times more representative of the area (in terms of the constraint variables and the make-up of the survey dataset) than the individual with an IPF weight of 0.001. Probabilistic approaches to integerisation ensure that all such differences between decimal weights are accounted for.

4.7.1.5 The proportional probabilities approach

This approach to integerisation treats IPF weights as probabilities. The chance of an individual being selected is proportional to the IPF weight:

$$p = \frac{w}{\sum W} \quad (4.5)$$

Sampling until $Pop_{sim} = Pop_{cens}$ with replication ensures that individuals with high weights are likely to be repeated several times whereas individuals with low weights are

unlikely to appear. The outcome of this strategy is correct from a theoretical perspective, yet because all weights are treated as probabilities, there is a non-zero chance that an individual with a low weight (e.g. 0.3) is replicated more times than an individual with a higher weight (e.g. 3.3). (In this case the probability for any given area is $\sim 1\%$, regardless of the population size). Ideally, this should never happen: the individual with weight 0.3 should be replicated either 0 or 1 times, the probability of the latter being 0.3. The approach described in the next section addresses these issues.

4.7.1.6 Truncate, replicate, sample

The problems associated with the aforementioned integerisation strategies demonstrate the need for an alternative method. Ideally, the method would build upon the simplicity of the rounding method, select the correct simulated population size (as attempted by the threshold approach and achieved by using ‘proportional probabilities’), make use of all the information stored in IPF weights *and* reduce the error introduced by integerisation to a minimum. The probabilistic approach used in ‘proportional probabilities’ allows multiple answers to be calculated (by using different ‘seeds’). This is advantageous for analysis of uncertainty introduced by the process and allows for the selection of the best fitting result. Consideration of these design criteria led us to develop TRS integerisation, which interprets weights as follows: IPF weights do not merely represent the probability of a single case being selected. They also (when above one) contain information about repetition: the two types of weight are bound up in a single number. An IPF weight of 9, for example, means that the individual should be replicated 9 times in the synthetic microdataset. A weight of 0.2, by contrast, means that the characteristics of this individual should count for only 1/5 of their whole value in the microsimulated dataset and that, in a representative sampling strategy, the individual would have a probability of 0.2 of being selected. Clearly, these are different concepts. As such, the TRS approach to integerisation isolates the replication and probability components of IPF weights at the outset, and then deals with each separately. Simple rounding, by contrast, interprets IPF weights as inaccurate count data. The steps followed by the TRS approach are described in detail below.

Truncate

By removing all information to the right of the decimal point, truncation results in integer values — integer replication weights that determine how many times each individual should be ‘cloned’ and placed into the simulated microdataset. In R, the following command is used:

```
count <- trunc(w)
```

where w is a matrix of individual weights. Saving these values (as `count`) will later ensure that only whole integers are counted. The decimal remainders (`dr`), which vary between 0 and 1, are saved by subtracting the integer weights from the full weights:

```
dr <- w - count
```

This separation of conventional and replication weights provides the basis for the next stage: replication of the integer weights.

Replicate

In spreadsheets, replication refers simply to copying cells of data and pasting them elsewhere. In spatial microsimulation, the concept is no different. The number of times a row of data is replicated depends on the integer weight: an IPF weight of 0.99, for example, would not be replicated at this stage because the integer weight (obtained through truncation) is 0.

To reduce the computational requirements of this stage, it is best to simply replicate the row number (`index`) associated with each individual, rather than replicate the entire row of data. This is illustrated in the following code example, which appears within a loop for each area (`i`) to be simulated:

```
ints[[i]] <- index[rep(1:nrow(index),count)]
```

Here, the indices (of weights above 1, `index`) are selected and then repeated. This is done using the function `rep()`. The first argument (`1:nrow(index)`) simply defines the indices to be replicated; the second (`count`) refers to the integer weights defined in the previous subsection. (Note: `count` in this context refers only to the integer weights above 1 in each area). Once the replicated indices have been generated, they can then be used to look up the relevant characteristics of the individuals in question.

Sample

As with the rounding approach, the truncation and replication stages alone are unable to produce microsimulated datasets of the correct size. The problem is exacerbated by the use of truncation instead of rounding: truncation is guaranteed to produce integer microdataset populations that are smaller, and in some cases much smaller than the actual (census) populations. In our case study, the simulated microdataset populations were around half the actual size populations defined by the census. This under-selection of whole cases has the following advantage: when using truncation there is no chance of over-sampling, avoiding the problem of simulated populations being slightly too large, as can occur with the threshold approach.

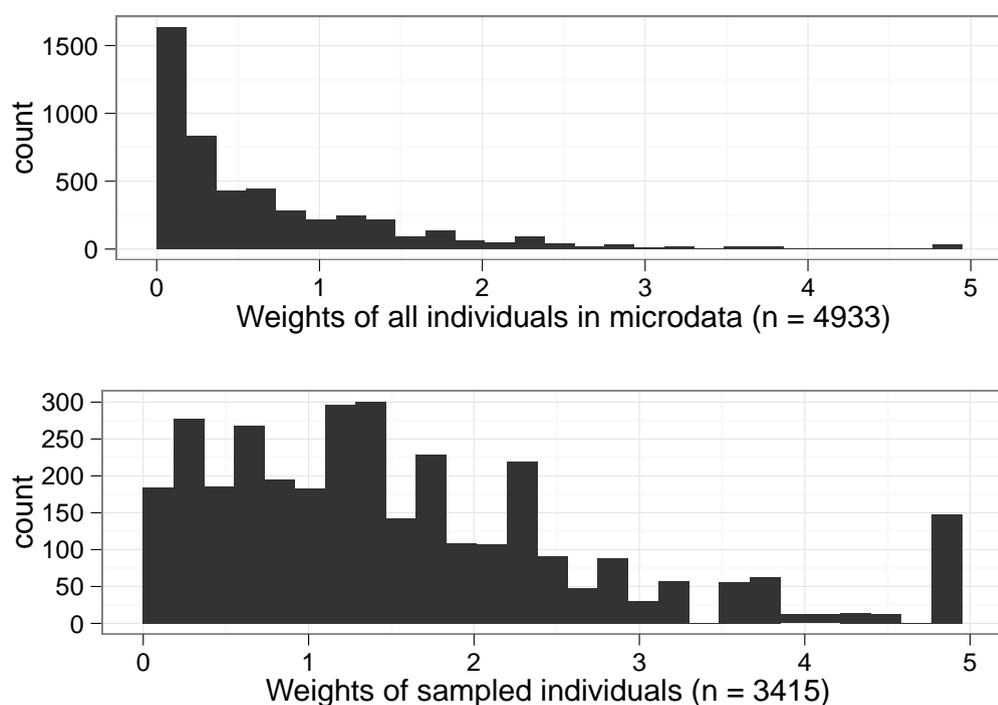


FIGURE 4.22: Histograms of original microdata weights (above) and sampled microdata after TRS integerisation (below) for a single area — zone 71 in the case study data.

Given that the replication weights have already been included in steps 1 and 2, only the decimal weight remainders need to be included. This can be done using weighted random sampling without replacement. In R, the following function is used:

```
sample(w, size=(pops[i,1] - pops[i,2]), prob= dr[,i])
```

Here, the argument `size` within the `sample` command is set as the difference between the known population of each area (`pops[i,1]`) and the size obtained through the replication stage alone (`pops[i,2]`). The probability (`prob`) of an individual being sampled is determined by the decimal remainders. `dr` varies between 0 and 1, as described above.

The results for one particular area are presented in Fig. 4.22. The distribution of selected individuals has shifted to the right, as the replication stage has replicated individuals as a function of their truncated weight. Individuals with low weights (below one) still constitute a large portion of those selected, yet these individuals are replicated fewer times. After TRS integerisation individuals with high decimal weights are relatively common. Before integerisation, individuals with IPF weights between 0 and 0.3 dominated. An individual-by-individual visualisation of the Monte Carlo sampling strategy is provided in Fig. 4.23. Comparing this with the same plot for the probabilistic methods (Fig. 4.21), the most noticeable difference is that the TRS and proportional probabilities approaches

include individuals with very low weights. Another important difference is average point density, as illustrated by the transparency of the dots: in Fig. 4.21, there are shifts near the decimal weight threshold (~ 0.4 in this area) on the y-axis. In Fig. 4.23, by contrast, the transition is smoother: average darkness of single dots (the number of replications) gradually increases from 0 to 5 in both probabilistic methods.

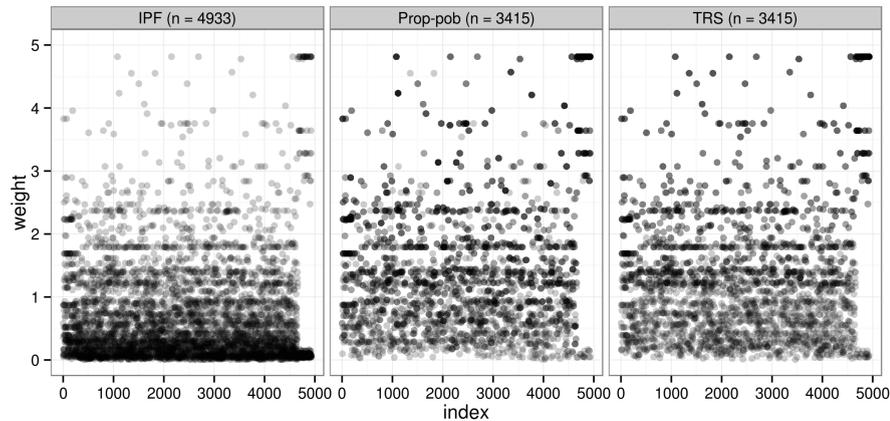


FIGURE 4.23: Overplotted scatter graphs of index against weight for the original IPF weights (left) and after proportional probabilities (middle) and TRS (right) integerisation for zone 71. Compare with Fig. 4.21.

Fig. 4.24 illustrates the mechanism by which the TRS sampling strategy works to select individuals. In the first stage (up to $x = 1,717$, in this case) there is a linear relationship between the indices of survey and sampled individuals, as the model iteratively moves through the individuals, replicating those with truncated weights greater than 0. This (deterministic) replication stage selects roughly half of the required population in our example dataset (this proportion varies from zone to zone). The next stage is probabilistic sampling ($x = 1,718$ onwards in Fig. 4.24): individuals are selected from the entire microdataset with selection probabilities equal to weight remainders.

4.7.1.7 The test scenario: input data and IPF

The theory and methods presented above demonstrate how five integerisation methods work in abstract terms. But to compare them quantitatively a test scenario is needed. This example consists of a spatial microsimulation model that uses IPF to model the commuting and socio-demographic characteristics of economically active individuals in Sheffield. According to the 2001 Census, Sheffield has a working population of just over 230,000. The characteristics of these individuals were simulated by reweighting a synthetic microdataset based on aggregate constraint variables provided at the medium super output area (MSOA) level. The synthetic microdataset was created by ‘scrambling’

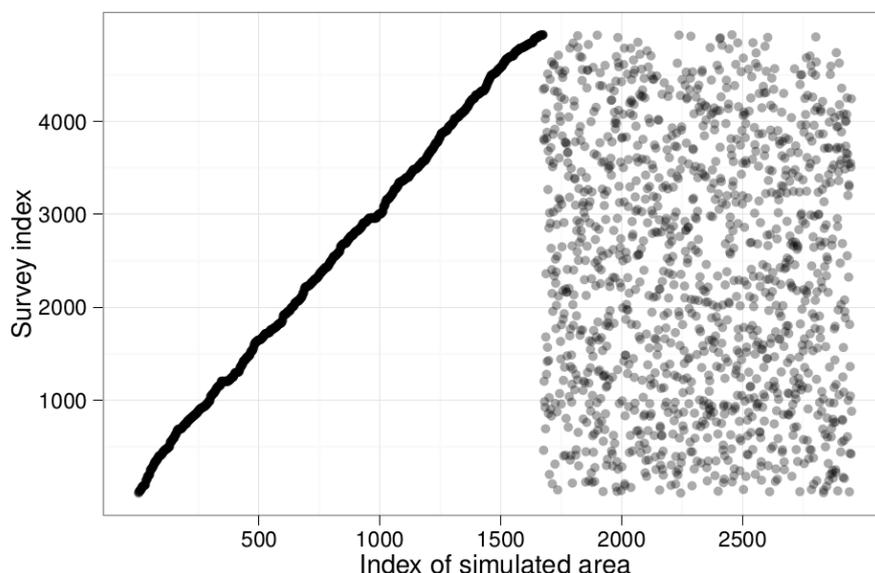


FIGURE 4.24: Scatter graph of the index values of individuals in the original sample and their indices following TRS Integerisation for a single area.

a subset of the Understanding Society dataset (USD).³⁸ MSOAs contain on average just over 7,000 people each, of whom 44% are economically active in the study area; for the less sensitive aggregate constraints, real data were used. These variables are summarised in Table 4.11.

TABLE 4.11: Summary data for the spatial microsimulation model

		Aggregate data		Survey data	
		71 zones, average pop.: 3077.5		4933 observations	
Variable	N. categories	Most populous		Mean	Most populous
Age / sex	12	Male, 35 to 54 yrs		40.1	-
Mode	11	Car driver		-	Car driver
Distance	8	2 to 5 km		11.6	-
NS-SEC	9	Lower managerial		-	Lower managerial

The data contains both continuous (age, distance) and categorical (mode, NS-SEC) variables. In practice, all variables are converted into categorical variables for the purposes of IPF, however. To do this statistical bins are used. Table 4.11 illustrates similarities between aggregate and survey data overall (car drivers being the most popular mode of travel to work in both categories, for example). Large differences exist between individual zones and survey data, however: it is the role of iterative proportional fitting to apply weights to minimize these differences.

³⁸See <http://www.understandingsociety.org.uk/>. To scramble this data, the continuous variables (see Table 4.11) had an integer random number (between 10 and -10) added to them; categorical variables were mixed up, and all other information was removed.

IPF was used to assign 71 weights to each of the 4,933 individuals, one weight for each zone. The fit between census and weighted microdata can be seen improving after constraining by each of the 40 variables (Fig. 4.25). The process is repeated until an adequate level of convergence is attained (see Fig. 4.26).³⁹ The weights were set to an

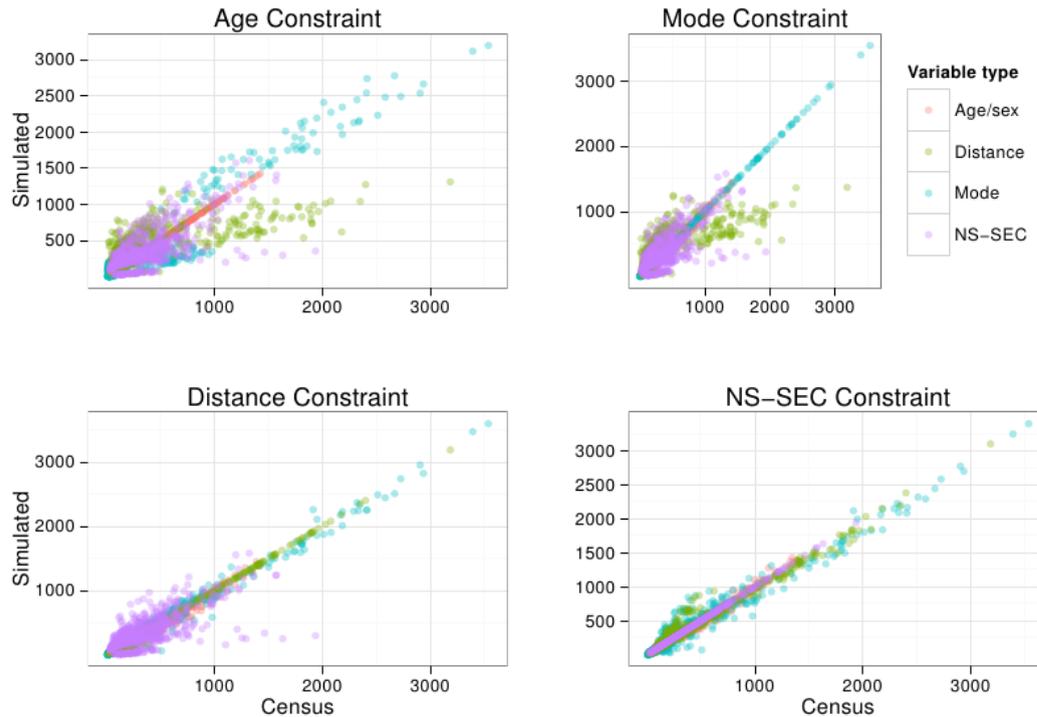


FIGURE 4.25: Visualisation of IPF method. The graphs show the iterative improvements in fit after age, mode, distance and finally NS-SEC constraints were applied (see Table 4.11). See footnote 4 for resources on how IPF works.

initial value of one.⁴⁰ The weights were then iteratively altered to match the aggregate (MSOA) level statistics.

Four constraint variables link the aggregated census data to the survey, containing a total of 40 categories. To illustrate how IPF works, it is useful to inspect the fit between simulated and census aggregates before and after performing IPF for each constraint variable. Fig. 4.25 illustrates this process for each constraint. By contrast to existing approaches to visualising IPF (see Ballas et al., 2005d), Fig. 4.25 plots the results for all variables, one constraint at a time. This approach can highlight which constraint variables are particularly problematic. After 20 iterations (Fig. 4.26), one can see that distance and mode constraints are most problematic. This may be because both variables depend largely on geographical location, so are not captured well by UK-wide aggregates.

³⁹What constitutes an ‘adequate’ level of fit has not been well defined in the literature, as mentioned in the next section. In this example, 20 iterations were used.

⁴⁰An initial value must be selected for IPF to create new weights which better match the small area constraints. It was set to one as this tends to be the average weight value in social surveys (the mean Understanding Society dataset interview plus proxy individual cross-sectional weight is 0.986).

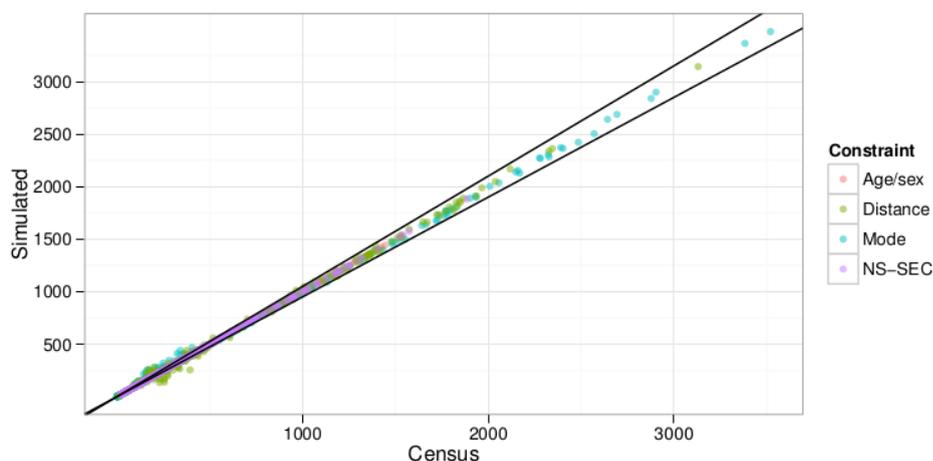


FIGURE 4.26: Scatter graph illustrating the fit between census and simulated aggregates after 20 IPF iterations (compare with Fig. 4.25).

Fig. 4.25 also illustrates how IPF works: after reweighting for a particular constraint, the weights are forced to take values such that the aggregate statistics of the simulated microdataset match perfectly with the census aggregates, for all variables within the constraint in question. Aggregate values for the mode variables, for example, fit the census results perfectly after constraining by mode (top right panel in Fig. 4.25). Reweighting by the next constraint disrupts the fit imposed by the previous constraint — note the increase scatter of the (blue) mode variables after weights are constrained by distance (bottom left).

However, the disrupted fit is better than the original. This leads to a convergence of the weights such that the fit between simulated and known variables is optimised: Fig. 4.25 shows that accuracy increases after weights are constrained by each successive linking variable.

4.7.2 Results

This section compares the five previously describe approaches to integerisation — rounding, inclusion threshold, counter-weight, proportional probabilities and TRS methods. The results are based on the 20th iteration of the IPF model described above. The following metrics of performance were assessed:

- speed of calculation
- accuracy of results
 - sample size

- Total Absolute Error (TAE) of simulated areas
- anomalies (aggregate cell values out by more than 5%)
- correlation between constraint variables in the census and microsimulated data.

Of these performance indicators accuracy is the most problematic. Options for measuring goodness-of-fit have proliferated in the last two decades, yet there is no consensus about which is most appropriate (Voas and Williamson, 2001). The approach taken here, therefore, is to use a range of measures, the most important of which are summarised in Table 4.12 and Fig. 4.27.

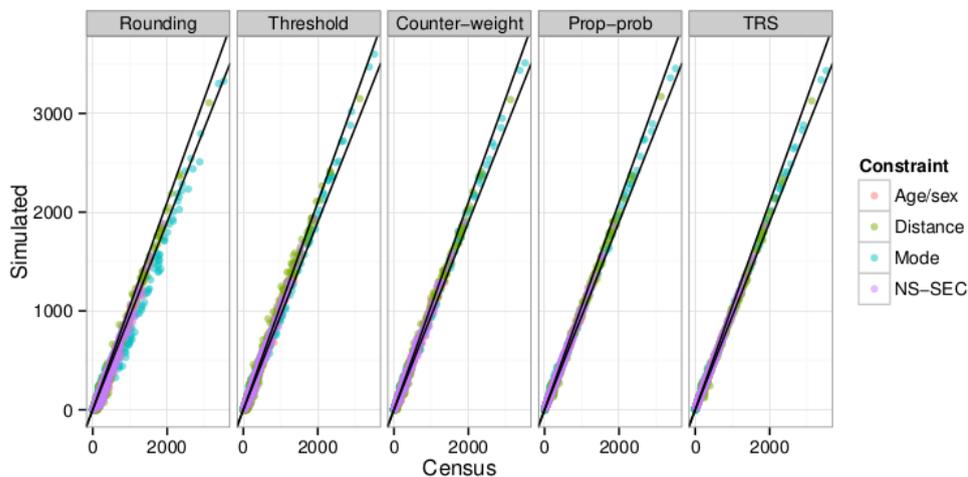


FIGURE 4.27: Scatterplots of actual (census) and simulated population totals for four integration techniques. The black lines represent 5% error in either direction.

4.7.2.1 Speed of calculation

The time taken for the integration of IPF weights was measured on an Intel Core i5 660 (3.33 GHz) machine with 4 Gb of RAM running Linux 3.0. The simple rounding method of integration was unsurprisingly the fastest, at 4 seconds. In second and third place respectively were the proportional probabilities and TRS approaches, which took a couple of seconds longer for a single integration run for all areas. Slowest were the inclusion threshold and counter-weight techniques, which took three times longer than simple rounding. To ensure representative results for the probabilistic approaches, both were run 20 times and the result with the best fit was selected. These imputation loops took just under a minute.

The computational intensity of integration may be problematic when processing weights for very large datasets, or using older computers. However, the results must be placed

in the context of the computational requirements of the IPF process itself. For the example described in Section 4.7.1.7, IPF took approximately 30 seconds per iteration and 5 minutes for the full 20 iterations.

4.7.2.2 Accuracy

In order to compare the fit between simulated microdata and the zonally aggregated linking variables that constrain them, the former must first be aggregated by zone. This aggregation stage allows the fit between linking variables to be compared directly (see Fig. 4.27). More formally, this aggregation allows goodness of fit to be calculated using a range of metrics (Williamson et al., 1998). We compared the accuracy of integerisation techniques using 5 metrics:

- Pearson’s product-moment correlation coefficient (r)
- total and standardised absolute error (TAE and SAE),
- proportion of simulated values falling beyond 5% of the actual values,
- the proportion of Z-scores significant at the 5% level
- size of the sampled populations

The simplest way to evaluate the fit between simulated and census results was to use Pearson’s r , an established measure of association (Rodgers, 1988). The r values for all constraints were 0.9911, 0.9960, 0.9978, 0.9989 and 0.9992 for rounding, threshold, counter-weight, proportional probabilities and TRS methods respectively. IPF alone had an r value of 0.9996. These correlations establish an order of fit that can be compared to other metrics.

TAE and SAE are crude yet effective measures of overall model fit (Voas and Williamson, 2001). TAE has the additional advantage of being easily understood:

$$TAE = \sum_{ij} |U_{ij} - T_{ij}| \quad (4.6)$$

where U and T are the observed and simulated values for each linking variable (j) and each area (i). SAE is the TAE divided by the total population of the study area. TAE is sensitive to the number of people within the model, while SAE is not. The latter is seen by Voas and Williamson (2001) as “marginally preferable” to the former: it allows cross-comparisons between models of different total populations (Kongmuang, 2006).

TABLE 4.12: Accuracy results for integerisation techniques.*

Method	Variables	TAE	SAE (%)	E > 5% (%)	Zm ² (%)
IPF	Age/sex	9	0.0	0.0	0.0
	Distance	4874	2.3	13.7	4.9
	Mode	4201	2.0	6.4	4.2
	NS-SEC	0	0.0	0.0	0.0
	All	9084	3.1	4.5	2.1
Round- ing	Age/sex	26812	12.5	81.5	39.8
	Distance	31981	14.9	80.1	65.1
	Mode	30558	14.2	81.4	48.9
	NS-SEC	27493	12.8	76.5	57.1
	All	116844	13.6	80.1	51.3
Thresh- old	Age/sex	11076	5.1	49.2	8.1
	Distance	27146	12.6	82.4	57.7
	Mode	14770	6.9	68.6	33.9
	NS-SEC	13770	6.4	55.2	24.1
	All	66762	7.8	62.5	28.7
Counter- weight	Age/sex	10242	4.8	47.7	6.6
	Distance	17103	8.0	70.2	39.3
	Mode	10072	4.7	60.4	21.6
	NS-SEC	11798	5.5	49.6	17.1
	All	49215	5.7	56.1	19.6
Propor- tional proba- bilities	Age/sex	9112	4.2	48.0	3.1
	Distance	8740	4.1	47.4	10.4
	Mode	8664	4.0	60.8	9.0
	NS-SEC	7778	3.6	37.6	3.3
	All	34294	4.0	49.0	6.2
TRS	Age/sex	5424	2.5	27.9	0.4
	Distance	10167	4.7	48.8	16.4
	Mode	7584	3.5	56.1	6.7
	NS-SEC	5687	2.6	24.9	1.1
	Total	28862	3.4	39.2	5.5

* The probabilistic results represent the best fit (in terms of TAE) of 20 integerisation runs with the pseudo-random number seed set to 1000 for replicability — see Supplementary Information.

The proportion of values which fall beyond 5% of the actual values is a simple metric of the quality of the fit. It implies that getting a perfect fit is not the aim, and penalises fits that have a large number of outliers. The precise definition of 'outlier' is somewhat arbitrary (one could just as well use 1%).

The final metric presented in Table 4.12 is based on the Z-statistic, a standardised measure of deviance from expected values, calculated for each cell of data. We use Z_m , a modified version of the Z-statistic which is a robust measure of fit for each cell value Williamson et al. (1998). The measure of fit is appropriate here as it takes into account absolute, rather than just relative, differences between simulated and observed

cell count:

$$Zm_{ij} = (r_{ij} - p_{ij}) / \left(\frac{p_{ij}(1 - p_{ij})}{\sum_{ij} U_{ij}} \right)^{1/2} \quad (4.7)$$

where

$$p_{ij} = \frac{U_{ij}}{\sum_{ij} U_{ij}} \quad \text{and} \quad r_{ij} = \frac{T_{ij}}{\sum_{ij} U_{ij}}$$

To use the modified Z-statistic as a measure of overall model fit, one simply sums the squares of zm to calculate Zm^2 . This measure can handle observed cell counts below 5, which chi-squared tests cannot (Voas and Williamson, 2001).

The results presented in Table 4.12 confirm that *all* integerisation methods introduce some error. It is reassuring that the comparative accuracy is the same across all metrics. Total absolute error (TAE), the simplest goodness-of-fit metric, indicates that discrepancies between simulated and census data increase by a factor of 3.2 after TRS integerisation, compared with raw (fractional) IPF weights.⁴¹ Still, this is a major improvement on the simple rounding, threshold and counter-weight approaches to integerisation presented by Ballas et al. (2005a): these increased TAE by a factor of 13, 7 and 5 respectively. The improvement in fit relative to the proportional probabilities method is more modest. The proportional probabilities method increased TAE by a factor of 3.8, 23% more absolute error than TRS.

The differences between the simulated and actual populations ($Pop_{sim} - Pop_{cens}$) were also calculated for each area. The resulting differences are summarised in Table 5, which illustrates that the counter-weight and two probabilistic methods resulted in the correct population totals for every area. Simple rounding and threshold integerisation methods greatly underestimate and slightly overestimate the actual populations, respectively.

TABLE 4.13: Differences between census and simulated populations.

Metric	Rounding	Threshold	Others (CW, PP, TRS)
Mean	-372	8	0
Standard deviation	88	11	0
Max	-133	54	0
Min	-536	0	0
Oversample (%)	-13	0.3	0

⁴¹In the case of a sufficiently diverse input survey dataset, IPF would be able to find the perfect solution: TAE would be 0 and the ratio of error would not be applicable.

4.7.3 Discussion and conclusions

The results show that TRS integerisation outperforms the other methods of integerisation tested in this section. At the aggregate level, accuracy improves in the following order: simple rounding, inclusion threshold, counter-weight, proportional probabilities and, most accurately, TRS. This order of preference remains unchanged, regardless of which (from a selection of 5) measure of goodness-of-fit is used. These results concur with a finding derived from theory — that “deterministic rounding of the counts is not a satisfactory integerization” (Pritchard and Miller, 2012, p. 689). Proportional probability and TRS methods clearly provide more accurate alternatives.

An additional advantage of the probabilistic TRS and proportional probability methods is that correct population sizes are guaranteed.⁴² In terms of speed of calculation, TRS also performs well. TRS takes marginally more time than simple rounding and proportional probability methods, but is three times quicker than the threshold and counter-weight approaches. In practice, it seems that integerisation processing time is small relative to running IPF over several iterations. Another major benefit of these non-deterministic methods is that probability distributions of results can be generated, if the algorithms are run multiple times using unrelated pseudo-random numbers. Probabilistic methods could therefore enable the uncertainty introduced through integerisation to be investigated quantitatively (Beckman et al., 1996; Little and Rubin, 1987) and subsequently illustrated using error bars.

Overall the results indicate that TRS is superior to the deterministic methods on many levels and introduces less error than the proportional probabilities approach. We cannot claim that TRS is ‘the best’ integerisation strategy available though: there may be other solutions to the problem and different sets of test weights may generate different results.⁴³ The issue will still present a challenge for future researchers considering the use of IPF to generate sample populations composed of whole individuals: whether to use deterministic or probabilistic methods is still an open question (some may favour deterministic methods that avoid pseudo-random numbers, to ensure reproducibility regardless of the software used), and the question of whether combinatorial optimisation algorithms perform better has not been addressed.

⁴²Although the counter-weight method produced the correct population sizes in our tests, it cannot be guaranteed to do so in all cases, because of its reliance on simple rounding: if more weights are rounded up than down, the population will be too high. However, it can be expected to yield the correct population in cases where the populations of the areas under investigation are substantially larger than the number of individuals in the survey dataset.

⁴³Despite these caveats, the order of accuracy identified in this section is expected to hold in most cases. Supplementary Information (Section 4.4), shows the same order of accuracy (except the threshold method and counter-weight methods, which swap places) resulting from the integerisation of a different weight matrix.

Our results provide insight into the advantages and disadvantages of five integerisation methods and guidance to researchers wishing to use IPF to generate integer weights: use TRS unless determinism is needed or until superior alternatives (e.g. real small area microdata) become available. Based on the code and example datasets provided in the Supplementary Information, other are encouraged to use, build on and improve TRS integerisation.

A broader issue raised by this research, that requires further investigation before answers emerge, is ‘how do the integerised results of IPF compare with combinatorial optimisation approaches to spatial microsimulation?’ Studies have compared non-integer results of IPF with alternative approaches (Smith et al., 2009; Ryan et al., 2009; Rahman et al., 2010; Harland et al., 2012). However, these have so far failed to compare like with like: the integer results of combinatorial approaches are more useful (applicable to more types of analysis) than the non-integer results of IPF. TRS thus offers a way of ‘levelling the playing field’ whilst minimising the error introduced to the results of deterministic reweighting through integerisation.

In conclusion, the integerisation methods presented in this section make integer results accessible to those with a working knowledge of IPF. TRS outperforms previously published methods of integerisation. As such, the technique offers an attractive alternative to combinatorial optimisation approaches for applications that require whole individuals to be simulated based on aggregate data.

Chapter 5

Energy use in personal travel systems

The previous chapter described the data and methods needed to model the diversity of commuting behaviours at individual and geographical levels. This chapter shows how the results of spatial microsimulation can be translated into information about energy use. Before any numbers are presented, however, this chapter takes a brief detour to consider what energy actually is, and how it gets ‘used’ in personal transport (section 5.1). This will ensure that the energy use estimates presented later on are interpreted correctly (and not oversimplified). Physical considerations also help understand the potential for and limitations of technological advance to reduce energy use into the future (Mackay, 2009). Future efficiency gains, important in what-if scenarios, are tackled in section 5.5.

As stated in the previous chapter, good official estimates of the energy costs of personal travel overall, let alone for travel to work exclusively, are in short supply: they are limited in terms of the modes covered, geographical resolution and temporal coverage. The approach used here, therefore, is to infer energy use based on behaviour:¹ the mode, distance and frequency of travel to work. Of course, this requires good estimates of vehicles’ energy use per unit distance to convert the distance travelled into energy use. The best official data source for this task are the CO₂ ‘emission factors’ compiled by the government department Defra which (bizarrely) appear to be outside the remit of the Department for Energy and Climate Change (DECC). These emission factors, and the calculations that convert them into energy units, are described in section 5.2.

¹The alternative is to use energy use statistics directly. Official datasets are limited here and unofficial, privately owned information on the subject is also limited. Petrol station data, for example, has the potential to inform us about overall energy use in general areas, but is limited by the fact that consumers can many miles to access the cheapest fuel, long-distance refuelling, the impossibility of disaggregating by reason for trip and the public inaccessibility of petrol station sales data. There is, however, much potential for using this data source more, as no energy-transport studies could be found that do.

The subsequent section presents data and equations for estimating energy use at the system level, to include the additional energy costs of fuel, road and vehicle production (section 5.3). Deeper analysis reveals that the energy use per mode estimates presented in the preceding two sections (e.g. that buses use 2.13 MJ/pkm on fuel) are rather gross oversimplifications of reality: there is strong evidence of substantial variability in energy use for different *types* of vehicle, driver, trip and road/guideway conditions. Assumptions about frequency of trips to work each year also have a large impact on estimated annual energy use due to commuting. Evidence on these issues is reported, and their inclusion in the models of energy use discussed, in section 5.4. Building on this evidence-base, section 5.5 and section 5.6 discuss and attempt to quantify changing ‘fleet efficiencies’ of cars over time and space.

Finally, section 5.7 concludes the chapter by reporting our best estimates of energy use by mode, which result from factors considered in the preceding sections. These values are provided a section of their own, as they are used in subsequent sections and are critical to the results of the model. Before looking at these issues in detail, a few comments on complexity and the dominance of the car are in order.

An idea that any naive reader should dispel immediately is that energy use in transport is simple. It is complex, more so than energy use in industrial and domestic settings, so energy use values must be treated with care. There is no single ‘right’, global or final answer to questions such as “how much energy does a person use per unit distance travelled?” As with many such simplistic questions asked of complex systems, the answer is ‘it depends’, on how the question is defined and a number of other factors, even before considering spatial and temporal variation (International Energy Agency, 2005; Berry and Fels, 1973; Lenzen, 1999). In rough descending order of importance, these include the following, each of which is considered below:

- the make, model, and condition of the vehicle in use
- behavioural factors such as propensity to accelerate (which are in turn influenced by legal, cultural and economic factors, as well as obstacles such as traffic lights)
- the nature of the physical and road environment such as road surface, topography and traffic
- ambient conditions including temperature and wind
- circuitry and straightness of roads

Because of the complexity of these interacting factors, effort has been made to make it simple to update existing estimates of energy use (or refine them by adding geographical

variability) if and when better energy use estimates emerge. (It is hoped that the estimates presented in this section could spur better energy-in-transport reporting by government agencies.) Another factor, not included in the above bullet points, that cross-cuts all of them, is the system boundaries of energy analysis: energy use will increase (in some cases substantially) as the indirect costs of fuel, vehicle, road/path construction and even unquantifiable knock-on impacts of our transport systems are included. This becomes apparent when the fundamentals of energy use in transport (section 5.1) are considered. This is another reason for producing several estimates for each mode of transport when calculating energy use in transport models, allowing sensitivity analysis and scenarios of the future that incorporate the indirect energy costs of transport.

The final introductory comment is that this chapter dedicates more attention to cars than to other modes. This is a deliberate decision: cars totally dominate the energy costs of commuting, using over 20 times more energy than all other modes put together.

5.1 Fundamentals of energy use in transport

Energy is an objective and quantifiable concept that spans the sciences. Frequently the term is defined loosely as the ‘ability to do work’, but this raises the question: work on what? and fails to convey the importance of energy for both the physical sciences and modern life (Rouse and Smith, 1975, p. 99):

As we view the physical world, we find that energy is one of the most fundamental and important concepts in science. Energy is essential to our everyday experience. From the time we turn off the electric alarm clock to the time we jump into our automobiles, ... until we sit down to the evening meal, the use of energy in various forms is a central feature of our daily activity.

This quote reinforces the reasons set out for the energy focus laid-down in the introduction, and adds a new one: we depend on energy. How different would daily life be in the absence of continuous flows of concentrated energy? The above quote illustrates how embedded external (and often invisible) energy sources have become in our life. Later in the book, Rouse and Smith (1975) urge others to shed light on energy costs of different processes, in the context of the 1970s oil crisis. In the context of 21st century environmental change and fossil fuel depletion, this thesis — by focussing the method

on energy use — seeks to follow in the footsteps of other researchers who sought to use energy as a yardstick against which to quantify and evaluate complex processes.²

Another physics textbook describes energy as “natural money” (Knight, 2007, p. 269). This description is apt, amalgamating all the types of energy into a single concept that conveys its importance as the enabler of change. A value is placed by the laws of physics on every type of physical phenomenon, and this value can be approximated. Transport, like everything else, must abide by the laws of thermodynamics:

1. Energy cannot be created or destroyed, just converted from one form to another.³
2. When energy is converted from one form to another in a closed system, the amount of useful energy always decreases (entropy increases).

The second law of thermodynamics is critical here, because it means that only certain types of energy allow us to do useful work; the rest is just background heat (Soddy, 1912). Although the Earth is not a thermodynamically closed system in which net entropy *always* increases, it is a materially closed system almost entirely dependent on the sun for its energy supplies. From this understanding stems the realisation that humanity is essentially spending its capital stock of energy: approximately 90% of all commercial energy use (meaning energy conversion, staying true to the first law of thermodynamics) comes from the burning of fossil fuels which took millions of years to accumulate in the Earth’s crust and can never be replaced on human time-scales (Smil, 2008). Our reliance on fossil fuels, combined with understanding of the second law of thermodynamics, leads to the realisation that our economy is fundamentally unsustainable as it will eventually run out of low-entropy resources, primarily fossil fuels. This, when considered alongside the diffuseness and low energy-densities of renewable sources (Mackay, 2009), provides a powerful argument to reduce to energy use in the medium-term. Even more urgently, the best available evidence suggests that no more than *half* of commercially viable fossil fuel resources can be burned to avoid ‘dangerous’ (2° C) climate change (Berners-Lee and Clark, 2013).

²Other pioneers of energy-in-society research include Soddy (1933, 1935), Odum (1971); Odum and Odum (2001), Steadman (1977) and Smil (1993, 2005, 2008).

³If energy cannot be destroyed, the frequent use of the terms “energy use” and “energy consumption” in this thesis and other studies of energy in transport could be criticised for contradicting the laws of thermodynamics. Based on literal, physical interpretations of energy the objection is entirely justified, and terms such as “consumption of low-entropy energy resources” or simply “fossil fuel use” may be more appropriate. However, these alternative terms have their own problems, of long-windedness and inaccuracy (not all low-entropy energy resources worth conserving are derived from fossil fuels). Therefore the term “energy use” is used throughout, based on the assumption that readers will interpret energy in this sense to refer to high quality (low entropy) energy resources such as fossil fuels, food and electricity.

5.1.1 The factors driving energy use in transport

With these laws in mind, let us return to the physical reasons for low-entropy energy use (henceforth and beforehand shortened to ‘energy use’) in transport. Transport must obey the laws of thermodynamics whilst “using up” energy, but where does all the energy actually go? In a narrowly defined transport system (in which the system boundary includes only the vehicle and its immediate surroundings — see figure 5.3), all energy use in transport is dedicated to overcoming inertia (acceleration) and friction (e.g. wind resistance). When the system boundary is expanded to accept the full complexity of transport systems and their dependence on myriad sub-processes, many more energy flows are added. Still, knowledge of thermodynamics can be used to understand how transport degrades high quality energy resources into heat and ephemeral kinetic energy. The latter is also eventually converted into low-grade heat through braking or other sources of friction (figure 5.1).

5.1.2 System boundaries

As emphasised in chapter 1, transport does not happen in isolation from the wider world. External considerations such as friends, family and quality of life all affect the commuter patterns people follow. The same is true of energy use. Let us consider a car journey as an example: does one only include the chemical energy stored in the petrol burned in the pistons? Or do we also include the primary energy consumed in getting the fuel out of the ground and into the petrol tank?⁴ Do we include the energy costs required to feed active travel modes? Cooking requirements? The embodied energy in vehicles, roads, footpaths and railways? The costs of decommissioning disused vehicles, or the net energy they save through recycling? The list could go on and on, to include seemingly distant energy costs such as washing machine and shower usage, influenced by whether the transport mode is active or passive. Taken to its extreme, it could even include knock-on impacts through society, such as shopping patterns, holiday destinations, health and the reshaping of social space (Illich, 1974).

What is clear from the above is that the energy costs of transport is not the simple hard-and-fast science that it appears at the outset. It is complex. A conceptual framework is needed to deal with this complexity and help decide which factors to include in the analysis and which ones to leave out. A useful analogy of this comes from economics: the price of goods can vary depending on whether the additional costs incurred by ownership

⁴The extraction costs include searching for the oil, the embedded energy in the pipelines, drilling rigs, personnel and refinery processes. The distribution costs include diesel or electric pumps to force the oil to flow, shipping and trucking costs and even the embedded energy of the roads and ships needed to enable these systems to function.

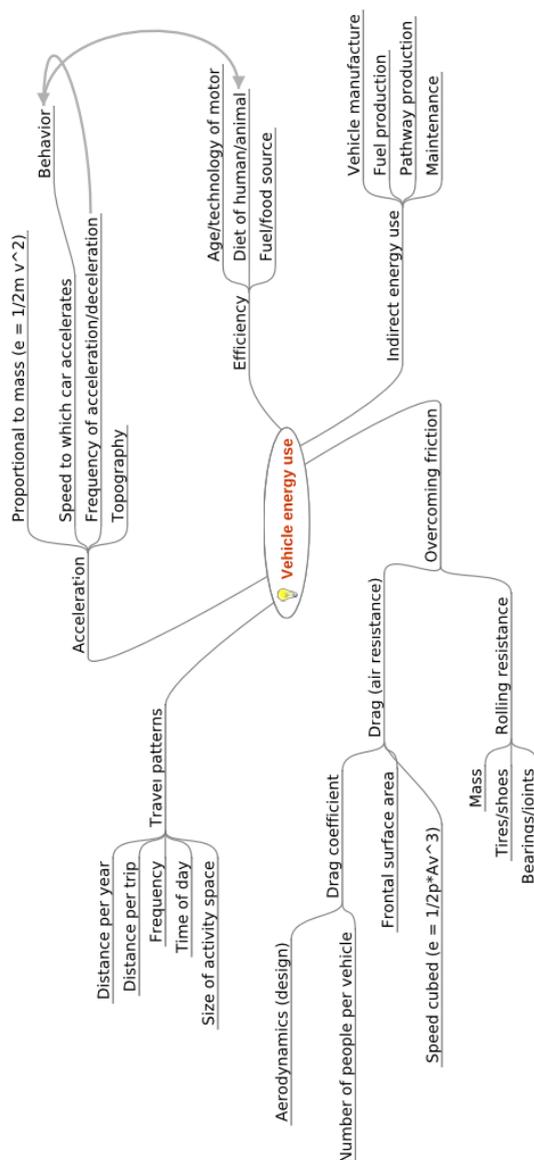


FIGURE 5.1: Schematic diagram of the factors causing energy use in transport.

are taken into account, let alone externalities such as pollution, bureaucracy and disposal (Perman, 2003). The costs of personal transport can be divided into variable and fixed costs, which in turn are sub-divided (figure 5.2). The precise proportion of the total cost attributable to each of these is variable depending on the type of car and the regulatory framework in the country in which the car is used.⁵ However, because only a couple of these costs are highly visible to consumers (the initial price of the car and the petrol), the wider system costs are often forgotten. The same is true of energy costs.

⁵In The USA, for example, fuel accounts for roughly one sixth of the overall lifetime cost; in the European Union and Japan, higher taxes push this up, to over a third (Smil, 1993).

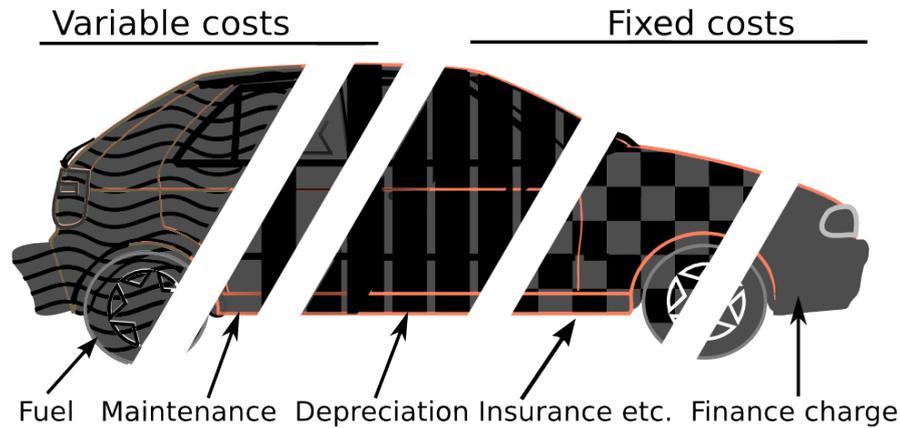


FIGURE 5.2: Rough approximation of relative importance of fixed and variable costs of car ownership in the USA, based on Smil (1993, p. 114). Car image from openclipart.org.

A systematic method for analysing system level energy costs is provided by the framework of *system boundaries* (Ekvall and Weidema, 2004). The system boundaries determining the energy costs of personal transport can be visualised as a set of concentric components, whose magnitude tends to reduce, but become less certain, from the centre to the edges figure 5.3. The order of components in figure 5.3 has been selected to reflect their ease of quantification and uncertainty (these tend to increase from the inner component of direct fuel use to the outer category of vehicle disposal). This order of energy-use components has influenced the decision of which ones to include in the analysis: vehicle disposal costs are small and difficult to calculate, so probably not worth calculating. The indirect energy costs of fuel, vehicle and road production are larger and probably easier to estimate, so more attractive for inclusion in energy analyses of the transport. (This explains why these indirect energy costs are quantified in section 5.3, while others were not.) Still, it is important to remember that most energy analyses of transport systems include only the direct energy costs, so any expansion of energy cost estimates beyond this single component should be advocated. The direct energy cost of fuel use is always the easiest, and usually the largest, energy use component, however. For this reason it is considered first.

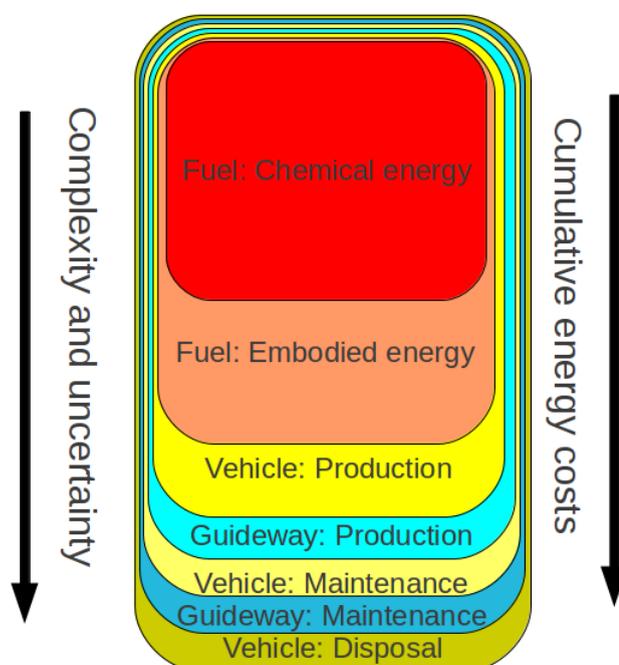


FIGURE 5.3: Schematic of physical system boundaries in personal transport systems.

5.1.3 Early quantifications of energy use in transport

The energy costs of different travel modes have been investigated since the advent of motorised travel, in the form of railways.⁶ Since then there have been a number of estimates and a great deal of speculation about which forms of travel are most efficient. However, there still remains little hard data about real-world performance of different modes.

The first comprehensive study into the energy impacts of personal travel that could be found was Fels (1975). This detailed paper built on earlier work that investigated the energy costs of automobile manufacture (Berry and Fels, 1973). The study was pioneering in its inclusion of a wide range of indirect energy costs, and in the 1975 paper, these were calculated for the main US modes of transport. Table 5.1 shows the results. This has been used (although not as much as one may have expected, given the importance of transport) as an input in subsequent studies (e.g. McNeil and Hendrickson,

⁶Engineer Thomas Tredgold, for example, went to great lengths to calculate the efficiency of the steam engines of the day, expressing the result not in terms of ‘energy’ (a term which was still more commonly used to describe individual enthusiasm and mental effort) but in terms of coal use. His intuitive and practical unit of choice for efficiency was lbs of coal used for a day’s horse work. The results of his investigations show an early interest in efficiency and wastage: “From the various causes of loss of effect, the quantities we have given may be increased about 30 percent, making the coals equivalent to the day’s work of a horse 123 lbs. in the best locomotive engines likely to be invented.

As for the engines on the Newcastle rail-roads, they at an average consume at least twice the last quantity to do the same work” (Tredgold, 1835, p. 82).

1985). Although seriously outdated by now, this research provide a benchmark against which more recent estimates and methods can be compared.

TABLE 5.1: The direct and indirect energy costs of personal travel (Fels, 1975). (Original values converted into SI units ($1 \text{ kWh/mile} = 2.237 \text{ MJ/km}$)).

Mode \Rightarrow	Car			Taxi					
Contribution (MJ/km) \downarrow	Big	Small	City bus	Rail	Petrol	Diesel	Moto.	Bike	Walk
Operation	7.14	3.65	21.41	37.36	11.70	6.06	1.34	0.09	0.14
Vehicle manufacture	0.87	0.47	0.67	0.89	1.21	1.83	0.11	0.09	-
Guideway manufacture	0.07	0.07	0.20	1.57	0.11	0.11	0.07	0.03	-
Total per ve- hicle mile	18.06	9.36	49.84	89.07	29.12	17.91	3.40	0.49	0.32

The main problem with Fels' estimates is that they do not match the current transport system in either space or time. Manufacturing techniques have advanced drastically in the intervening 40 years and it is clear that the UK fleet and roads are different from those of the USA, where things are larger. Therefore the numbers presented in Fels (1975) are used only for comparison with more recent energy use data.

5.2 Direct energy use: published estimates

Official UK data on the energy costs of transport were not easy to find. Because of this issue, the initial approach was to search for published estimates of energy costs of each mode, one by one. This resulted in a 'patchwork' of results, with a different source for each mode (table 5.2). There are numerous inconsistencies of date, place and method of data collection in this dataset, but it was the best that could be found throughout the majority of the thesis. The planned approach to this data quality issue was to follow Lovelace et al. (2011) and accept the uncertainty of the estimates and take them into account using sensitivity analysis.

In early 2013 a better data source was discovered (Defra, 2012).⁷ Although the Defra dataset is primarily concerned with greenhouse gas emissions with the aim of complying with the 2008 Climate Change Act, CO₂ and energy use are two sides of the same coin. In fact, emissions factors of different fuels per unit energy are contained within the same report. This allows for direct conversion into energy costs, without needing to

⁷Thanks to Alex Singleton, who mentioned the dataset during a talk on the CO₂ emissions from the school commute at the 'GISRUK2013' conference. This dataset was also used by Smith (2011), to calculate the CO₂ emissions from travel to work at the geographical level of administrative wards.

TABLE 5.2: Direct energy use of selected modes

Mode	Ef (MJ/vkm)
Bicycle	0.093 ^a
Bus	7.34 ^b
Car	2.98 ^c
Metro	– ^d
Motorbike	1.87 ^e
Train	63.4 ^b
Walking	0.13 ^a

a: (Coley, 2002), b: (Hansard, 2005), c: (Mackay, 2009), d: (DfT, 2011a), d: (London Underground, 2007), e: (ORNL et al., 2011)

pass through the usual intermediary stage of volume, when the type of fuel is known. The emissions allocated to each major mode of motorised transport (excluding cars) and some sub-divisions are presented in table 5.3. This dataset is extremely useful, as it already takes into account variations in occupancy and vehicle specification, allowing average numbers to be used. Also, geographic variation is accounted for to a limited extent through the distinction between sub-modes (i.e. light rail/tram vs Underground, local bus vs London bus and regular taxi vs black cab, the latter of which dominate in London).

TABLE 5.3: Direct greenhouse gas emissions associated with different forms of personal transport (Defra, 2012).

Mode ↓	kg CO ₂ eq./pkm ⇒	CO ₂	CH ₄	N ₂ O	Total
Taxi	Regular Taxi	0.14626	0.00004	0.00126	0.14756
	Black cab	0.15587	0.00003	0.00118	0.15709
Bus	Local bus	0.12269	0.00013	0.00098	0.12380
	London bus	0.08201	0.00007	0.00055	0.08263
	Av. local bus	0.11097	0.00012	0.00086	0.11195
Rail	Coach	0.02810	0.00007	0.00057	0.02874
	National rail	0.05501	0.00005	0.00312	0.05818
	International rail	0.01502	0.00001	0.00009	0.01512
	Light rail/tram	0.06709	0.00003	0.00041	0.06753
Ferry	Underground	0.07142	0.00004	0.00044	0.07190
	Foot passengers	0.01912	0.00001	0.00015	0.01928
	Car passengers	0.13216	0.00004	0.00101	0.13321
	Average	0.11516	0.00004	0.00088	0.11608

Further breakdowns of this data (by car model, bus region and occupancy level of trains, for example) are contained within this report.⁸

⁸Notable examples of the level of breakdown include the type of train: national rail, international rail (Eurostar), light rail and tram and London Underground are each included. Converting CO₂ emissions into energy use in the electrified cases rely on best estimates of the carbon intensity of grid electricity.

In terms of car energy use, energy costs can be broken down to the level of emission tax band, from A (“mini”) to I (“MPV”) for diesel and petrol cars and if the fuel type of the car is unknown. Emission factors convertible into energy are also provided for cars with the following alternative fuel types: hybrid, LPG (Liquified Petroleum Gas) and CNG (Compressed Natural Gas). (Interestingly, no emissions estimates are provided for battery-electric vehicles (BEVs) or electric bicycles, which are both growing in market share and have been touted for their energy performance.)

The most important categorisation of cars from the perspective of the Understanding Society dataset (USd), the primary source of individual level microdata in this project, is into small, medium and large cars. These categories are used to classify vehicles at the household level (variable *ensize1* in the USd). The three bands are deemed to be a suitable level of simplification to model and improve understanding of energy use in transport, and can account for variations in the vehicle fleet in different areas. No fuel type is specified in the USd, so the average energy use (\overline{Ef}) of each engine band was calculated. The following equation was used:

$$\overline{Ef}(MJ/vkm) = \sum_{ft} P_{ft} \times \frac{kg\ CO_2}{vkm\ ft} \times \frac{MJ}{kg\ CO_2\ ft} \quad (5.1)$$

where ft represents fuel type (in this case only petrol or diesel, although more fuel types could be included as their market share increases), P is the market share of the fuel type, and $\frac{kg\ CO_2}{vkm\ ft}$ and $\frac{MJ}{kg\ CO_2\ ft}$ represent the known emissions per kilometre and energy release per kg CO₂ released of the particular fuel type in question, respectively.⁹ The closeness of the average energy costs of driving reported by Mackay (2009) (presented in table 5.2) and our own estimates calculated through equation (5.1) and presented in table 5.4 (2.98 and 3.02 MJ respectively) provide confidence in the suitability of our method.

Because larger cars are more likely to have diesel engines, it is not adequate to assume that the petrol/diesel split (which is roughly 3:1) remains constant over all car classes. Defra (2012) do not state explicitly what proportion of cars are diesel in each category, so this information was calculated using the following re-arrangement:

$$\overline{Ef} = P_{ft1} \times E_{ft1} + P_{ft2} \times E_{ft2} \quad (5.2)$$

⁹The first two arguments of this equation are displayed in table 5.4. The CO₂ emissions resulting per unit of energy use are provided by (Defra, 2012, Table 1c) as 0.23963 and 0.24989 kg CO₂ / kWh for petrol and diesel respectively. To convert this into MJ per kg CO₂ emitted, the final argument of equation (5.1), take the inverse and multiply by 3.6 (the number of MJ in one kWh): 15.0 and 14.4 MJ/kg CO₂ for petrol and diesel respectively. Values for “100% mineral petrol” and “100% mineral diesel” were used rather than biofuel blends as the undiluted product still dominates the market and is less susceptible to variability over time.

TABLE 5.4: Conversion table from emissions (kg CO₂/km, presented in the first three columns of data) to energy use by size of car, based on equation (5.1). Emissions data and conversion tables from Defra (2012).

Engine size ↓ Fuel ⇒ Units ⇒	Petrol Emissions (<i>kg CO₂/vkm</i>)	Diesel Emissions (<i>kg CO₂/vkm</i>)	Unknown Emissions (<i>kg CO₂/vkm</i>)	P_{Petrol} (%)	Energy use (<i>MJ/vkm</i>)
Small (<= 1.4 l)	0.170	0.143	0.166	83.3	2.47
Medium (1.41 to 2.0 l)	0.211	0.179	0.200	65.9	2.97
Large (> 2.0 l)	0.298	0.242	0.268	46.8	3.95
Weighted average	0.208	0.192	0.203	72.7	3.02

$$P_{ft1} = \frac{\bar{E} - E_{ft2}}{E_{ft1} - E_{ft2}} \quad (5.3)$$

where E are the emissions per unit distance and P is the proportion of cars in each fuel type (ft). The results, also shown in table 5.4, show that it is dangerous to assume that the 3:1 petrol:diesel split remains constant over all car classes and in all areas.

The methodology to convert the CO₂ costs presented table 5.3 for buses, trains, trams and taxis is simpler than that used for cars because there are fewer sub-divisions within the other modes of transport. Also, a single fuel type can be assumed in most cases.¹⁰ A major difference between the energy cost estimates for cars and other modes is occupancy: the figures presented in table 5.4 apply per vehicle whereas those calculated for other forms of transport apply per person. This is a major advantage of using the Defra data rather than the variety of sources referenced in table 5.2: occupancy has already been carefully factored in based on UK conditions by Defra, reducing the need to identify occupancy figures at the national level and then decide which are the most reliable.¹¹

With estimates of the energy costs of different modes, the next stage is to calculate the energy costs per trip. The average direct energy used per trip (ETF) is a simple function of the fuel energy use of the mode in question multiplied by the distance:

$$ETF(i, j) = 2dR(i, j) \times Ef \quad (5.4)$$

¹⁰The dataset is less useful for trains because the emissions of trains combine both electric and diesel power sources. A separate government document states that “CO₂ emissions from diesel trains make up almost 90% of rail GHG emissions” (Department for Transport, 2011a, p. 13). Electric trains have only marginally lower emissions — between 20 and 35 percent (Hickman, 2012) — and some trains still rely on coal and gas oil (pushing emissions in the opposite direction) (Department for Transport, 2011a). These facts suggest that assuming all national trains are powered by diesel would provide a reasonable estimate of the overall average energy costs. The energy costs of international rail is a different matter not tackled here as few people commute internationally by train.

¹¹Clearly occupancy also varies from region to region and depending on the time of travel. For the purposes of modelling energy use, however, a single national number is a good place to start.

TABLE 5.5: Conversion of CO₂ emissions data to energy use for motorised modes of transport. Data from (Defra, 2012)

Mode	Emissions	Fuel type	Carbon content	Energy content	Energy use
Units ⇒	$\frac{kgCO_2}{pkm}$	-	$\frac{kgCO_2}{kWh}$	$\frac{MJ}{kgCO_2}$	$\frac{MJ}{pkm}$
Bus (local)	0.14754	Diesel	0.25	14.41	2.13
Coach	0.03000	Diesel	0.25	14.41	0.43
Motorbike	0.11606	Petrol	0.24	15.02	1.74
Taxi	0.21040	Diesel	0.25	14.41	3.03
Train	0.05340	Diesel	0.25	14.41	0.77
Tram	0.07101	Electricity	0.45	8.08	0.57

where Ef is the fuel energy used per kilometre by mode and $dR(i, j)$ is the route distance between points i and j . The value is multiplied by two because trips to work are two way. Chapter 6 describes how this equation can be used as the basis for estimating total energy costs over the course of the year. The next stage, however, is to look into the indirect energy costs of personal travel.

5.3 Calculating system level energy use

As described in section 5.1, transport consumes energy through a wide range of pathways, only the most obvious of which — energy directly consumed in vehicle engines for propulsion — is covered by official statistics¹² and the majority of energy-transport research (e.g. Schipper et al., 1992; Wohlgemuth, 1998; Hickman et al., 1999; Brand et al., 2013). The discussion presented in section 5.1 makes it clear that not all indirect energy impacts can be realistically quantified. Therefore only a subset of the indirect energy costs of commuting is included in this section. The three most important and easily quantified costs are:

- the energy costs of fuel and food production (Efp)
- the energy costs of vehicle manufacture (Ev)
- the energy costs of guideway manufacture (e.g. roads and railways) (Eg)

¹²Even in terms of direct energy use of transport the governments statistics are limited. As described in the previous section, geographical breakdowns do not extend below the coarse Local Authority level, or to non-road modes. There is no initiative to report energy or emissions by reason for trip, making it hard for transport planners and other decision makers to know where to focus mitigation strategies. Also, energy use is not reported directly but as emissions. This means that researchers interested in energy must convert emissions factors into energy use, as was done in the previous section.

For the purposes of simplicity, it can be assumed that the system level energy costs equal the sum of these indirect energy costs and direct energy costs:

$$E_{sys} = Ef + Efp + Ev + Eg \quad (5.5)$$

This formula requires that all arguments are provided in the same units. The direct energy costs of personal transport are calculated above in SI units of megajoules per passenger kilometre (MJ/pkm). Yet the energy costs of producing a car or building a road is generally reported as a single energy expenditure (e.g. ~ 300 GJ per car) and not per unit distance. The first paper that formalised this problem in the context of system level energy costs of transport was by Fels (1975), so the calculation of energy costs in this thesis is strongly influenced by this paper. Formally, the total (system level) energy use for each trip (E_{sys}) can be defined, for each mode (m), as follows Fels (1975):

$$E_{sys_m} = Ef_m + \frac{EMv_m}{Lv_m} + \frac{EMg_m}{Lg_m} \quad (5.6)$$

where EMv and EMg are the ‘one-off’ embodied energy costs of vehicles and guideways and Lv_m and Lg_m are their lifespans, measured in kilometres and vehicle-passes (the number of passing vehicles a road can take before it needs to be replaced), respectively. It should be instantly clear that equation (5.5) is a simpler and more generalised version of equation (5.6), and indeed it is derived from Fels’ work, where

$$Ev = \frac{EMv}{LV} \quad \text{and} \quad Eg = \frac{EMg}{Lg}. \quad (5.7)$$

Fels (1975) did not include the energy costs of fuel production, despite the size of this component.

The above equations can be used to calculate system level energy costs for single trips to work and back (ET_{sys}): because E_{sys} is provided in the same units as Ef , one simply replaces the latter with the former in equation (5.4). However, the calculation of system level energy costs is rarely undertaken, and merits further comment before discussing the data that enable system level energy costs to be estimated.

Fels’ framework for calculating system level energy costs has been available to researchers for almost 40 years. Despite this, most researchers continue to use only direct energy costs in their analysis (notable exceptions include Treloar et al., 2004; Lenzen, 1999; Mackay, 2009; Lovelace et al., 2011). This reluctance to engage with system level energy costs can be attributed to a variety of factors, the most important of which are probably the invisibility of indirect energy costs, the tendency to favour simple, easy energy calculations and uncertainty. Uncertainty is the most critical of these: it is fine to have formulae that *can* work out system level energy costs, but this is only useful if

H	I	J	K	L	M	N	O	P	Q	R	S	T
Mode	Ef (MJ/km)	Energy req	Ef(em) (MJ/km)	Emy (GJ/v)	Emg (TJ/Ly)	Lg (million k)	Epkm (MJ/k)	Emy/Ly (MJ)	Emg/Lg (TJ)	Ef (MJ/vkm)	Occupancy	
Bike	0.06	5.75	0.33	1.00	0.00	20000.00	1	0.44	0.05	0.00	0.39	1
Bus	7.34	0.40	2.94	1000.00	27.20	750000.00	65700000	1.34	1.33	0.41	10.28	9
Car (small)	2.47	0.40	0.99	85.00	27.20	150000.00	157680000	4.20	0.57	0.17	3.46	1
Car (average)	3.02	0.40	1.21	100.00	27.20	150000.00	131400000	5.10	0.67	0.21	4.23	1
Car (large)	3.95	0.40	1.58	130.00	27.20	150000.00	105120000	6.65	0.87	0.26	5.53	1
Coach	96.40	0.40	38.56	1500.00	27.20	750000.00	65700000	5.49	2.00	0.41	134.96	25
Moto	1.87	0.40	0.75	33.33	27.20	100000.00	394200000	3.02	0.33	0.07	2.62	1
Train	96.40	0.40	38.56	0.00	0.00	1.00	1	1.02	0.00	0.00	134.96	132
Metro	0.54	0.67	0.36	0.00	0.00	6.00	1	0.01	0.00	0.00	0.90	100
Walking	0.13	5.75	0.75	0.00	0.00	1.00	1	0.87	0.00	0.00	0.87	1

FIGURE 5.4: Screen shot of the spreadsheet used to calculate system level energy costs.

the input dataset is sufficiently reliable. The bulk of this section is therefore dedicated to describing the evidence that is available on indirect energy costs of food and fuel production, vehicle manufacture and the infrastructure these vehicles rely upon. It is acknowledged that this adds complexity to the energy analysis, but the complexity can be justified: indirect energy costs of vehicle production and road construction can have a large impact on total energy use calculations (Lovelace et al., 2011; Lenzen, 1999; Wee et al., 2000), with associated impacts for climate change and energy security. The ultimate aim is to provide estimates of indirect energy costs per passenger kilometre (pkm) of different modes. These estimates serve as inputs into energy use calculations based on distance and mode, allowing the user to choose whether to focus attention on direct or indirect energy use (figure 5.4). The results of these equations are given after evidence on the magnitude of indirect energy costs has been presented, in table 5.13.

5.3.1 The embedded energy of fuel

In the context of multi-mode transport energy costs, ‘fuel’ here refers not only to petrol and diesel, but to electricity and food as well. It is all too easy to assume that vehicles only use the energy released by the degradation of these low-entropy resources. However, each of these fuel sources require very large energy inputs before they are available at the point of use.

5.3.1.1 Liquid fuels

Liquid fuels, which dominate transport energy costs, consume a huge amount of energy even before they are burned in the oxygen-rich atmosphere. In fact, “the oil and gas industry is traditionally the most energy-using industry”, at least in the USA (Guilford et al., 2011). Most of these inputs are hidden from public view: consumers only interact with the end product and even then it is kept out of sight by petrol pumps and hidden fuel tanks. Energy is used during every stage however: in prospecting, drilling, pumping,

refining, transport and, increasingly, enhanced oil recovery (EOR), horizontal drilling and bitumen processing techniques. In layman's terms, previous estimates include "only the energy in the petrol, not the energy used at the oil refinery that makes the petrol, nor the energy used in trundling the oil and petrol from A to B" (Mackay, 2009, p. 104). The transformation of crude oil from a far-flung deposit of variable quality into a finished product is difficult to follow. Its energy costs are therefore variable over time and space (Cleveland, 2005); the same would apply to food or any other 'fuel', all of which require energy to produce. The aim in this section, therefore, is to find best estimates of energy costs, rather than exact answers. The few studies that are dedicated to these costs tend to use round numbers and avoid error bars, emphasising that the level of uncertainty in their estimates is unknown.

Estimates of the energy costs of producing liquid fuels products have been undertaken by a number of researchers. Cleveland (2005) aimed at estimating the energy return on energy investment (EROEI) of American crude oil production over time, based on data from the Census of Mineral Industries. This is an unusually detailed dataset, which "reports the quantities of fuel and electricity used in the petroleum sector at 5 year intervals from 1954 to 1997" (Cleveland, 2005, p. 777). The findings show that oil is energy intensive to produce and that these costs have increased over time, rising from $1/20^{th}$ to $1/11^{th}$ (EROEI values of 20:1 and 11:1) of the overall quality-adjusted energy content of crude oil between the 1970s and 1990s. Building on this study, Guilford et al. (2011) employed new datasets and methods to update the EROEI estimates into the 21st century. They also found long-term increases in oil production energy costs, reaching $1/10^{th}$ of the energy content of the crude oil by 2007. Such detailed datasets of oil industry energy use are not available for the UK, let alone worldwide, so the study should be used as guidance only. There has, however, been one preliminary study of the energy costs of global oil production, which broadly supported Cleveland's findings. In it, the EROEI of crude oil production was found to have dropped from 26:1 in 1992 to 18:1 in 2006: clear evidence of increasing indirect energy costs (Gagnon et al., 2009).

It is important to remember that the aforementioned EROEI studies focussed only the energy costs of crude oil production: refining, distribution and other costs are omitted, so the 'well-to-wheel' costs would be substantially higher. This problem is tackled in the life cycle analysis (LCA) literature for biofuels (e.g. Cherubini et al., 2009), but no study dedicated to the EROEI (or simply EROI as it is sometimes called) could be found for the main transport fuels, petrol and diesel. Yet it would make little sense to use values for crude oil production at the well head when in fact cars use much lighter products at the petrol pump. The latter require far more complex and energy intensive processes than pumping the oil alone. More research is needed into the energy costs of liquid fuel production overall. However, this is not the place to conduct such an overdue

energy analysis. Instead, ‘best’ (most reliable and broadly accepted in the academic community) estimates from the literature must be relied upon. This seems to be the approach taken by Professor David MacKay also, who uses an EROEI value of 2.5 for transport fuels taken from a previous study. He provides the following justification: “Its been estimated that making each unit of petrol requires an input of 1.4 units of oil and other primary fuels (Treloar et al., 2004)” (Mackay, 2009, p. 30).¹³ This estimate is neither up-to-date nor based on UK data. However, in the absence of comprehensive *well-to-wheel* energy analyses for diesel and petrol production, it appears to be the best source available, implying that $Efp = Ef \times 0.4$ for modes that burn petrol and diesel. More up-to-date estimates should be included as soon as they emerge.

5.3.1.2 Food

Bicycles and walking are sometimes portrayed as ‘zero emission’ travel options. This statement is clearly misleading, on several levels. Bicycle and shoe manufacture (unless second-hand bicycles or shoes are used) take energy, even though the implied emissions would be a tiny fraction of that emitted from the energy costs of manufacturing a car. In terms of direct emissions, the phrase appears, at face value, to be correct: no pollution can be seen emanating from an accelerating bicycle, and the human power source can be assumed to require food and drink inputs regardless of his or her activity levels (Brand, 2006). The possibility of limited correlation between food consumption and physical activity is further supported by evidence of a worldwide ‘obesity epidemic’ (Caballero, 2007), which implies an excessive consumption of food, and therefore energy, amongst some of the least active members of society (Michaelowa and Dransfeld, 2008).

On the other hand, it has been observed that exercise tends to increase food consumption, although not in a linear or entirely predictable way (Melzer et al., 2005). Given these uncertainties and caveats, past literature is relied upon. Lovelace et al. (2011) assumed a linear relationship between cycling and food energy use for the purpose of simplicity, and this approach is continued here. This assumption is based on the best evidence that could be found on the subject of energy use correlates of walking and cycling, from a widely cited paper published in *Energy Policy* (Coley, 2002). (The place of publication is relevant in this case, because most literature related to energy intake and physical activity is published in health journals, so is not directly applicable to energy analysis.) Coley (2002) analysed this issue in detail, and concluded that it is a mistake

¹³This estimate is in fact based on an earlier study: “a primary energy factor of 1.4 was assumed for all liquid fuels, as it takes 1.4 GJ of oil and other primary fuels to make 1 GJ of petrol (Treloar, 1997)” (Treloar et al., 2004, p. 46). The 1997 article (which is highly cited) could not be accessed, however, so the opinion of David MacKay that this estimate is reliable was deferred to in this case. The search for this number reveals a wider question: how can such an important number be so little researched and so hard to find?

not to provide emission factors for walking and cycling in the same way that they are included for motorised forms. The work estimated the average energy intake for different activities, with the aim of providing recommendations to overcome this shortfall. The chemical and embodied energy of additional food used by cyclists was calculated be 94 kJ/km and 539 kJ/km respectively, assuming a fixed embodied:chemical energy ratio of 5.75. For walking, the estimated energy costs are approximately 50% greater: 129 and 740 kJ/km respectively. It is assumed that the change in food demand from driving is negligible.¹⁴

These values are far from the final word on the matter, as the study failed to account for differences in diet and food behaviours. Cyclists, for example could be assumed to have a more environmentally aware diet as many identify with an environmentalist identity (Gatersleben and Appleton, 2007). Amplifying this effect could be the issue of food wastage: from an environmental perspective it is not the food eaten that causes indirect energy use and emissions, but the act of purchasing the product that drives demand. It is, of course, impossible to estimate how much more (or less) food walkers and cyclists waste compared with those who travel by other modes.¹⁵ The system boundary surrounding the energy costs of food consumption could expand even further, to include the transportation energy costs of buying the food, which have been found to be of critical importance (Coley et al., 2009). Again, however, this knock-on impact is very hard to estimate and is therefore excluded from the analysis. This explains why Coley's estimates are used here: as with the EROEI question of liquid fuel production, the best estimate from the literature is used. Taking Coley's (2002) values, E_{fm} for food can be assumed to be $5.75 \times E_f$ 0.74 and 5.4 MJ/pkm for walking and cycling respectively.

5.3.1.3 Electricity

The final energy source used for transportation is electricity. Currently the share of passenger kilometres powered by the national grid is low in the UK, amounting to just over 1% of the total (Mackay, 2009, p. 104, table 18.3, figure 5.5).

Currently, electricity use for personal travel is limited to electric rail and a few hundred electric cars (unless telecommuting is counted as personal travel, which it is not in this thesis), although the proportion is forecast to grow into the future (Skea et al., 2010).

¹⁴One could argue that driving increases one's marginal food intake in a similar way, but it seems that driving requires no more energy than average, everyday activities such as housework and shopping, based on an inventory of activity types and metabolic rate (Ainsworth et al., 2000). In fact the relative metabolic rate of "driving at work" (MET = 1.5) is lower than that of many other common activities such as "childcare" (MET = 2.5 - 3) and "putting away groceries" (MET = 2.5) (Ainsworth, 2003).

¹⁵Data from the Living Costs and Food Survey (LCFS) could potentially be used to analyse the varying food buying habits of cyclists compared with non-cyclists as it contains questions on cycling.

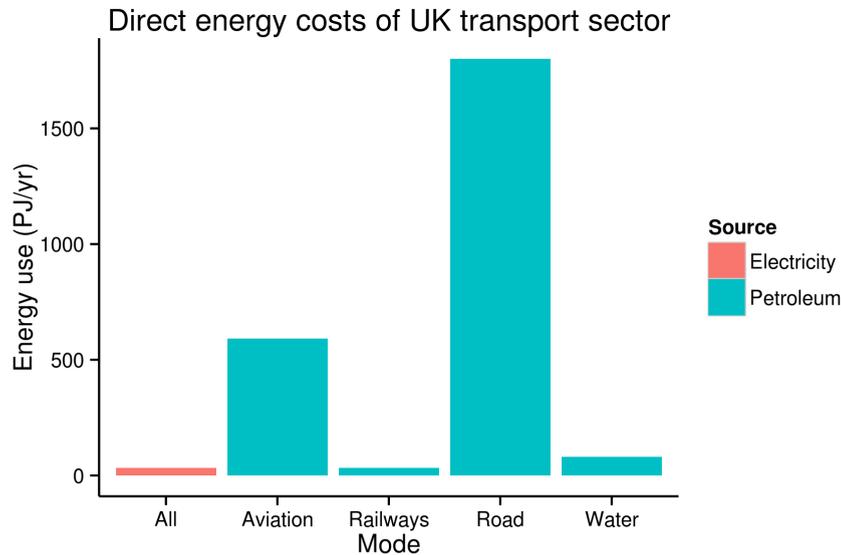


FIGURE 5.5: UK transport energy consumption by mode and primary energy source in 2006 (Mackay, 2009, p. 104).

Even ignoring the future energy use of electric cars, the indirect energy costs of electricity production must be estimated if tram and underground trips are to be treated the same as other modes in the system level energy cost calculations: to produce 1 kWh (3.6 MJ) of electricity at the point of use actually requires much more than that in terms of fossil fuels due to efficiency losses during generation and distribution. Energy security and climate change, the underlying issues driving this research, are both affected by these efficiency losses, so it is important to include the fossil fuel energy consumed by electricity production for fair evaluation.

As with food and liquid fuels, the production costs of electricity vary widely over time and space. As more renewable energy sources (which are generally assumed to be 100% efficient, but which do have a heavy reliance on fossil fuels for their construction) and next-generation power plants come online, the fossil energy costs will surely decline. Yet the power generation sector is notoriously slow-changing, so today's estimates should be approximately valid for the next few years. As with the energy costs of liquid fuel production, there are also questions about the system boundary of the analysis: should only the energy content of the input fuels (primarily coal and gas) be considered, or should the energy costs of extraction be included also? One study on the life-cycle emissions from British coal-fired power stations calculated indirect emissions arising from transportation and mining: they were small ($\sim 2\%$) compared with the direct emissions of burning the coal (Odeh and Cockerill, 2008). Based on this estimate, and knowing that carbon dioxide emissions are roughly proportional to energy use, it can be said that

the energy costs of fossil fuel extraction for electricity production are unlikely to have a major impact on the final result: only the energy content of the fuel is considered.

In 2012, the largest sources of electricity were coal (39% of electricity output) and gas (28%) (DECC, 2013b). The rest was mostly produced by nuclear (19%) and renewables (11%). However, these proportions shift around on an annual time-scale, depending on demand and the price of different fuels: in 2011 40% of electricity was produced by gas alone. Of course, each of these sources has different efficiencies that can be defined in different ways. It therefore makes little sense to allocate precise values to the energy costs of electricity production when they are so variable: efficiencies shift around even during the day, as (generally inefficient) plants come online to meet the afternoon peaks. A full estimation of the energy costs of electricity production for transport would take all these factors into account, for example by comparing the usage times with the load profile of the national grid.

The purpose of this section is not accuracy or precision, however; it is to gain insight into the approximate impact of indirect energy costs of transportation on the overall system level energy costs of transport to work. Therefore, simplifications are made that should be approximately right over a long time, rather than a single precise value that is correct for one very specific moment in time. So, following Mackay (2009), a ‘back-of-the-envelope’ calculation is made, based on the best available evidence.

Loosely speaking, electricity generation can be divided into thirds, with coal, gas and nuclear/renewables each providing roughly equal input. Efficiencies of typical UK coal and gas power plants are known: 35% and 50% respectively (Graus and Worrell, 2006). Reliable numbers on the energy inputs into nuclear power plants (and they would be much lower, excluding decommissioning) are lacking, so these are omitted from the analysis for simplicity. The total fossil energy input required for 1 kWh of electricity can therefore be calculated as:

$$1/3 \times (1/\eta_{coal} + 1/\eta_{gas}) \approx 5/3 kWh \quad (5.8)$$

To avoid double-counting, the energy that has already been included as energy used directly in the electric motors of the trams, trains and electric cars is subtracted¹⁶ (1 kWh): $Efp \approx 2/3Ef$ for electric modes.

¹⁶In practice, the efficiency of car batteries are not 100%, so this would be included in an assessment aiming for high precision; another simplification.

5.3.2 Vehicle manufacture

How much energy does it require to manufacture a car? This question has been asked before, and a handful of estimates has been provided. These numbers are usually reported in abstract energy units that bear little relation to everyday life for most people. (Reported in megajoules, they can be used as inputs the system level energy cost calculations described above). Before describing these numbers, this section begins with a more intuitive way to understand the energy costs of car manufacture: to inspect, in detail, the workmanship that goes into a modern engine (figure 5.6). The following thought experiment serves this purpose well: first, study in detail an iron ore deposit or mine, then spend an equal amount of time studying a car engine, and imagine the processes that must occur for the former to turn into hundreds of thousands of the latter. The vast difference between the two should provide a qualitative insight into the energy requirements of car manufacture that is more powerful than only knowledge of the numbers. Categorising and quantifying these processes is a difficult task. The organisational supply chain that transforms low quality (high entropy) natural resources into a complex and highly accurate vehicle component such as an engine is long and complex. Tracing the manufacturing processes, technologies and material and energy consumption is even harder; this is the subject matter of life cycle analysis (LCA), an academic field in its own right, with a substantial branch dedicated to energy life cycle analysis (Kuemmel et al., 1997; Cornelissen and Hirs, 2002). It should come as little surprise, therefore that “the literature shows a large variation in estimates of the energy needed to manufacture a car (Moll, 1993)” (Wee et al., 2000, p.139).¹⁷ As with the energy costs of fuel production, this is an uncertain science, and ‘best estimates’ from the literature must be used, combined with some common sense and reason. Some estimates of the energy costs of cars are presented in table 5.6. The range of methods and vehicles analysed is reflected in the range of estimates: the highest (272 GJ) is more than *three* times larger than the smallest. At this stage the following dilemma presents itself: do we select the estimate that seems: Most authoritative? Most recent? most related to the UK car fleet? Do we use this as the basis for best and worst-case scenarios? Or do we take some kind of average?

Presented with these choices, it was decided to follow Mackay (2009) and place comprehensibility over accuracy: 100 GJ is a round number that, to some degree, summarises the estimates presented in table 5.6, and will be used as the central estimate of *EMv*. This ‘rough estimate’ is a deliberate departure from previous work published by the

¹⁷The original 1993 dissertation, entitled “Energy counts and materials matter in models for sustainable development, dynamic life-cycle modelling as a tool for design and evaluation of long-term environmental strategies” is available on the University of Groningen’s website, but only as a scan of the introduction.

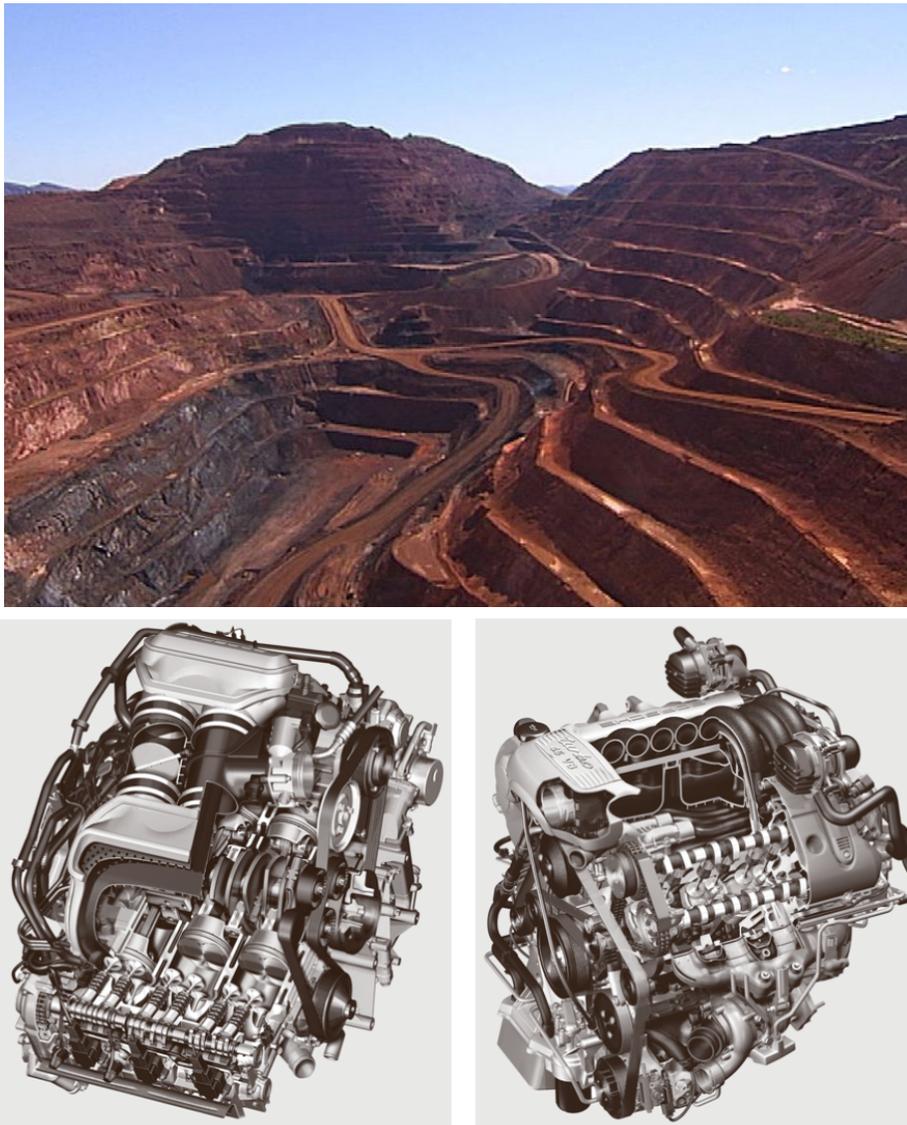


FIGURE 5.6: Iron ore mine and 3D CAD images of two modern car engines. The iron ore mine is located in Pilbara, western Australia (<http://tinyurl.com/bde9y56>). The 3D CAD images are of two modern car engines. These 6 (left) and 8 (right) cylinder Porsche engines may be larger than typical car engines, but are not much more intricate, and share the same basic design as all modern internal combustion engines for cars (Grote and Antonsson, 2009, p. 1043).

author (Lovelace et al., 2011), in which the most ‘authoritative’ figure was selected (the 272 GJ estimate used by the authority figure, Professor David MacKay, so was assumed to be ‘correct’). The reasons for selecting using the 100 GJ value is that the variability in previous estimates suggests that the true value is only really known to one significant figure. In place of using an estimate that inspires confidence with its precision (e.g. 272 MJ), this estimate acknowledges that the energy costs of car manufacture are highly uncertain and variable over time, and require updating with more evidence. As with the energy costs of fuel production, any estimate that is overly precise risks being outdated

very quickly.

To account for the fact that large cars require more natural resources and hence energy to produce, Mikkola and Ahokas (2010) assumed that embodied energy costs of manufacture are roughly proportional to weight. Following this approach, the next stage is to allocate the car categories that are provided in survey data (small, medium and large) to average weights, and adjust the energy use estimate accordingly. In fact, weight data on the UK car fleet was found to be elusive, especially cross-tabulated with the 3-way categorisation of size used in the Understanding Society and National Travel Survey datasets. The best source of information on the weight bands of different cars that could be found was an appendix of *Cars Fit for Their Purpose* (Plowden and Lister, 2008).¹⁸ Five categories of ‘conventional’ cars, representative of the British car fleet, were selected for comparison with ‘eco cars’: supermini, lower medium, upper medium, executive and multi-purpose (4 X 4s and people carriers); with the follow weights: 1096, 1175, 1440, 1735, and 1674 kg. To match these to the 3 categories supplied by survey data, it is assumed that the ‘small’ car category corresponds to the supermini class. For the ‘medium’ and ‘large’ categories, the average of lower medium and upper medium, and the average of executive and multi purpose vehicles are taken respectively. This results in the following weights: 1.1, 1.3 and 1.7 tonnes. Thus, small and large cars are assumed to be 15% and 30% lighter and heavier than the fleet average, respectively.¹⁹ Although these values are not considered to be accurate,²⁰ they do coincide with other weight figures (e.g. those presented in (Transport Research Laboratory, 2006, appendix 2), who quote an average weight for the EU’s fleet as 1376 kg.), reflecting the fact that the weight distribution of cars is positively skewed and providing intuitively easy to remember values providing no false sense of accuracy. These average weights will be used to adjust the 100 GJ Ef_{car} value.

No research directly tackling the energy costs of bus manufacture could be found. However, an article looking at agricultural machinery approached the problem by focussing on weight (Mikkola and Ahokas, 2010). The same approach is taken here: it is assumed that the energy inputs per kilogram will be the same for cars as for larger vehicles. From a search of bus specifications, it was discovered that buses tend to weigh a little more

¹⁸Another source of information considered was a joint report by national transport research consultancies for the European Union tackling the issue of safety (Transport Research Laboratory, 2006, appendix 2). They report the weights of 3 types of passenger vehicle specified by the British Standard on crash tests, EN 1317-1: 825, 1300, and 1500. These last two values seem representative compared with other figures, but the first is far lower than cars in the supermini class.

¹⁹These rounded values were attained by using the medium-sized car weight $((1440 + 1175) / 2 = 1307.5)$ as the denominator: $1096/1307.5 = 0.838$ was rounded up to 15% lighter for simplicity; $(1735 + 1674) / (1440 + 1175) = 1.304$.

²⁰The definitions used to define small, medium and large cars are not defined in terms of weight in the survey questionnaire, precluding any hope of precision.

TABLE 5.6: Estimates of the energy costs of car manufacture (EMv)

Source	EMv (GJ)	MJ/kg	Comments
Burnham et al. (2006)	110		Typical US car, assumes materials are recycled
MacLean and Lave (1998)		86.6	Detailed, widely referenced study
Mikkola and Ahokas (2010)	81.2	134	Data presented in MJ/kg from a large (1.6 tonne) car
Simonsen and Walnum (2011)	85.56		VW Golf (VW estimate)
Sorensen (2004)	87		Toyota Camry
Sorensen (2004)	88		VW Lupo, production and materials
Sorensen (2004)	178		DaimlerChrysler F-Cell
Treloar et al. (2004)	272		Economic-based calculation, used in MacKay (2009)
Usón et al. (2011)	114.3		Used commercial life cycle analysis software

than 10 tonnes.²¹ Inter-city coaches are heavier, due to their additional size (for seating capacity and luggage space) and the fact they do not need to accelerate as frequently as buses so are less dependent on weight for fuel consumption: they were assumed to be on average 20 tonnes, or approximately 15 times the weight of a typical car.²² Based on these weights, the energy cost of coach and bus manufacture was estimated to be EMv_{car} multiplied by 10 and 15 respectively.

A similar logic was used to estimate the embodied energy of bicycles: a typical bicycle weighs ~ 12 kg, 100^{th} the weight of an average car so the energy costs of its manufacture are assumed to be 100 times less as well. Similar techniques could be used to estimate the embedded energy costs of trains, trams and even walking (due to the energy costs of new shoes). However, given the relatively small proportion of trips made by these ‘vehicles’, coupled with the lack of evidence about their embodied energy costs, EMv was not calculated for these modes.

²¹Alexander Dennis’s Enviro200, “the world’s most popular midi bus” weighs 13.1 tonnes (alexander-dennis.com); the Enviro300, also very common in the UK, weighs 14.4 tonnes (Wikipedia); the double-decker Wrightbus NB4L, common in London, weighs 12.65 tonnes; the Cummins engine 23-34 passengers inner city bus weighs 12 tonnes. At the top end of the range, the Alexander Dennis Enviro35OH, an electric-hybrid bus (i.e. with additional weight due to batteries) weighs 19 tonnes. These weights were supported by a paper comparing the fuel use of three ‘state of the art’ buses (Pelkmans et al., 2001): they each weighed between 11 and 14 tonnes. Incidentally, each of these boasts new and improved fuel use, due in part to their light weight.

²²The Volvo 9700, for example, weighs 18 tonnes (volvobuses.com).

As Fels' formula (equation (5.6)) shows, the average vehicle lifespan (Lv) is needed to convert these embodied energy costs into costs per unit distance. The best available estimates that could be found of Lv were 150,000, 750,000 and 20,000 km for cars, buses and bicycles respectively.

5.3.3 Guideway manufacture

Returning to the thought experiment conducted for vehicle manufacture, it should be clear that it can be taken further. Imagine the car in isolation from the rest of society: placed into the pre-industrial natural environment, it would be of little use, even if petrol were available. It is only with supporting infrastructure including roads and the flat, compressed ground that they depend on, petrol stations, garages, bridges etc. that cars can move people. All of these objects require large one-off energy inputs to be created, and continual energy inputs for maintenance. By considering the natural environment next to the man-made environment for cars, another, longer-term energy cost becomes clear: without incessant energy inputs the built environment would tend to degrade, gradually returning to its natural state.²³ The concept of entropy may be helpful here: roads and other built objects can be seen as having a lower level of entropy than their surroundings, an imposition of straight edges and surfaces on a largely stochastic and fractal landscape. Yet the second law of thermodynamics states that entropy always increases in closed dynamic systems; this explains why motorised transport infrastructure not only requires large energy inputs at the outset, but also commits future generations to future inputs if they want them to work.

The above discussion makes it clear that road and rail construction is a highly energy intensive activity. However, only one recent study could be found that quantified the energy costs of road construction. Treloar et al. (2004) conducted a very detailed 'hybrid life-cycle analysis', attempting to convert the full range of processes and materials — including the embodied energy contained in concrete, steel and cement, as well as the processes of construction and financing needed to make the contract happen — into energy units. Eight estimates of embodied energy were presented for eight different road types, ranging from 'granular' tracks (42 TJ for 5 km, with a lifespan of 20 years) to heavy duty 'full-depth asphalt' roads (195 TJ for 5 km, lifespan of 40 years). For their main case study, of 'continuously reinforced concrete' roads, the energy costs of construction were found to be 136 TJ for a 5 km stretch (27.2 GJ/m). Adding maintenance energy

²³Post-collapse Soviet settlements and parts of Europe most seriously affected by the post-2008 recession (e.g. Southern Spain) illustrate this process well: tree roots eventually crack and rupture roads; weeds overtake abandoned petrol stations and bridges eventually fail without regular maintenance.

costs of 4% per year, the total cost increased by a factor of 4.6. This is equivalent to 35,000 kWh/m overall.²⁴

Mackay (2009, p. 90) used these estimates as the basis of his estimates of road energy costs in the UK, per person: “Lets turn this into a ballpark figure for the energy cost of British roads. There are 28,000 miles of trunk roads and class-1 roads in Britain (excluding motorways). Assuming 35,000 kWh per metre per 40 years, those roads cost us 2 kWh/d per person.”²⁵ Given that roads are used for 500 billion pkm each year (Mills, 2011), this translates into an average energy cost of $EMg_{road} = 0.3$ MJ/pkm.²⁶

Of course, this value would vary greatly depending on a number of factors. It is entirely feasible, for example, that larger cars cause more energy costs due to road maintenance and that motorcycles cost less per pkm in terms of road repairs. However, this estimate is so crude that adjusting it to account for such factors (which appear not to have been sufficiently explored in the LCA literature) would be presumptuous. As with the estimates of the energy costs of fuel and car manufacture, round numbers are used to emphasise our uncertainty in the result.

The availability of data required for the calculation of EMg for railways is even worse, so this value is applied to road-based modes (which account for ~98% of commuting pkms) only. The energy costs of bicycle lanes and footpaths would also be hard to calculate and, in any case, would probably be negligible in comparison with the energy costs of roads.

Of course, the values presented above vary from person to person and over time and space, depending on a number of factors. This ‘intra-mode’ (within vehicles of the same type) variability is the subject of the next three sections.

5.4 Additional factors affecting energy use

Of the factors causing energy use in transport described in the first section of this chapter, only the mode of travel has been analysed in detail so far. Granted, mode of travel incorporates to some degree many other factors such as mass, speed, acceleration and aero dynamics²⁷ and the indirect impacts of guideway and vehicle construction.

²⁴ $27.2 \times 4.6 = 125$ GJ/m. $125 \div 3.6 = 35$ MWh/m.

²⁵This result was independently verified as follows: $35,000 \div (40 \times 365) = 2.40$ kWh/m/d. $2.40 \times (28,000 \times 1.61 \times 1000) \text{ m} = 108,000,000$ kWh/d. $108 \div 60$ million people = 1.8 kWh/p/d.

²⁶ 125000 MJ/km $\times (28000 * 1.61 * 1000) = 5.64$ PJ for all road transport over 40 years. 5.64 PJ divided by the number of pkms travelled by UK citizens over that time ($500 \times 10^9 \times 40$) provides this answer. The raw calculation using computer arithmetic in MJ, is as follows: $(125000 * (28000 * 1.61 * 1000)) / (500 * 10^9 * 40) = 0.282$.

²⁷These, in combination, help explain why the direct energy use of bicycles is approximately 30 times less than that of cars per kilometre.

However, there are a number of other factors that are mostly or completely omitted by simple average values over all annual passenger kilometres which are seldom included in estimates of energy use (Schipper et al., 1993). Factors not yet considered, in rough descending order of importance, include the following:²⁸

- Frequency of trip: the majority of this section assumes that distance is already known, and this is true a large extent on a per trip basis. However, cumulative distance travelled each year depends on how frequently the journey to work is made, including holidays.
- Occupancy: full vehicles use less energy per pkm than empty ones.
- Trip distance: the average energy use per vkm varies greatly depending on the trip's distance: short trips tend to involve more frequent acceleration events per unit distance and therefore entail higher energy intensities.
- Circuitry, a concept first encountered in chapter 2, impacts on energy use directly when distances are estimated based on known Euclidean distances, and indirectly through the likelihood of twists and bends associated with circuitous routes.
- Traffic jams and general congestion are frequent in many settlements, and entail much higher energy intensities per pkm than the open road.
- Behaviour clearly affects the energy performance of vehicles, although measuring its impact is extremely difficult.
- Environmental conditions such as temperature, topography, road roughness and precipitation all affect vehicle energy use in a variety of ways.

It is the impact of these factors on energy use, and their implications for the accuracy of our energy cost estimates over time and space, to which our attention is now directed.

5.4.1 Frequency of trip

This chapter has, until now, made the implicit assumption that travel to work distance is known, or can at least be estimated reliably based on census statistics. This is indeed the case for estimates of usual one-way trip distance, with a few exceptions. However, if the energy costs of travel to work are to be compared with other energy uses, it is vital

²⁸Other factors could have been included on this list such as the diet of active travellers, speed limits and demographics. These undoubtedly play a role, the scope of the analysis is limited, to avoid trying to cover everything at the risk of covering nothing in detail. Another important factor is technological: recent and well-maintained vehicles tend to use less energy than old and poorly maintained ones. This issue is partly covered (for cars) in section 5.6.

that they have the same denominator: not energy use per trip to work, but something more common such as energy use per year.

The translation of energy use per trip (E_{trp}) into energy use per (ET_{yr}) year is simple in theory:

$$ET_{yr} = n_{trps} \times E_{trp} \quad (5.9)$$

where n_{trps} is the number of return trips made to work each year. This number clearly has a large effect on our estimates of annual energy use for commuting, as it is directly proportional to ET_{yr} so it is important that good estimates are made.

On the individual level, the factors that affect n_{trps} are the type of job (part time or full time), holidays (how many weeks per year multiplied by the number of trips usually made per week) and days off sick or working from home. There is good data on each of these variables (except duration of holidays) from the National Travel survey; Understanding Society contains variables on number of hours worked (an imperfect proxy for number of days) and whether the job is part or full-time.²⁹ The number of trips made to work and back each week can be extracted directly from the National Travel Survey, counting the number of work trips made by individuals. This information is plotted in figure 5.7, which shows the distribution of trip frequency by mode of travel to work.

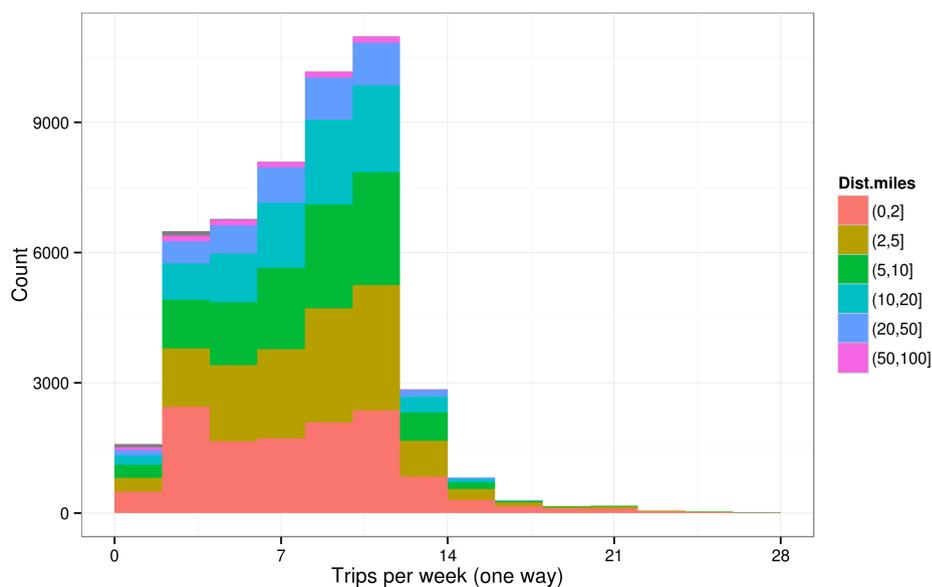


FIGURE 5.7: Frequency of one-way trips to work each week, by route distance (bin width = 2). Source: National Travel Survey 2002-2008.

The most common frequency of trip represented in figure 5.7 is 10 return trips per week, the standard for a 5 day working week, as would be expected. However, people who make

²⁹The variable ‘a_pjbptft’ reports whether the current job is part-time or full-time; ‘a_jbhrs’ reports the number of hours normally worked per week.

9 to 11 trips per week (around 1/3 of respondents, bizarrely, report travelling on one-way trips to work and back an odd number of times) account for only 30% of all commuters. The average number of work trips made each week is actually substantially lower, 7.3 per week, due largely to the influence of part time workers. Based on this information, it could be assumed that this average value is representative of all commuters and applied to all individuals: it accounts both for the effect of part time work, and the fact that many commuters work from home some of the time (see figure 4.5 in the previous chapter). However, it is clear that shorter trips are likely to be made more frequently than longer trips (figure 5.8), which reduces the annual energy use estimates. To take this effect into account at the individual level, a simple regression model was run to find the relationship between average trip distance and trip frequency, based on the information plotted in figure 5.9. It was found that the relationship was approximately linear (despite the non-linear appearance of figure 5.9, due to varying bin sizes on the x axis), and the following formula could account for the majority (adjusted R-squared = 0.87) of the variation in average trip frequencies:³⁰

$$f = 7.9 - 0.023dR \quad (5.10)$$

where dR is the route distance in km. At the aggregate level, this information is more useful as a table of bin-wide averages, calculated after converting miles into km and route distance into Euclidean distance (table 5.7). For aggregate level calculations, these frequencies can be multiplied by the number of people travelling in each distance band, before multiplying by the number of working weeks per year (assumed to be 44, account for holidays and periods between jobs).

TABLE 5.7: Average frequency of trips for Euclidean distance bins

D (km, Euclidean)	(0,2]	(2,5]	(5,10]	(10,20]	(20,30]	(30,40]	(40,60]	(60,200]
F (trips/wk)	7.2	7.6	7.4	7.3	7.0	6.9	6.5	4.3

Another way of encapsulating these factors, harnessing data that is available in the Understanding Society dataset, is to express the number of trips made as a function of hours worked. This makes sense for a number of reasons: it accounts for the fact that ‘full-time-ness’ and ‘part-time-ness’ are not the binary categorical variables that census data claim, but a continuum between working all day every day to working a couple of hours per week. In addition, it harnesses information that is available in the Understanding Society survey dataset (variable ‘a.jbot’ hours worked per week) and produces more realistic distribution of trips per year, that depend on social attributes, than the single values per distance proposed above. (Also, one could add a part-time/full-time

³⁰The R code to produce this result is available in the file “[trip-plots.R](#)” in the [thesis-reproducible](#) Github repository.

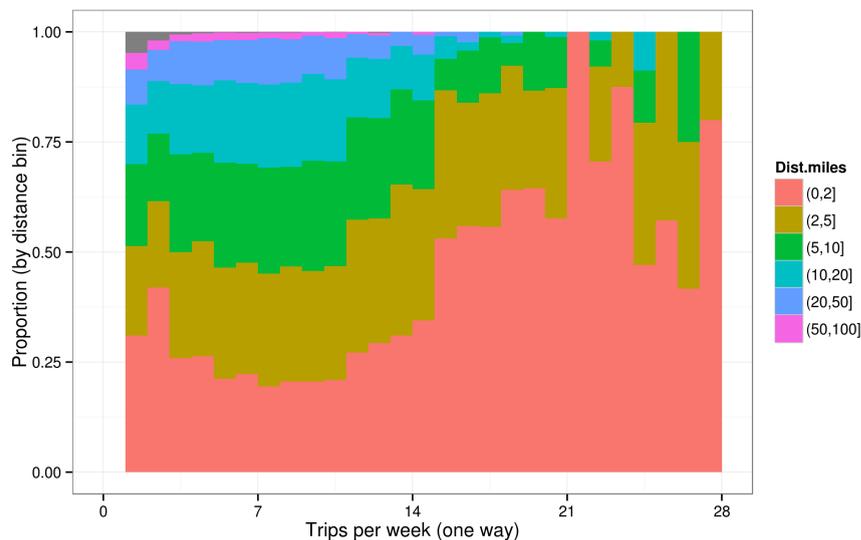


FIGURE 5.8: Proportion of distance bands in for each frequency of one-way trips to work each week (bin width = 1). Source: National Travel Survey 2002-2008.

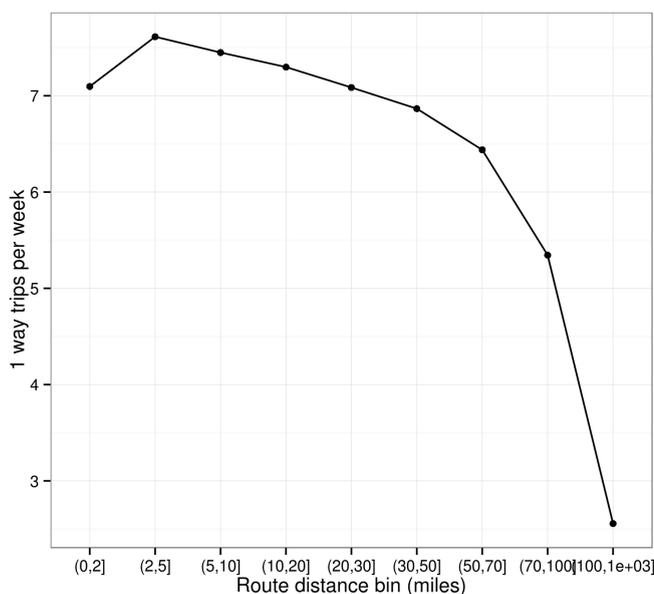


FIGURE 5.9: Number of trips made to work per week as a function of distance. Source: National Travel Survey 2002-2008.

constraint based on geographic census data, although this has not been done). The difficulty here is to account for holidays and variable shift lengths.³¹ It was assumed that the average shift length was 6 hours, based on “conventional working hours” being 09:00–17:00 (8 hours) (Harrington, 2001), combined with the knowledge that typical shifts in hotels and restaurants are closer to 4 hours, and the fact that some people

³¹20 hours worked per week, for example, could imply 2 home-work trips for long 10 hour shifts or 4 journeys if each shift is 5 hours long, the latter using double the energy of the former.

travel home during lunchtimes or work half days during the weekend (each factor making the working day shorter). Further, it was assumed that 6 weeks of holiday were taken per year, meaning 44 weeks of work per year. This assumption follows a similar logic as that employed to estimate the duration of an average working day: the mean number of weeks worked per year by British adults is 47.5, but this number was reduced to account for the fact that people change jobs (leaving a period of unemployment) and do not always travel to work on ‘work days’ due either to time off sick or working from home.

To include these crude estimates into our estimates of annual energy costs, the following R code was used.

```
# Assuming 8 hr days, 44 weeks/yr (8 holiday)
trips <- round(all[[i]]$a_jbhrs / 8 * 44 ,digits=0)
# Preventing people travelling to work more than 365 times/yr
trips[which(trips > 365)] <- 365
# Assuming part-time work or telecommuting (no response in survey)
trips[which(trips < 10)] <- 100
```

LISTING 5.1: Code used to translate hours worked per week into number of trips per year

Of course, these estimates of number of trips per year are not at all accurate and therefore introduce a large amount of uncertainty into our energy use estimates. For this reason, for the majority of the analysis presented in the subsequent chapter, energy use is represented in units of energy use per trip (*E_{trp}*). However, the ability to transfer these estimates into energy use per year estimates proves useful when developing metrics of vulnerability, or comparing the relative importance of commuting with other energy-using activities.

5.4.2 Occupancy

Occupancy (*Occ*) is defined as the number of people travelling in a vehicle, and is often presented as an average value, aggregated over large expanses of time and space. Although occupancy is already factored in to the energy-use calculations mentioned above (and is implicit in census statistics for cars, which discriminate between passengers and drivers) it can vary widely, with large energy impacts. Occupancy is roughly inversely proportional to energy use per person, meaning that a single passenger in a car can halve its energy use per pkm compared with the driver being the sole occupant, whereas a

single additional traveller on a bus containing 20 people will only result in a 5% energy saving.³²

An alternative way of expressing occupancy is the concept of *load factor*,³³

$$Lf = \frac{Occ_{average}}{Occ_{max}} \quad (5.11)$$

the observed average occupancy divided by the mode's "practical maximum" (Jackson, 1975, p. 562) capacity under ideal conditions. This metric is used primarily to standardise occupancy rates for public transport modes (to account for the fact that maximum occupancy varies), and has since been deployed to analyse energy use in public transport (Pisarski and Terra, 1975; Schafer and Victor, 1999). Load factors have also been applied to cars occasionally, resulting in the conclusion that empty seats in cars represent a vast waste of resources (Jackson, 1975). The main advantage of load factors, for all modes, is that they relate to the vehicles *potential* energy efficiency and its actual efficiency.

Based on both measures of occupancy, it is clear that small variations in low occupancy modes can have a relatively large impact on energy use, whereas small variations in public transport occupancies will make of less of a difference overall. With this characteristic in mind, this section proceeds to discuss car occupancy primarily before tackling bus, rail and coach occupancy rates.

The average occupancy of cars is reported at the national level and has tended to decline over time in Britain, following trends in household occupancy, although the rate of decline in occupancy rates is small compared with those reported for the European Union as a whole and Ireland (figure 5.10). Car occupancy also varies substantially depending on reason for trip, as shown in table 5.8. In fact, commuting is the type of trip associated with the lowest rate of occupancy (1.2) and highest proportion of single-occupant journeys (86% of car trips to work contain only a single person), joint with business travel. The historical fall in occupancy rates, combined with the very low rates of car sharing for the trip to work suggest there is much room for improvement here.

In terms of our energy calculations, these statistics make little difference. That is because the Census sensibly treats driving to work separately from taking a lift in someone else's car. Therefore, the energy savings of car sharing show up as a result of fewer people driving or travelling by other forms of transport. The alternative would be to merge

³²These values assume that no extra energy is required of the vehicle in question, which is not strictly true. Assuming that energy use is proportional to mass (in fact the relationship would be 'sub-proportional' as extra weight has no impact on air or rolling resistance, the other two critical forces in driving), a 1.3 tonne car carrying an extra 80 kg of person and luggage would use 6% more energy, which is treated as negligible. The marginal impact on a 12 tonne bus would be even less.

³³Some authors have used the term 'load factor' interchangeably with the concept of occupancy (e.g. Jennings et al., 2013), which could lead to confusion.

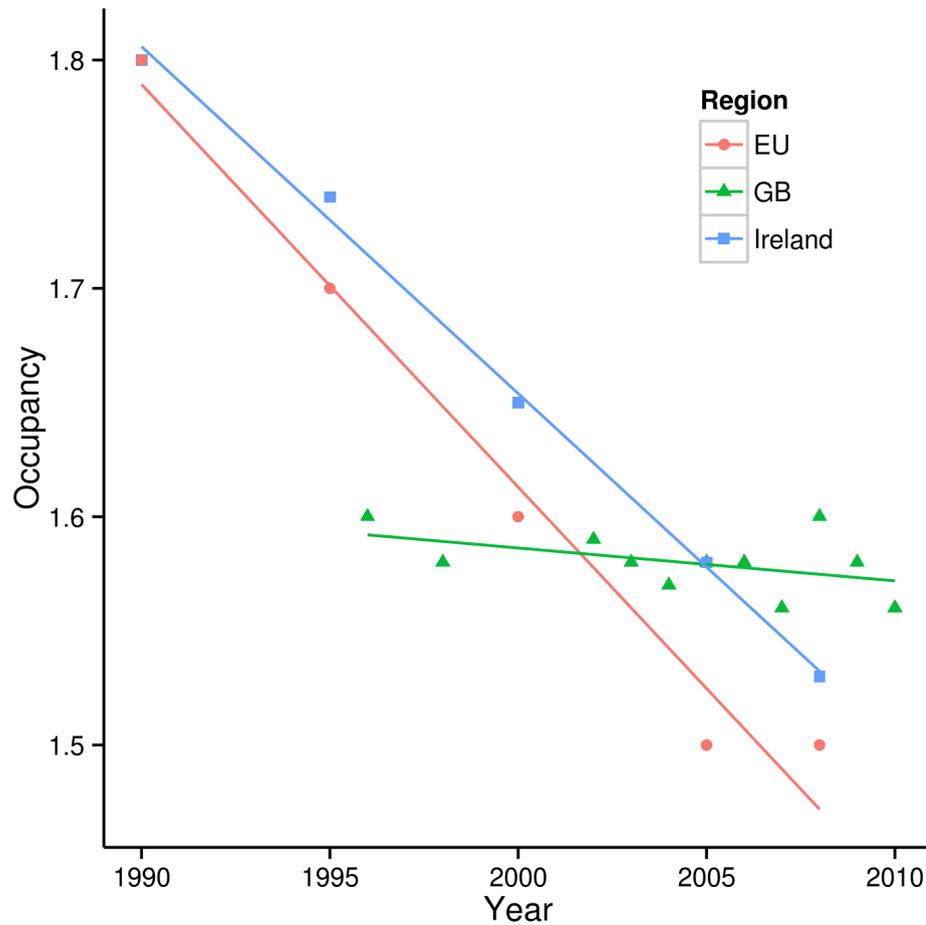


FIGURE 5.10: Average car occupancies over time in three regions. GB data from NTS (2012, table 0905), EU and Ireland data from (Jennings et al., 2013).

“car driver” ($car.d$) and “car passenger” ($car.p$) into the single category of the car, and set its average energy costs as follows:

$$Ef_{car} = \frac{car.d}{Occ_{car}} \quad (5.12)$$

This option adds extra complexity to the energy use calculations, however, hence our reporting of car drivers and passengers as different modes. This approach also allows for the calculation of the occupancy rate of commuter car trips in different areas:

$$Occ = 1 + \frac{car.p}{car.d} \quad (5.13)$$

This formula, used in conjunction with origin-destination flow data by mode, could be useful for identifying areas in which could benefit most from car sharing schemes.

TABLE 5.8: Average occupancy of car journeys by reason for trip. Data from NTS (2012, table 0906).

Purpose	Average occupancy	Single occupancy rate
Commuting	1.2	86
Business	1.2	86
Education	2.0	36
Shopping	1.7	50
Personal business	1.4	68
Leisure2	1.7	53
Holiday/day trip	2.0	40
Other including just walk	2.0	35
Total	1.6	61

5.4.3 Efficiency impacts of trip distance

The European Union certified test cycle involves two separate tests of energy and emissions performance for different driving scenarios. This, and the combined fuel economy measure that results, reflect the understanding that more energy is used per unit distance during short trips (which predominate in urban areas) than during long trips (generally inter-city). It would therefore seem sensible to refine the estimates of Ef presented in table 5.5 by the disaggregating them based on trip distance. If most car trips are short, for example, our overall estimate could be optimistically low.

Some research has been conducted in this area, although there seems to be a reluctance to make generalised statements about the relationship between distance and fuel economy for different modes. This is because, as with so many things in transport systems, the results will be context-dependent. In areas where long-distance car trips are associated with very high speeds (e.g. between two towns connected by an unregulated fast-flowing motorway), the fuel economy could in fact rise above the average because energy use per unit distance rises rapidly above around $\sim 90kph$ (figure 5.11). As a general trend, however, short car trips tend to be less fuel economical due to the stop-start nature of urban traffic (Anas and Hiramatsu, 2012).

The best multi-mode quantitative evidence that could be found on the matter was (Bouwman, 2000). Using a micro level model written in Matlab, simulated data recording the impacts of infrastructure, congestion, and vehicle fleet on total energy use across 8 modes, as part of a PhD thesis (Bouwman, 2000). The results, which are normalised (by dividing the values by the all-distance average for each mode) for a clear visualisation of how the issue affects each mode differently, are presented in figure 5.12. Bouwman's 2000 model results in relatively small shifts in fuel use as distance increases, declining

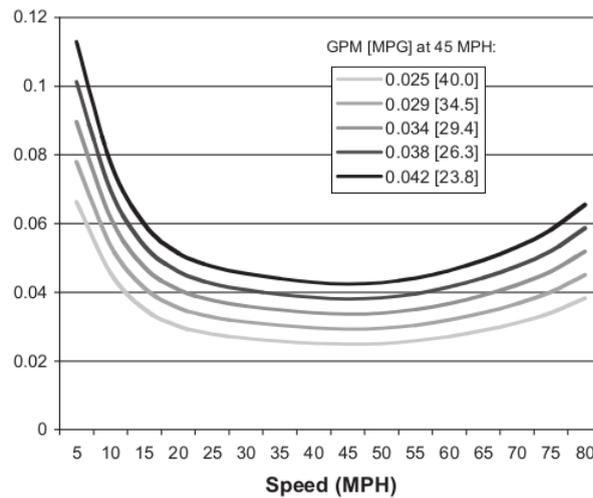


FIGURE 5.11: The impact of car speed on efficiency, from (Anas and Hiramatsu, 2012).

by only 10% between the shortest trips and the least efficient trip distance, which was deemed to be 10 to 20 km. The calculations made in the model are not described in sufficient detail Bouwman's thesis to comment on the likely reliability of the results, and could not be accessed elsewhere. An additional problem with these estimates is that they were developed for the Dutch transport system specifically, so may not be applicable to the UK, even if there were high confidence in the estimates. Therefore, taking these issues into account, it was decided not to include Bouwman's (2000) estimates in the final energy cost calculations: better evidence is needed on the matter.

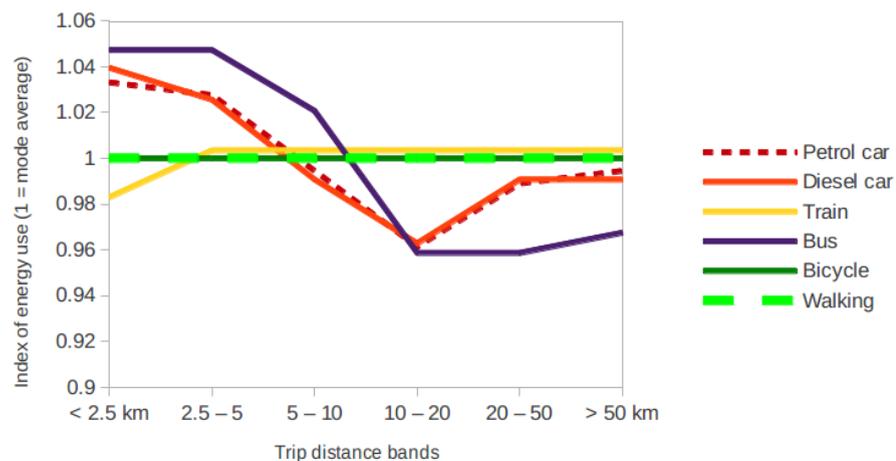


FIGURE 5.12: Line graph of energy intensity vs trip distance. Data from Bouwman (2000).

In the event of discovering better national (or even localised) estimates of the relationship between distance and average energy usage, the method of calculation is ready to accept these values.

5.4.4 Circuitry

In practice, the network of roads, paths and other guideways of the transport system rarely lead from a to b (or rather i to j , in our notation) directly. Instead they form a more or less circuitous path (figure 5.13). Previous work on this has been conducted with respect to transport to work. There is strong empirical evidence that circuitry (Q) is *not* constant, but varies depending on the length of trip (Levinson and El-Geneidy, 2009) and the structure of the transport network (Parthasarathi et al., 2012), which varies between countries (Ballou et al., 2002) and continuously over space (Barthélemy, 2011).

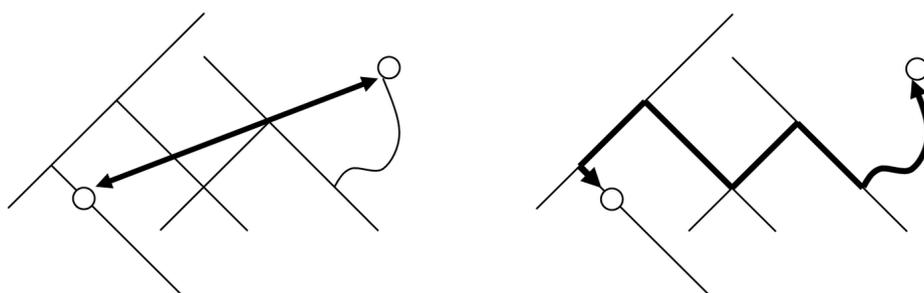


FIGURE 5.13: Schematic of Euclidean and network distances. Thanks to David Levinson, who licensed this work, originally published in Levinson and El-Geneidy (2009) with a Creative Commons licence.

Regarding typical values, Q values between 1.21 and 1.23 have been reported for walking trips to rail stations in Calgary, Canada (O’Sullivan, 1996). Levinson and El-Geneidy (2009) analysed the circuitry of 5,000 home-work trips in and around Portland, USA, and found an average circuitry of 1.18 overall. In the same study, it was also confirmed that circuitry is highly dependent on the distance travelled: for 50,000 random point-pairs, circuitry decreased from 1.58 to 1.2 as the distance increased from 5 km and less to over 45 km. Based on these results, a preliminary analysis suggests that the relationship is logarithmic (figure 5.14). Circuitry (referred to as a “detour index”) was reported by Cole and King (1968, p. 565) for 12 districts in England, Scotland and Wales. Values ranged from 1.17 (in Somerset) to 2.19 (Aberdovey); the mean was 1.4 overall.

This result was corroborated by Ballou et al. (2002), who found an average circuitry of 1.4 for England as a whole, based on a sample of 37 points. Other than Levinson and El-Geneidy (2009), none of these studies included the impact of distance on average circuitry values, instead reporting single values for entire areas. Levinson and El-Geneidy (2009) provide strong evidence to suggest that circuitry, taken as an average value over hundreds of measurements, actually declines with distance, in a way that would be compatible with all the previously mentioned estimates of circuitry.

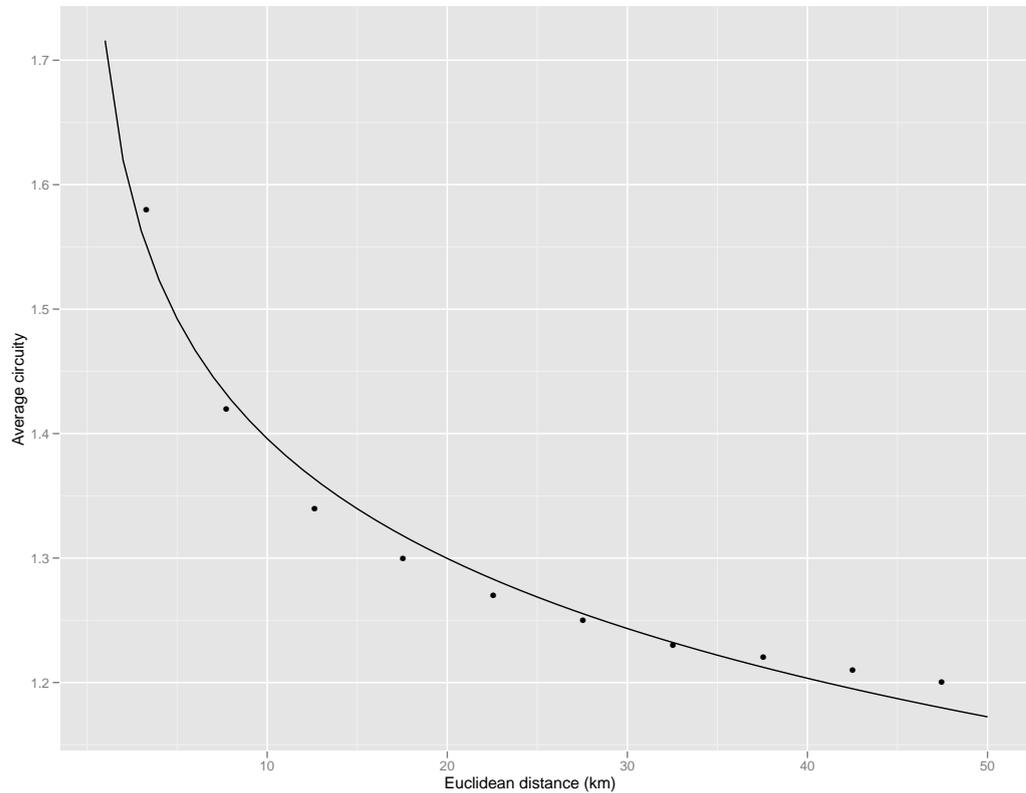


FIGURE 5.14: The decay of circuitry with distance travelled. Data from (Levinson and El-Geneidy, 2009), plotted here with a logarithmic decay ($y = a + b * \log(x)$), where $a = 1.72$ and $b = -0.14$. Coefficients calculated using the command `nls` in R.

Analysis of the results from Levinson and El-Geneidy (2009) suggest that Q decays logarithmically with increasing distance (see figure 5.14):

$$Q = a + b \times \log(dE) \quad (5.14)$$

where a and b are coefficients calculated to be 1.72 and -0.14, respectively, based on the Levinson and El-Geneidy (2009) paper. Of course, using the results of a US study as the basis for assumptions in the UK is no guarantee that the assumptions will hold in practice, especially when Q varies from country to country (and almost certainly at lower levels also, depending on the local road network and proximity of impassable obstacles such as rivers, railways and motorways). There is additional support for Q decaying with increasing dE from theoretical sources (Barthélemy, 2011). The evidence reviewed suggests that, if one must assume that $dR = f(dE)$ (as is the case here, as only Euclidean distances are provided in the census data), equation (5.14) is likely to provide a more accurate description of reality than assuming that $dR = dE$. The principle of Occam's razor states that the simplest solution that fits the data should generally be preferred. In this case recent evidence shows that $dR = dE$ simply does not fit the data, so $Q = 1.7 + -0.14 \times \log(dE)$ is used here. If a single circuitry factor is required, Ballou's

(2002) estimate of 1.4 for the UK is recommended, especially as this coincides with the circuitry value interpolated in figure 5.14 around the 10 km mark, roughly the median distance travelled to work in the UK.

Of course, circuitry is affected by many other variables in addition to Euclidean distance. In addition, it is wrong to assume that more circuitous paths are always more energy intensive, as a complex range of factors combine to determine the most energy efficient path to take at any particular time (Ericsson et al., 2006). There are also large inter-modal variations in circuitry: pedestrians and cyclists have been found to have particularly low Q values (Iacono et al., 2010). It can be expected that public transport users must endure longer route lengths due to the need to get to and from train stations, bus stops and other nodes to join the network, whereas cars and cycles can join almost anywhere. In addition, it would be possible to weight Q area by area, based on local estimates of *global accessibility* (see section 2.6) that can be computed by calculating the difference between dR and dE for randomly (or intelligently) selected origin-destination pairs.

Beneficial as this process would be, yet these factors still omit the impact of car park proximity, car sharing, and multi-mode trips: in a more complex (potentially agent-based) model these could conceivably be included. For the time being it is assumed that equation (5.14) holds for all trips of the same distance: quantitative evidence of the impact of other factors is scarce. If more data to weight Q by other factors such as mode emerges, the model should be updated.

5.4.5 Efficiency impacts of congestion

The increased energy use of inner city driving compared with the rarely realised (but frequently advertised) ideal of driving on open roads is well established. It is a result of far higher frequencies of acceleration/deceleration events, due to the increased number of obstacles (e.g. traffic lights) on urban roads and the stop-start nature of congested traffic. The impacts of this are reflected in the European Union's test cycle requirements, that are used as the basis of CO₂ and fuel consumption values that must be displayed by law on all car adverts (figure 5.15): two efficiencies are calculated — urban and extra-urban. According to Pelkmans and Debal (2006), urban driving uses around 30% more energy per unit distance than extra-urban driving in a Skoda Octavia TDi. Another paper reporting real-world tests found that “fuel consumption was about two times higher [in city traffic] than for ring roads, which generally gave the lowest values” (Vlieger et al., 2000, p. 4649).

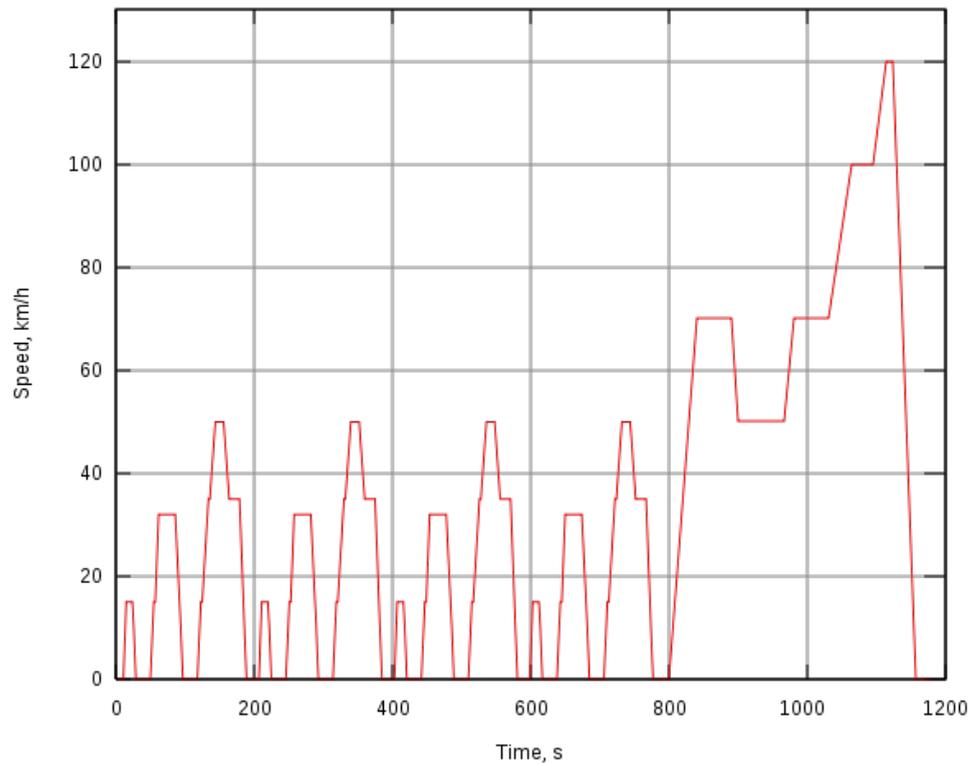


FIGURE 5.15: EU test cycle. Up to the 800 second mark, the car is in the ‘urban’ part of the test. Beyond that point, the ‘extra-urban’ stage begins. (This test cycle design explains why car adverts contain 2 or 3 mileage values.)

Part of the difference between the increased energy use of city driving reported in Pelkmans and Debal (2006) and Vlieger et al. (2000) is illustrated in figure 5.16, which shows that the difference between inner city and rural driving is not constant across all cars. Of the randomly selected sample of models plotted, the extra energy use of driving in cities is on average 78% higher than the average energy costs of driving in the countryside, as measured by the (imperfect) European test cycles (figure 5.15). The efficiency impact ranges from a 34% increase for the Citroen C4 to more than double the energy use for the heavier Audi A6 and Ford Mondeo models.

Because of this variability, and the fact that it is not known which models predominate in different areas, it was decided not to include the energy impacts of city driving into the model. (It would have been possible to simply double the energy use for short trips in urban areas, but it was felt that there is not sufficient evidence for this additional layer of complexity in the energy efficiency calculations at this stage.) In any case, the energy impacts of congestion and city driving more generally undoubtedly has a very large impact on energy use for personal transport overall and commuting in particular, so attempts to quantify the effect should be included in future work. The reason why commuting trips are more likely to suffer from the effects of traffic jams than other types of trips is illustrated in figure 5.17 and can be summarised in two words: rush hour.

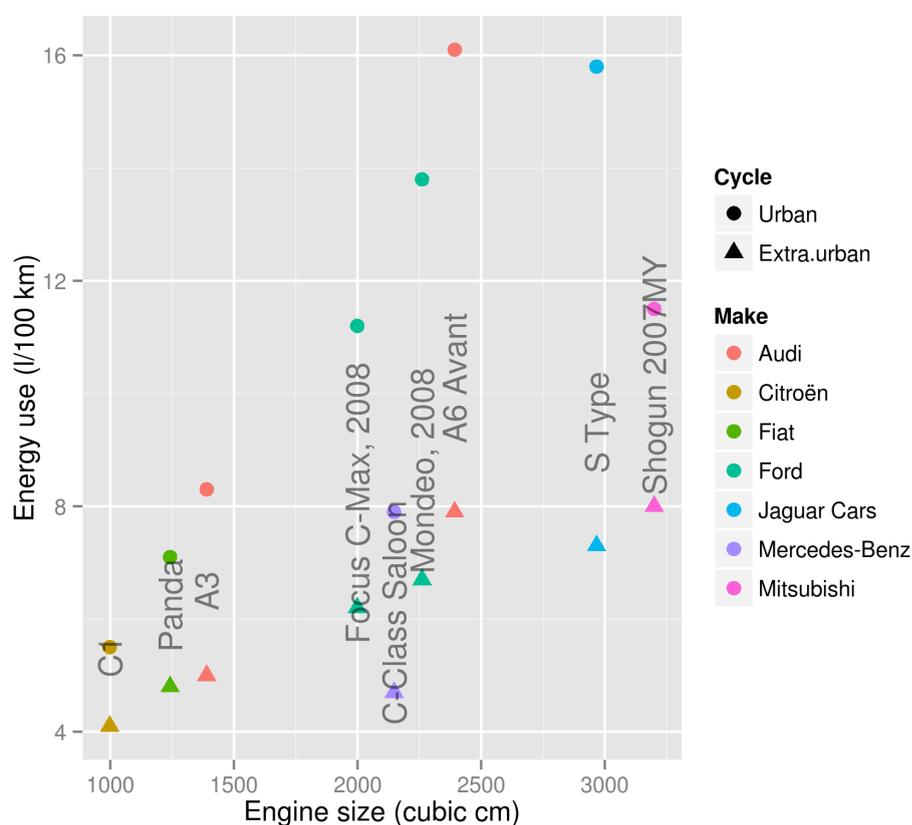


FIGURE 5.16: Urban and extra-urban energy use of selected models. Data from the Vehicle Certification Association.

The timing of commuter trips could therefore be an additional factor influencing overall energy use estimates. No attempt to quantify this effect is made here, however: no geographical data on the timings of commuter trips could be found. Rush hour traffic is the culmination of many individual decisions. As shown below, these behavioural factors are difficult to quantify.

5.4.6 Behaviour

The perceived impact of behaviour on vehicle energy use is demonstrated by Energy Saving Trust's endorsement of 'smart driving' to reduce fuel use and the AA's 'eco-driving' recommendations to "Save more than 10% on fuel".³⁴ A review of the literature to date supports the AA's claim: Barkenbus (2010) found that the handful of studies conducted on the matter supported the view that promotion of environmentally conscious driving could reduce fuel use by 10%, although values ranged from 5 to 25% and more research is clearly needed on the topic.

³⁴See energysavingtrust.org.uk and theaa.com/motoring_advice for further details on this advice.

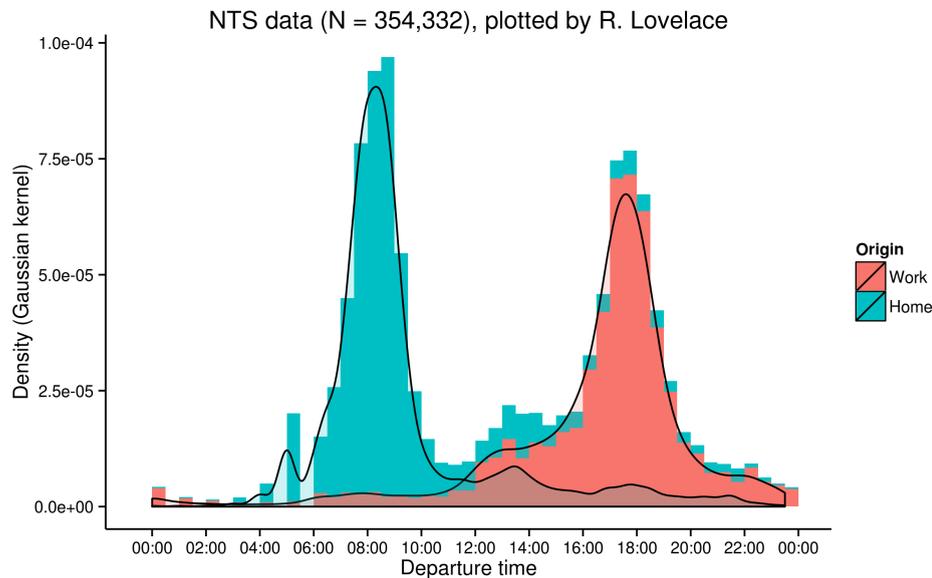


FIGURE 5.17: The concentration of commuter trips into morning and afternoon ‘rush hours’. Data source: the National Travel Survey.

This understanding could be harnessed in scenarios of the future, yet is of limited use in determining the impact of variability in driving habits on *current* energy use. It is feasible, for example, that young males are less efficient drivers due to faster speeds (Fleiter et al., 2007) and harder acceleration of this socio-demographic group. But this hardly translates into a solid foundation from which to allocate certain socio-economic groups to different efficiency bands, although this would be possible with the spatial microdata. That is not to take away from the importance of driver behaviour on energy use: empirical data from five passenger cars equipped with logging equipment in Sweden (Ericsson, 2001) suggests that fuel use per kilometre can vary widely depending on the driving style: the standard deviation of average efficiency measurements was 50% of their mean value (~ 10 L/km). If sufficient evidence were available it would, in theory, be possible to weight our efficiency estimates by a range of variables known to be correlated with efficient and inefficient driving styles. However, sufficient information does not appear to exist anywhere, let alone for the UK at present. Even if such a study *did* exist at the national level, there would be no guarantee that the relationships found would apply in the same way to all areas.

Based on the evidence presented above, behaviour seems to be an important factor to consider when estimating the energy costs of personal transport. The complexity of the issue and lack of real world behaviour-energy use measurement mean that it cannot be quantified and included in our model. Behaviour is one more variable that adds uncertainty to our estimates, and further research will probably be needed to reduce this uncertainty.

5.4.7 Environmental conditions

The impacts of environmental conditions on transport energy use is a large and complex area about which relatively little empirical work has been done (compared with the amount of work on the potential energy impacts of projected technological change such as electric cars, for example). The aim of this section is not to provide a comprehensive analysis of the subject — which could probably constitute a PhD topic in its own right. The approach from the outset has been to acknowledge that it is unrealistic to accurately quantify environmental impacts but flag what seem to be the most important and easily modelled issues for discussion and possible future research. ‘The environment’ in itself is a vast domain, ranging from the chemical composition of micro-climates to the soil permeability. Many of these would have an impact on the energy use of personal travel.³⁵ For brevity, the focus is on environmental variables which have been found to have an impact on transport energy use and can realistically be studied using existing techniques. These are described in rough descending order of urgency of inclusion (a combination of ease of accurate quantification and impact on energy use).

Topology has a large influence on energy use because extra energy is required to push vehicles and their occupants up hills. Without regenerative braking systems (which can never recover all the energy in any case), there is no way to restore this potential energy back into forms useful in the human economy, unless one is able and willing to roll down the hill every morning into work. Topology varies very little over time (unlike other environmental variables), has a large impact on energy use and there are high quality and ever-improving (due to the diffusion of low-cost remote sensing technologies such as LiDAR) datasets on its spatial variability. Despite this, there appears to be (based on searches of the academic literature) very little research on the impact of topology on transport energy use.

Park et al. (2011) suggest that topology is the most important determinant of fuel use on the road network. In an earlier study, Park and Rakha (2006) found that just a 1% road incline could lead to an 18 % increase in car energy use compared with flat roads and that a 6% gradient, not uncommon in some UK cities, could lead to a 94% increase in fuel consumption. This study was model-based. It would require real-world validation before the results were used to modify energy use calculations. It appears that many researchers do have a high level of confidence in their estimates of the energy impacts of topology, however. This is illustrated in studies investigating the potential

³⁵It is likely, for example, that vehicle operating in areas with high levels of particulate pollution would have increased energy use because of clogged air filters, although the impact is likely to be negligible compared with other factors. Similarly, one could argue that soil permeability affects energy use indirectly through altered chances of flooding. Again, the impact of this environmental factor is so slight and so hard to measure that any accuracy benefits would likely small in comparison with the costs of added complexity and the addition of untested assumptions.

for including topology in route-planning algorithms to maximise fuel economy (Minett et al., 2011; Ahn et al., 2011). This area therefore has great potential both to improve descriptions of current energy use and for creating scenarios of change. The Newtonian physics that describe the influence of topology on energy use should also make this issue fairly straightforward to include in high resolution geographical models of energy use.

Weather also has a major impact on fuel use, most notoriously through the phenomenon of ‘cold starts’, whereby cold temperatures affect the performance of internal combustion engines due to a range of factors including cold (and hence viscous) lubricants and fuels and catalysts. In this matter, Weilenmann et al. (2009, 2422) found that “fuel consumption increases almost linearly as a function of decreasing temperature” in the range of -20 to 20 degrees Centigrade, with fuel use doubled at the low end of the scale. This effect is only momentary however, lasting for ~ 200 seconds according to one paper (Singer et al., 1999). Therefore, the overall impact of cold starts is likely to be negligible.

Temperature and other weather variables such as precipitation, sunshine and wind also affect energy costs indirectly, via impacts on behaviour. There is strong evidence of seasonal variability in car use linked to cold weather, and Schipper et al. (1993) suggest that the seasonal impact could be 10% or greater in northern countries. The modes of transport most exposed to weather (walking and cycling) are also the lowest energy users, another reason for expecting energy use to be higher in areas with, or during periods of particularly inclement weather.

As with topography, there are readily available data about how key weather variables vary over space, with the added complexity that these variables also change continuously over time. The data collection, processing and matching to discrete travel events would pose a major challenge to researchers wanting to include weather as an input variable into energy use calculations. However, provided strong empirical evidence of the direct and indirect impacts of weather phenomenon (currently lacking) emerge, these challenges are not intractable. This area of future research will benefit from advances in computer hardware and software that will make it easier to process and make sense of the ‘big data’ contained within the continuously variable time-space phenomenon that is weather.

Road roughness, including potholes, bumpiness and other irregularities from the ideal of a perfectly smooth and flat motorway, like weather, have both direct and indirect effects on energy use. The direct impact is primarily on tire rolling resistance, about which there is strong evidence for “substantial and measurable increases in energy losses” due to rough roads (Velinsky and White, 1980). Increased energy use of up to 20% are reported in this study. More recent work has been done on the topic, but no conclusive impacts, that would be amenable to inclusion in a large scale transport model, could be found from the literature. This may be due partly to the complexity of the models

employed to estimate the energy costs of power dissipation through vibration (Smith and Swift, 2011).

An indirect (yet somehow more tangible) impact of poor road quality on transport energy use is that it can discourage people from buying a low powered and energy efficient car. This applies to the selection of sub-mode vehicle type³⁶ as well as the more obvious inter-mode choice such as a preference for driving over cycling in areas where the cycle paths are relatively rough and potholed. (On the other hand, extremely bad road conditions could encourage walking and cycling if motor vehicles physically cannot pass, although this is unlikely to be a common scenarios in developed Western economies such as the UK).

5.5 Variability over time

5.5.1 The improving fleet efficiency of cars

The previous section illustrates that fuel economy should not be seen simply as a fixed number, such as 3 MJ/km for cars. Even at the aggregate level, the average efficiency changes, depending on the year or geographical area of interest. Constant changes in technologies and the range of models made available by car manufacturers, combined with consumer trends such as the rush to “4 by 4s” in the early 2000s drive these changes.³⁷ Regulation is important too. In this context, the European Union is instrumental: it is a legal requirement that fuel economy and CO₂ emissions are displayed alongside car adverts (presumably affecting buying patterns). Perhaps more importantly, the European Commission has implemented (struggling) legislation stating that the fleet-wide efficiency of all cars must reach 130 gCO₂/vkm by 2015 (Fontaras and Samaras, 2010), equating to 1.9 MJ/km.³⁸ Because energy efficiencies are constantly shifting, it is important to allocate times to our energy use estimates. The values presented in section 5.2 were published in 2011, so are presumably valid for that year. This is problematic when one considers that the constraint variables taken primarily from the 2001 Census. (Fleet energy efficiency dropped from 2.89 to 2.46 MJ/km between 1999 and 2009, implying a 20% improvement in fleet efficiency within that decade, according to calculations from DECC (2011c, table 2.8), a substantial issue). It is not the purpose

³⁶For example, a powerful 4 by 4 would be preferred to a supermini in areas with very poor road conditions; a mountain bike would tend to be used over a road bike if the path is very rough.

³⁷This has been illustrated in a ‘gas guzzler’ map by the author. This time series choropleth map, uploaded to youtube (see <http://www.youtube.com/watch?v=1r3joV82AuQ>), shows the proportion of vehicle sales falling into the tax bands M and L in Yorkshire and the Humber from 2002 to 2010. It is clear that this has had a major (but as yet unquantified) energy impact.

³⁸Assuming an energy content of 14.6 MJ/kgCO₂, which was calculated based on a 3:1 petrol:diesel split and emission factors of 14.4 and 15 MJ/kgCO₂ respectively.

of this section, however, to apply modifiers to previously reported energy efficiency estimates. This is because the values presented so far come from a single source for all modes; altering the values for one mode whilst leaving the others unchanged would not be consistent. The purpose is to flag the issue and to illustrate, in general terms, how fleet efficiencies have shifted and how these changes can be accounted for.

Time-series statistics on energy use in transportation are reported in DECC (2011c), which is based on a range of secondary data sources over the past 40 years. Energy efficiency is reported in the preferred European fuel economy units of l/100 km. These values were translated into energy costs using a fixed conversion factor of 33 MJ/l.³⁹ The results show near constant improvements in new car energy performance since at least the late 1970s, as illustrated in figure 5.18. The average fleet-wide (including new and old cars) efficiency can also be derived from DECC (2011c), based on information on total vehicle kilometres travelled and energy used by cars. The pattern of fleet efficiencies relative to new car efficiencies presented in figure 5.18 is arguably predictable, as the former appears to have more ‘inertia’, trailing the latter by a few years, and falling by an average of 1.7% year over the last 10 years.⁴⁰ Improvements in new cars have happened more quickly, averaging 2.5% per year over the same period. The inertia of the existing fleet has been reduced somewhat by the UK’s subsidised ‘scrappage scheme’, although it still has major impacts for projections of energy efficiency into the future.

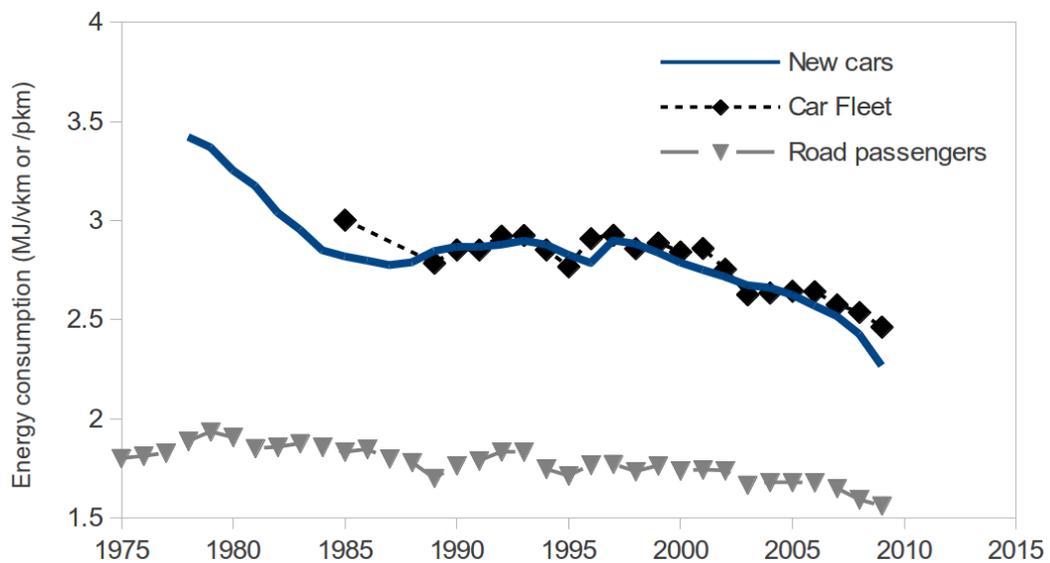


FIGURE 5.18: Energy consumption of new cars, the entire car fleet, and the energy intensity of road passengers transport kilometre over time. Data: (DECC, 2011c).

³⁹This average energy content per litre of transport fuel was calculated assuming a petrol:diesel split of 3:1 and volumetric energy densities of 32 and 36 MJ/l for each fuel respectively (Stephen et al., 2010).

⁴⁰Between 1999 and 2009 the fleet efficiency of British cars fell by 15%, from 2.89 to 2.46 MJ/km. The largest annual change was between 2008 and 2009, in which time energy use per unit distance dropped by 2.9%.

The above time-series data can be corroborated by a more recent statistical release from the Department for Transport (DfT, 2013, table VEH0256). In this dataset, the number of car sales in each emission band (from “up to 100” to “over 255 g/km”) is reported every quarter since Q1 2003 until Q1 2012, alongside estimates of the average emissions of new car sales each year. Using the same conversion technique described in section 5.2, this was converted into average efficiency values in SI units. The results inspire confidence: the values are within 7% of those derived from the DECC (2011c) data. The accelerating downward trend continues for new cars, falling by an average of 2.7% per year between 2002 and 2012 and by over 4% per year since 2007, as illustrated in figure 5.20. The dramatic acceleration in the rate of efficiency improvement seems less impressive when placed in the broader perspective (and with a y axis that starts at the origin): DfT (2013) and DECC (2011c) figures are compared in the same graph in figure 5.19, which also shows historical data from the USA and the UK (Schipper et al., 1993). It is interesting to note from this graph that rapid improvements in energy efficiency can be achieved through regulation: following the aggressive implementation of the Corporate Average Fuel Economy (CAFE) standards in the wake of the 1970s oil crises, the average fuel use of new cars dropped on average by more than 5% per year in the decade following 1973, before levelling out during the 1980s.

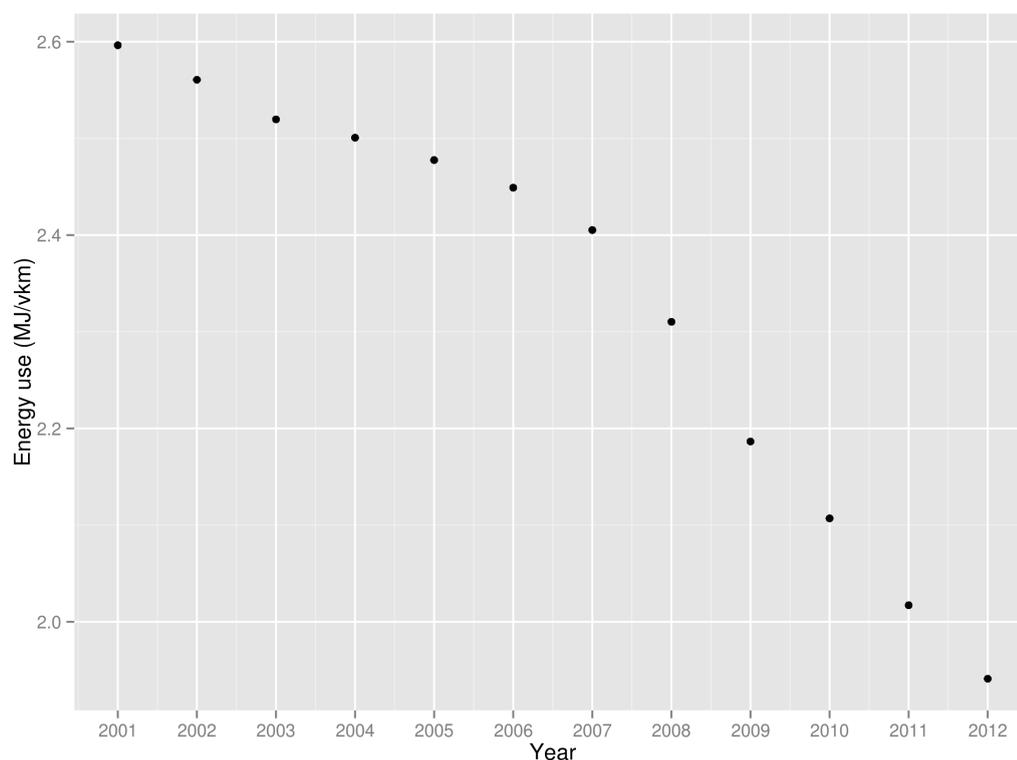


FIGURE 5.19: Comparison of UK car fleet efficiency estimates over time (DfT, 2013).

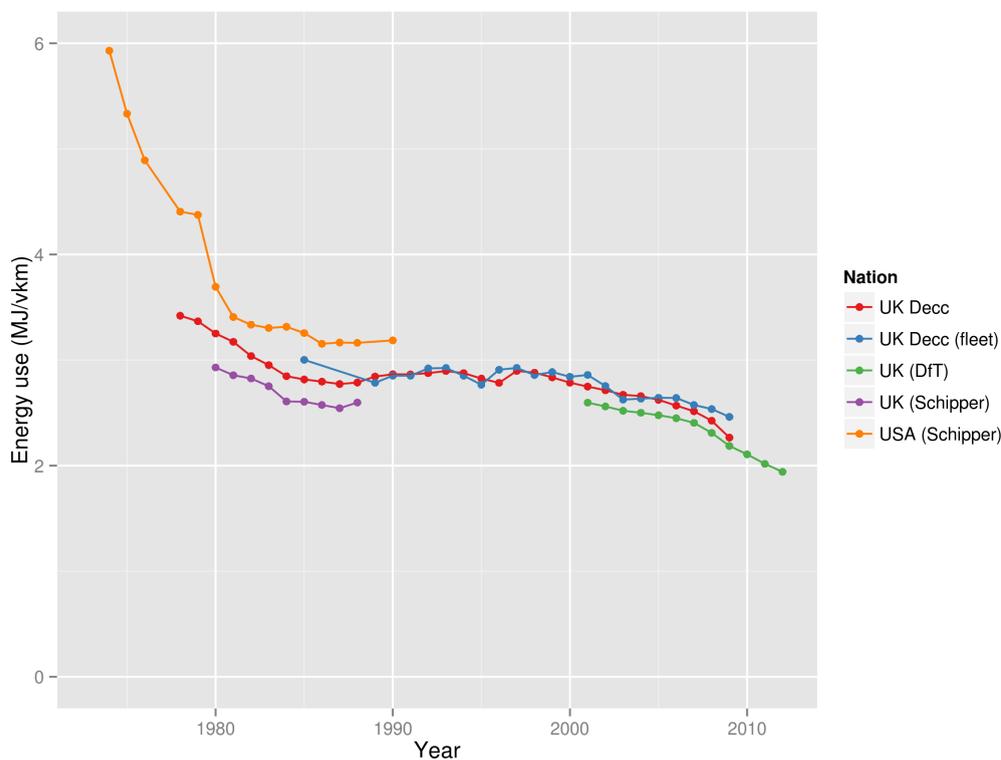


FIGURE 5.20: Fleet efficiencies of new cars in the UK and USA, 1977-2012. Data calculated from Schipper et al. (1993) (UK1, USA), assuming an energy content of fuel of 32 MJ/l, and the Department for travel (DfT, 2013, table VEH0256), assuming a conversion factor of 14.4 between kg of CO₂ and MJ.

The imperfect match between the estimates of energy efficiency over time from two independent official sources (both of which are more than 10% below the 3 MJ/km figure calculated from Defra (2012) in section 5.2), combined with the difficulty of ‘measuring’ energy economy in practice (Schipper et al., 1993),⁴¹ suggest that the DECC (2011c) estimate of Ef should be treated as a “best estimate” rather than an exact value that is set in stone. As highlighted throughout section 5.4, the performance of vehicles varies greatly depending on a range of factors, so it is unlikely that even rigorous tests that try to emulate real world driving match perfectly from actual figures. This point is emphasised by the “real mpg” project hosted by www.honestjohn.co.uk, whereby drivers are encouraged to enter their vehicles’ fuel economy data and compare the results with official values.

⁴¹CO₂ emissions tests, from which DECC’s Ef estimates are derived, are conducted in laboratory conditions on new cars. Therefore, the resulting data may not be 100% applicable to reality. Cold starts, driving behaviour, and congestion all influence Ef , meaning its variability is probably much greater than that illustrated here

5.5.2 Modal shift

Because the differences of energy use between modes are greater than the differences within modes (amongst current, commercially viable and desirable models at least), modal shift probably has the greatest potential to alter energy costs of commuting over time. The spatial microsimulation approach to estimating energy costs used here assumes that mode and distance categories are already known from the census — these constrain the spatial microsimulation model and thereby form the basis of our energy calculations. This a-priori knowledge about the key attributes of commuting behaviour allow us to focus on the more technical aspects influencing the energy costs of travel to work. This is useful, and represents a step forward in terms of method (there would be little point in attempting to quantify impact of many variables if not even the commonest modes and distance bands were known). However, it also brings the risk that mode and distance, which ultimately determine the energy costs of work travel, are taken for granted. It is this issue to which our attention now turns. The focus is on past modal shifts to provide understanding about the scale of the shift in our travel to work patterns that have happened over the past 100 years. (Speculation about and scenario building for future shifts are tackled in a later chapter.)

Increasing car dominance is the most striking feature of 20th Century transport to work. Data from a large (n=1010) survey extending back to the 1890s illustrates this shift (Turnbull, 2000; figure 5.21). The sampling technique used in this longitudinal survey (self selection) and lack of national data for corroboration before 1971 mean that these historical data may not precisely match the national picture. However, the close match between the results and recent surveys suggest that these issues “have not unduly distorted the picture of commuting” (Turnbull, 2000, p. 13). The data also show that commuter patterns can shift quickly in times of rapid economic and technological change: between 1940 and 1960, for example, the proportion of respondents driving to work increased from 6 to 36%, a 6-fold increase in 20 years! When this modal shift dataset is converted into energy use estimates, based on the (unfounded but useful) assumption of fixed distances and efficiency of each mode taken from recent data, the results are striking (figure 5.22): it appears that current commuter energy costs are around an order of magnitude greater than they were at the beginning of the century, with almost all the growth attributable to the rise to dominance of the car.

Recently, rates of modal shift at the national level have been much slower, however, as illustrated by figure 5.23. Knowledge of the spatial distribution of transport patterns, and how they have changed, is prerequisite to understanding geographical variation in the energy costs of work travel. Rather than merely taking a snapshot of current patterns overall, time-series maps can illustrate how the geography of different modes

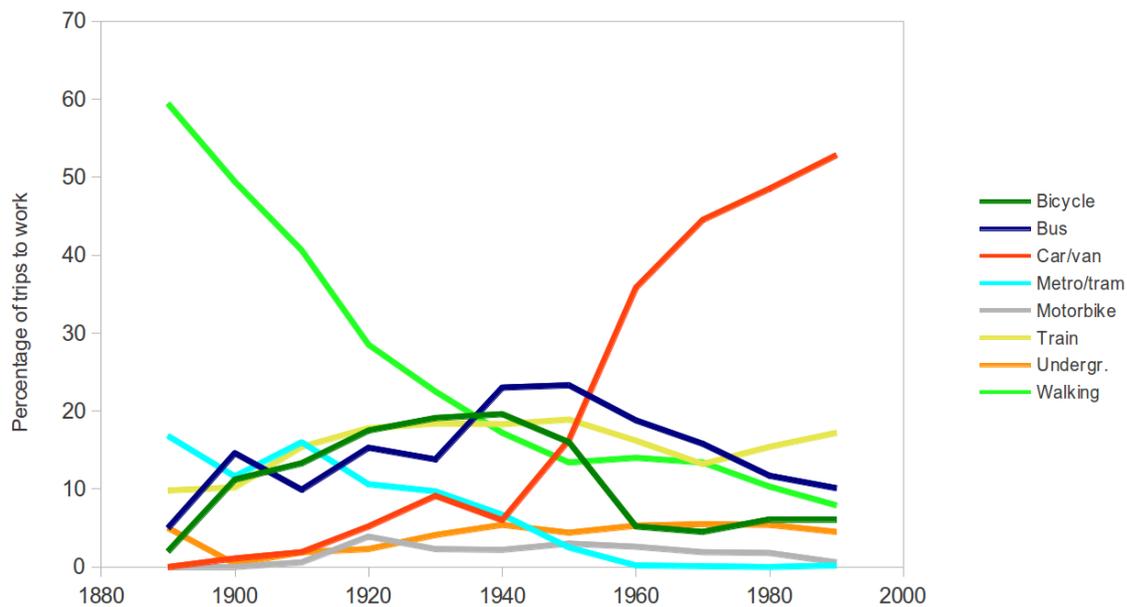


FIGURE 5.21: Mode of transport to work, 1890-1990, from a self-selected sample of 1010 respondents (data from Turnbull, 2000).

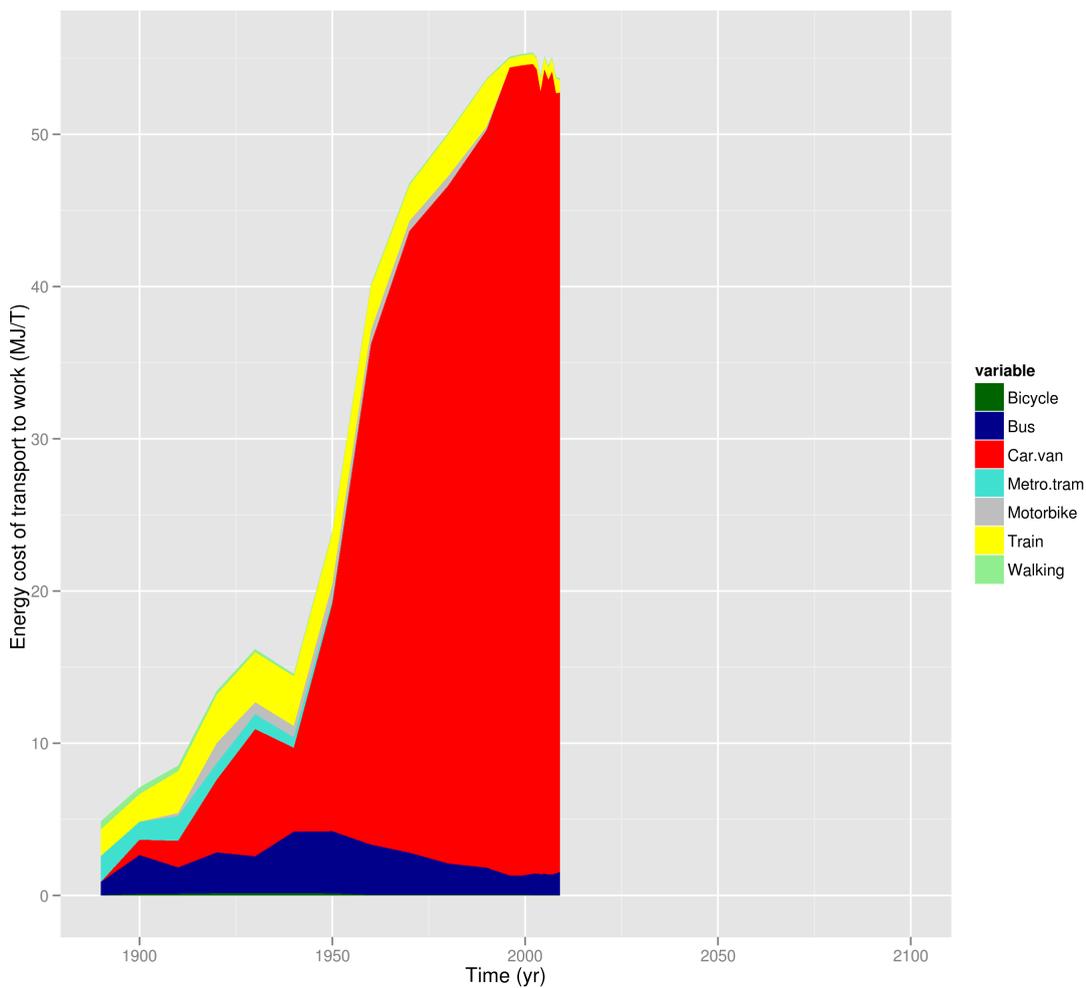


FIGURE 5.22: Estimates of energy use per commuter trip, 1890-1990.

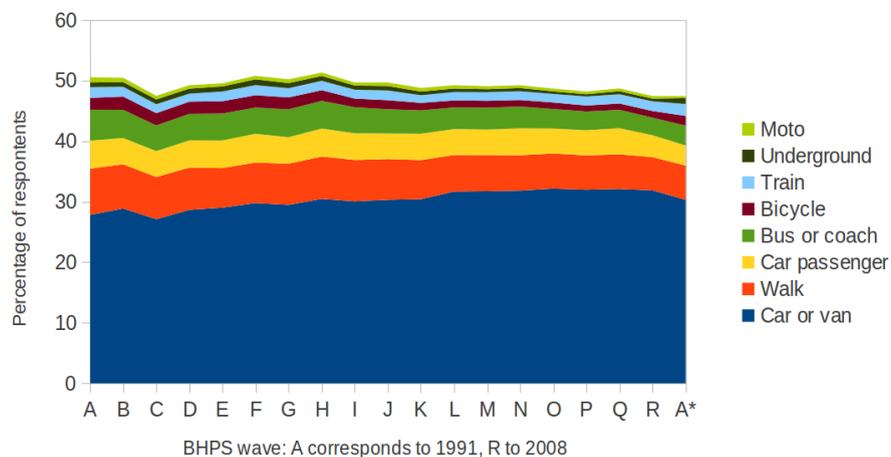


FIGURE 5.23: Modal split of travel to work over time, from the BHPS and (for wave A*) the USd.

has shifted over time, in addition to the non-geographical aggregate shifts. Cars have clearly risen to dominate the UK's work travel (figure 5.21), but this has not happened uniformly over space. This is dramatically illustrated by plotting the number of areas in which driving a car (as opposed to being a car passenger) is a more common form of commuting than all other commuter modes put together (figure 5.24).

The maps show that, although car drivers were already by far the most common type of commuter by 1980, they still only constituted more than 50% of the total, excluding those who work from home, in just over 1/3 of administrative areas (241 of 635 wards). Also of interest is the fact that many of these areas were urban, such as Ecclesall in central-west Sheffield, and city centre wards in Harrogate, Leeds and York. By 2001 car dominance was greater. Car drivers outnumbered all other commuters combined in 81% of MSOAs (563 of 694 areas). However, the trend for relatively high urban car use had reversed by this stage. This is clear from the patches of white which are almost exclusively limited to densely populated urban centres in 2001 figure 5.24.

5.5.3 Future efficiency improvements

A range of technological options exist to make cars 'fit for their purpose' in the short term (Plowden and Lister, 2008) and remove their dependence on fossil fuels in the long term by electrification. However, when talking about technological change in transport, there is a tendency to idealise and exaggerate the rate of change possible.⁴² In reality, the energy requirements of moving a large metal (or perhaps plastic, carbon fibre or

⁴²A good example of this tendency is illustrated by an article published by the British Broadcasting Corporation (BBC) seriously touting the possibility of flying cars catering for personal travel needs in the future: "As motorways become more and more clogged up with traffic, a new generation of flying cars will be needed to ferry people along skyways" (BBC News). If even the well-respected BBC could

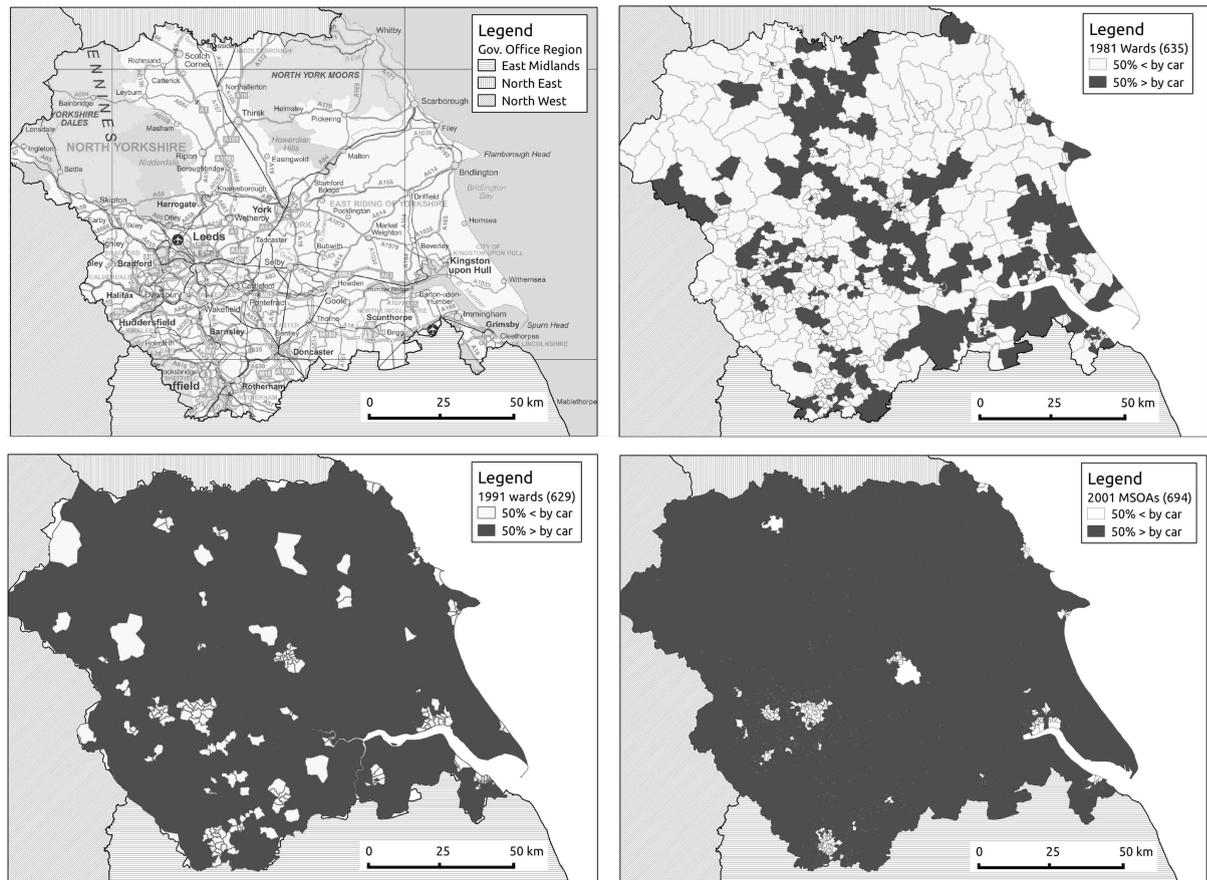


FIGURE 5.24: Areas in which driving to work accounts for more than half of all commuter trips in Yorkshire and the Humber. Ward level data from Casweb.

other material yet to be commercialised) box around at high speed are constrained by Newtonian physics, and are always going to be high compared with walking, cycling or the best public transport modes (Mackay, 2009). Focussing on the technologies that have been proposed and are receiving serious funding for development, it is clear that there are no ‘golden bullets’ to dramatically improve the efficiency of cars (the same would apply to other modes). This is illustrated in figure 5.25.

Some of the new technologies presented in figure 5.25 seem quite promising, with a few currently offering 3 fold energy savings compared with conventional cars. However, in all four cases which require below 1.5 MJ per kilometre, a glance at the energy source reveals the problem: each relies on either electricity — which requires around double the energy content in fossil fuels to produce as is stored in the car’s battery (section 5.3) — or hydrogen, which is a very long way from being (and may never be)

place sensation before evidence, there is no reason to suggest that media or funding-hungry academics could not do the same.

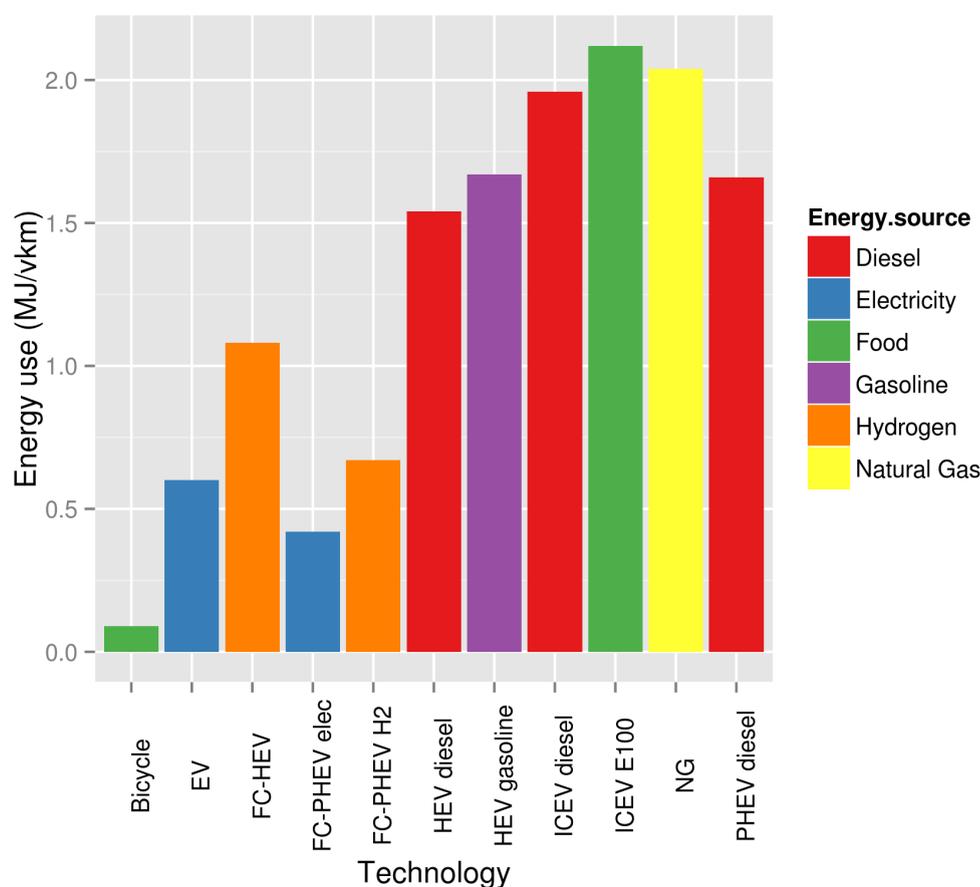


FIGURE 5.25: The fuel (or ‘tank to wheel’, TTW) energy use of a selection of the most promising future car technologies as they currently stand, from Baptista et al. (2012) alongside our own figure for the bicycle, for comparison. The acronyms are as follows: EV (electric vehicle), FC-HEV (fuel-cell hybrid electric vehicle), PHEV (plug-in hybrid electric vehicle), ICE (internal combustion engine) and NG (natural gas).

commercially viable.⁴³ Still, pending the rapid roll-out of new renewable and nuclear generating capacity (Dyke et al., 2010), battery electric vehicles (BEVs) clearly have huge potential to reduce energy costs due to the very high efficiencies of electric motors (>90%), if their worst problems can be overcome. These include:

- Reliance on rare earth metals for the motors and electronics.
- Additional strain on an ailing electricity grid (Dyke et al., 2010; Webster, 1999).
- The fact that electric cars are more expensive than comparable conventional cars due primarily to the costs of high quality lithium-ion batteries.

⁴³Hydrogen is very wasteful of energy to produce (Smil, 2008). It is difficult and energy intensive to store — due to high pressure and low temperature requirements — so is rejected as a realistic option to transition away from fossil fuels by some scientists (Mackay, 2009; Kreith and West, 2004). This judgement is followed here, avoiding the potential distraction of the ‘hydrogen economy’ advocated by some researchers (e.g. Kleijn and van der Voet, 2010).

- Poor range and (discounting a few models) performance.

Each of these factors have contributed to the poor UK sales of electric vehicles observed in 2011 (Vaughan, 2011) and 2012 (Cornish, 2012; Massey, 2013). In combination, these factors are likely to limit the penetration rate of BEVs below more optimistic projections (e.g. Shepherd et al., 2012).⁴⁴

The more realistic alternative replacement to the conventional car are hybrid models which contain both electric and internal combustion engines. However, as illustrated in figure 5.25 these options offer only minor improvements on the internal combustion engine. It would seem that these benefits are outweighed by the energetic disadvantages of hybrids: added weight and complexity of dual transmission systems imply greater acceleration and servicing energy costs, and the manufacturing requirements of the electrical power supply implies increased system level energy costs.

Assessing the literature on technological change in cars, it seems that probably the most viable option in the short to medium term is to better regulate conventional cars powered by the internal combustion engine. This is the argument made powerfully by Plowden and Lister (2008), who present strong evidence to suggest that manufacturers could rapidly reduce the energy and environmental costs of new cars, now, based on pre-existing, well established technology. Their lighter, lower-powered and more aerodynamic ‘eco cars’ were found, in a physics-based model, to emit around 30% less CO₂ per km than conventional cars in five classes of car. These savings could be further enhanced in the short-term if the ‘eco car’ models were rolled out alongside policies to reduce speed, increase occupancy rates and discouraging the purchase and use of the most energy intensive car classes (Plowden and Lister, 2008).

In terms of modelling future efficiency shifts, it seems that cars are sufficiently long-lived to discount the possibility of major non-linearities or ‘step changes’ in overall fleet efficiencies, barring fuel shocks (Lyons and Chatterjee, 2002) or drastic political intervention such as fuel rationing. (Both events are possible, but very difficult to model.) Based on this understanding of gradual change, there are two broad approaches to modelling future fleet efficiencies, and both of them produce neat (potentially misleadingly simplistic) curves of energy efficiency shifts. The first is showcased in Baptista et al. (2012), which involves selecting a range of technologies, assessing their stage of commercialisation, and proceeding to create scenarios of the future based on plausible (based on past evidence) rates of change. In a recent development, an addition to this approach has been suggested by Zuo et al. (2013). In this conference paper, a micro-simulation model, analogous to demographic models, was proposed, in which vehicles are ‘born’

⁴⁴Sales in the USA and Germany, two of the world’s largest and most lucrative car markets, have also been poor (Hepker, 2012; Mihalascu, 2013).

(are produced), ‘work’ (transporting people and goods) and then ‘die’. This approach would add a level of realism to the approach by explicitly considering the impacts of fleet longevity which, as illustrated in figure 5.18, can greatly slow the rate of change compared to the average efficiency of new cars.⁴⁵

The second option is simpler: it avoids the complexity of evaluating all the various available technologies and their level of commercial viability by approaching the problem from the ‘top down’. This means simple extrapolations of existing fleet efficiency data, perhaps combining the impact of trends in new car efficiencies based on the past relationship between new and overall fleet efficiencies. Which of these approaches to projecting fleet efficiencies is most is context specific and depends on the aims of the research: if aggregate national averages are preferred, then the simpler option would probably suffice. If the aim is accuracy and detail, and provided the its large appetite for data is satisfied, the more complex ‘bottom up’ approach could be preferable. This leaves open the intriguing possibility of modelling car fleets at the micro level.

The potential efficiency gains of public transport modes has received less attention in the academic literature, but could have large energy impacts in some scenarios that include investment in public transportation. From the government’s official figures, coaches are the most efficient form of long-distance personal travel. Yet coaches too could become more efficient by converting to electric drive chains, reducing losses in the engine. One example of this potential that is already in production is a 12 metre rapid transit bus powered by new Iron-Phosphate batteries. These, which are developed in China but already exported internationally, boast 24 hour continuous operation and an 88 kph cruising speed (Breaking Travel News, 2013). On the other hand, rail energy efficiencies could decrease if the High Speed rail network (HS2) is implemented, as rail efficiencies decrease rapidly with increasing speed of the trains. Buses have also become lighter and more energy efficient in recent years.

⁴⁵The inertia of the car fleet to change may be greater than previously expected, based on three factors that are potentially exacerbated by new technologies: 1) Cars become less energy efficient over time (this applies especially to any cars that rely on a battery for motive power, as batteries wear out rapidly after a certain number of life cycles). 2) More robust vehicles (which are generally heavier and more energy intensive) tend to last longer than fragile ones: many cars boasting the latest technology may need to be replaced more quickly than ‘tried and tested’ conventional models. 3) There is an argument to suggest that intensive models are used for longer trips than ‘eco car’ models (which tend to be aimed at purely intra-city travel), so the shift in average fleet efficiency may be greater than the *distance weighted* fleet efficiency. The latter is most useful when modelling trips at an aggregate level. (This issue is to some extent overcome in the spatial microsimulation approach, as long-distance drivers would be more likely to be allocated large cars if the phenomenon is present historically at the national level, which it should be.) Each of these factors could be accounted for in the approach suggested by Zuo et al. (2013).

5.6 Variability over space: local fleet efficiencies

The above analysis is explicitly non-geographical, taking national averages and best estimates of the different energy costs of the main commuter modes. It is clear that this national homogeneity does not translate into reality, as regional bus operators, train services, and taxi companies will have different ‘fleet efficiencies’ depending on a number of factors. It may be assumed that human-powered transport modes (walking and cycling) are less variable over space, as physiological differences between places are relatively small (Hayter, 1992; Shetty, 2007). However, regional differences in diet, in topography, and even behaviour can be expected to lead to variations in the energy efficiencies of human-powered transport over space (e.g. due to different traditional diets), time-space (as diets and fitness levels change in different areas) and at the individual level. Quantifying such variability across all modes is a major challenge: publicly available and geographically disaggregated data on the matter is lacking for most modes. Thus geographical variability in energy use of modes other than cars is outside the scope of the PhD. It is fortunate that the best data exists for cars because, as emphasised throughout this chapter, this mode accounts for the vast majority of the energy costs of personal travel.

The efficiency of any given car is highly variable depending on factors about which quantitative information is available: emission band, make, model and age condition. It also varies due to factors about which less is known, such as behaviour and occupancy, discussed in section 5.4). There is therefore a strong argument that using single ‘best estimates’ for each mode is a substantial oversimplification. This is the reasoning of Leith (2007), in which weighting factors were applied to different makes and models of cars to address the issue. Of course, the issue applies to all modes: an old, rusty bicycle requires more effort to ride than a shiny new one and new buses tend to be lighter and therefore less energy intensive. However, this section is focussed on cars, favouring depth for one dominant form of transport over breadth covering all. The geographical scope of this section is also limited, to Yorkshire and the Humber, to make the analysis of the large vehicle datasets more manageable. Before describing how fleet efficiencies vary over space, it is worth considering the data sources for which these estimates can be made.

Car efficiencies became a pressing political concern in the wake of the 1970s oil price shocks. Since then, climate change regulations from Europe have forced manufacturers to record the emissions from their vehicles in tests; this dataset is stored by the government for every car registered since March 2001 in a geographically disaggregated dataset. This dataset, which forms the basis of our estimates of the spatial variability of fleet

efficiencies, is ultimately based on the measurement and classification of emissions bands, described in table 5.9.

TABLE 5.9: Vehicle emissions bands of registered vehicles since 2001 and 2011 tax rates

Band ↓ Units →	CO2min gCO2/km	CO2max gCO2/km	CO2mean gCO2/km	Tax /yr
A	80	100	90.0	0
B	101	110	105.5	20
C	111	120	115.5	30
D	121	130	125.5	95
E	131	140	135.5	115
F	141	150	145.5	130
G	151	165	158.0	165
H	166	175	170.5	190
I	176	185	180.5	210
J	186	200	193.0	245
K	201	225	213.0	260
L	226	254	240.0	445
M	255	400	327.5	460

The 13 tax bands, from A to M, are defined by the car’s CO₂ emissions, measured during tests in controlled conditions, “carried out either by independent test organisations or by the manufacturers or importers themselves at their own test facilities” (Vehicle Certification Agency 2001).⁴⁶ These tests are designed to reflect typical driving conditions. However, the data comes with the following caveat: “The fuel consumption figures quoted in this guide are obtained under specific test conditions, and therefore may not necessarily be achieved under ‘real life’ driving conditions. A range of factors may influence actual fuel consumption” (Vehicle Certification Agency, 2011). Some of these factors are outlined in section 5.4. This caveat, and the fact that the dataset is only available since 2001, are major disadvantages of the dataset. However, the dataset provides insight into the geographical variation costs because tax band data can be converted energy efficiency values, as shown in section 5.2: combustion of 1 MJ’s worth of fuel emits 73 grams of CO₂ for petrol and 75 g for diesel (Dimitriou and Gakenheimer, 2009). Taking these values for carbon intensity of petrol and diesel fuels (*intp* and *intd*, respectively), and an assumed fleetwide petrol split (*sp*) of 70% in 2001 (diesel’s share has steadily risen since the 1970s, reaching 40% of new car sales by 2008 (Bonilla, 2009)), it is possible to estimate the average energy efficiency of each tax band:

$$Ef = CO2 \times intp \times sp + CO2 \times intd \times (1 - sp) \quad (5.15)$$

⁴⁶Quote taken from <http://www.dft.gov.uk/vca/fcb/the-fuel-consumption-testing-scheme.asp>.

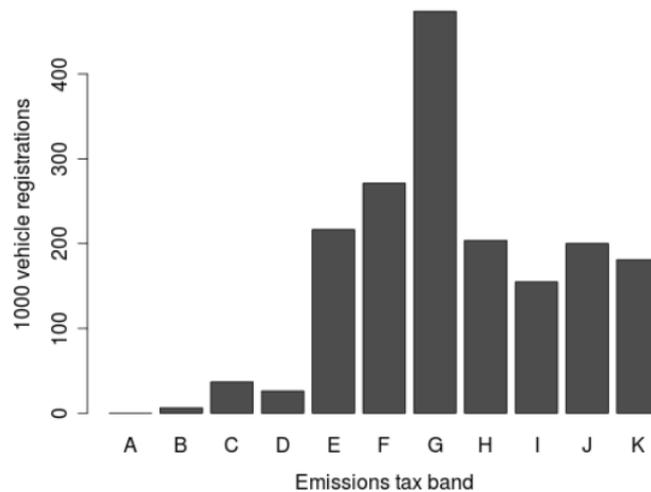


FIGURE 5.26: Barplot of 2001 car registrations by emission band (England and Wales). Raw data from DfT).

Applying this equation to the data presented in table 5.9 results in estimates of energy efficiency, presented in table 5.10. Using the proportion of cars in each tax band (regs02 for 2002 data) to weight the data, it is possible to directly compare fleet efficiencies estimated using this method with previously published estimates of fleet efficiencies:

TABLE 5.10: Estimates of average energy usage of cars by tax band in light of equation (5.15)

Band ↓ Units <i>rightarrow</i>	ef_p MJ/km	ef_d MJ/km	ef_{band} MJ/km	Proportion of 02 registrations %
A	1.23	1.20	1.22	0.0
B	1.45	1.41	1.43	0.3
C	1.58	1.54	1.57	1.9
D	1.72	1.67	1.71	1.3
E	1.86	1.81	1.84	10.9
F	1.99	1.94	1.98	13.6
G	2.16	2.11	2.15	23.9
H	2.34	2.27	2.32	10.3
I	2.47	2.41	2.45	7.8
J	2.64	2.57	2.62	10.1
K	2.92	2.84	2.89	9.1
L	3.29	3.20	3.26	6.8
M	4.49	4.37	4.45	4.1

From this analysis, the energy use of vehicles in England and Wales in 2001 calculated as 2.40 MJ/vkm. This is almost 20% lower than the figure calculated for the 2011 fleet (which should be *more* energy efficient) in section 5.2 and the figure of used by Mackay

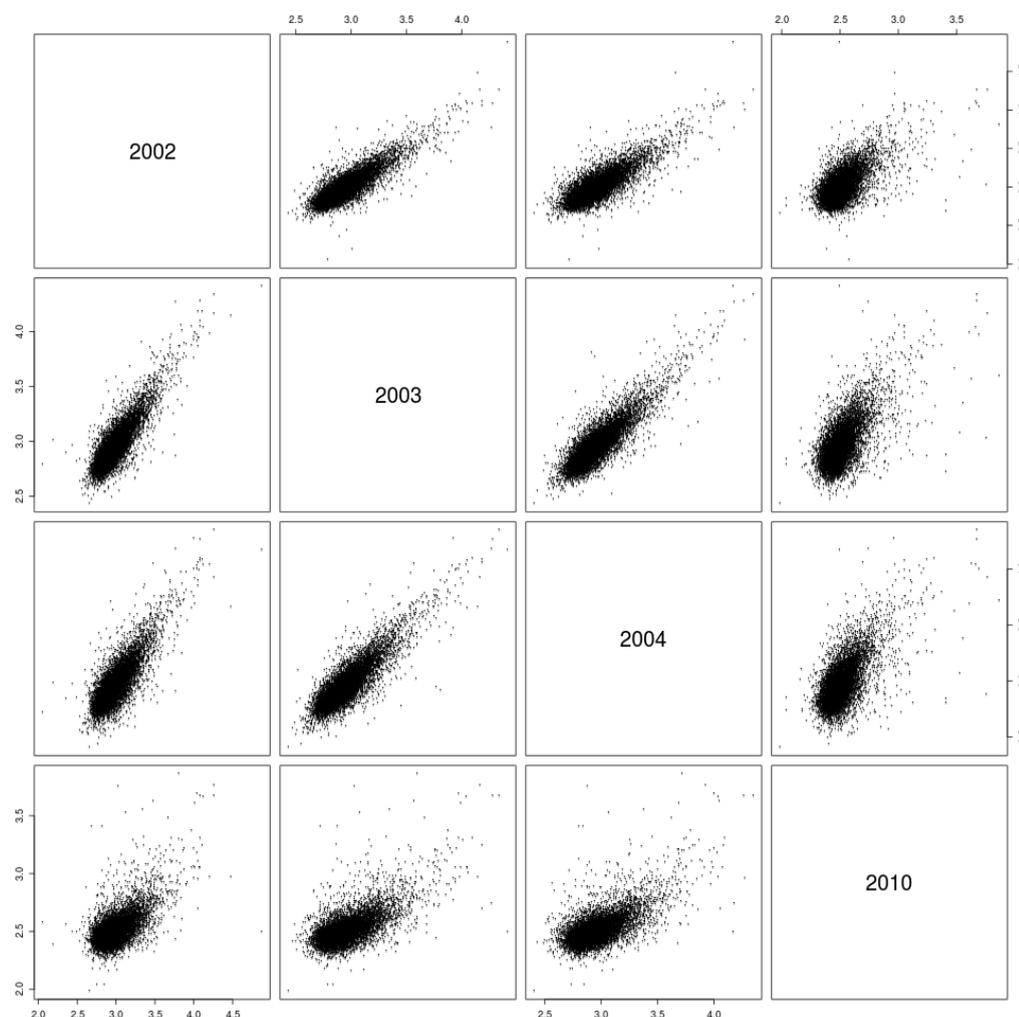


FIGURE 5.27: Scatterplots of estimated fleet efficiencies at MSOA level in England and Wales (MJ/km, both axes). Note the declines in correlation over time. See appendix DFT data for details on the construction of this graph.)

(2009). The value is slightly closer to the fleet efficiency estimates based on DECC (2011c) for 2001 (2.89 MJ/vkm). As alluded to by the Vehicle Certification Agency (2011), such differences are not unexpected: real world use (reported in DECC (2011c)) is different from controlled tests. Another explanation for the low energy use value is that the average efficiency of new cars has been improving over time so a lower value for cars registered since 2001 is to be expected, compared with cars registered before 2001, for which no emissions dataset is available: the data presented in figure 5.26 represents new cars sold in 2002, and do not include any of the car fleet that was on the road during 2001. The use of this data as a proxy for 2001 fleet efficiencies may be justified, however, by the relatively high correlation between estimated fleet efficiencies of wards, from year to year (figure 5.27, table 5.11).

In light of these considerations, the regional emissions band data seem to be better placed

TABLE 5.11: Pearson’s correlation matrix of fit between estimated efficiencies, 2002-2010, based on DfT data at the MSOA level in England and Wales. Some years omitted for simplicity.

	2002	2003	2004	2006	2008	2010
2002	1.00	0.85	0.81	0.77	0.70	0.61
2003	0.85	1.00	0.86	0.81	0.72	0.64
2004	0.81	0.86	1.00	0.84	0.74	0.64
2006	0.77	0.81	0.84	1.00	0.77	0.67
2008	0.70	0.72	0.74	0.77	1.00	0.71
2010	0.61	0.64	0.64	0.67	0.71	1.00

as a way of providing weights for adjusting the national average fleet efficiency, rather than absolute estimates of fleet efficiency. Caution should be used when interpreting the results, acknowledging the fact that the 2002 dataset is much more sparse on emissions estimates because the majority of cars in the vehicle fleet were registered before emission bands were introduced. The raw data on which MSOA level fleet efficiency estimates are based was provided by the DfT in 5 variables (table 5.12).⁴⁷

TABLE 5.12: The first 5 rows of the raw DfT emissions band data. All 1.3 million rows are available online at <http://ubuntuone.com/6inKDTsdhLkFQNat0O6QOK>

MidSOA	BodyType	Year	CO2Group	N
E02004277	CARS	2005	Band C: 111 - 120	21
E02001092	CARS	2007	Band I: 176 - 185	6
E02005251	OTHERS	2011	non-cars	4
E02005506	CARS	2004		3
E02003897	CARS	2007	Band F: 141 - 150	26

Once this data had been re-arranged into a more manageable form, converted into an efficiency estimate using equation (5.15), and re-weighted to reflect the nation-wide average fleet efficiency of 3 MJ/vkm, a subset including only 2002 registrations from MSOAs within Yorkshire and the Humber was taken. These calculations suggest the region’s car fleet is more efficient than the national average, although only by 3% (2.9 vs 3.0 MJ/km, respectively). Plotted at the regional scale, these estimates coincide with the expected trend for rich and rural areas to have relatively inefficient car fleets (figure 5.28).

Vehicle efficiency is clearly an important determinant of the energy costs of personal transport, and figure 5.28 demonstrates that it does vary over space in a (more or

⁴⁷Thanks to Daryl Lloyd, who created the bespoke dataset used for this purpose.

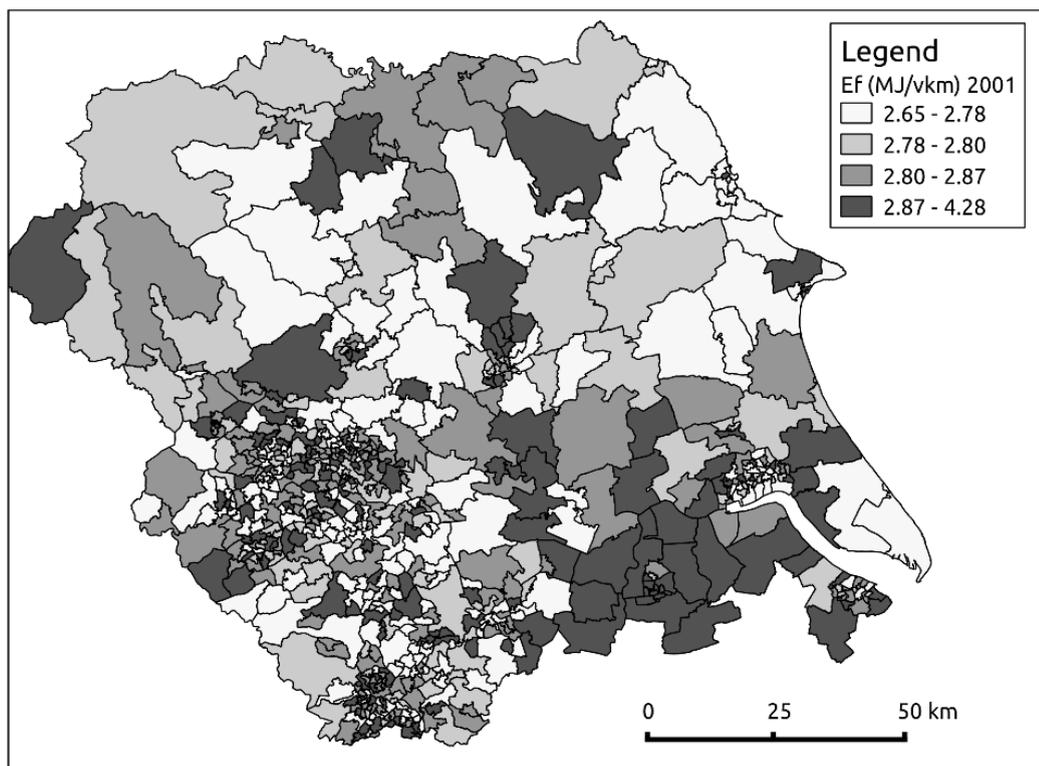


FIGURE 5.28: Car fleet efficiencies in Yorkshire and the Humber in 2001. Data from DfT.

less) predictable way. However, it is important to keep the relative ranges of these variations in context. The deviation from the mean of the most and least efficient car fleets at the MSOA level is only 25% and 27% respectively. This variability is far less than the difference between the efficiencies of different transport modes (see figure 5.29 below, where 30 and 10-fold differences exist between the fuel requirements of cars and bicycles for direct and system level fuel use respectively) and less than variability in the distances that people travel to work. Due to the risk of ‘double counting’ the impact of fleet efficiency (through the size of car variable and these fleet efficiency estimates), the fact that these fleet efficiencies are not distance weighted and the relatively minor variability of fleet efficiencies overall, this spatial dimension was not initially included in the energy cost calculations presented in the subsequent section. A method for including local fleet efficiencies has been demonstrated and this could be of use for policy makers developing locally targeted transport interventions, researchers aiming to create more spatially aware scenarios of the future and even businesses and 3rd sector organisations marketing and advocating low-energy transport solutions.

5.7 Final energy use estimates

This final section concludes the chapter on energy costs of personal travel with our final “best estimates” of energy costs. Four types of energy costs are included: direct energy use of the vehicle (Ef , calculated in section 5.2), and three indirect components of system level energy use ($Esys$): the energy used in fuel production (Efp) and the embedded energy of vehicles and guideways (Ev and Eg , see section 5.3). The results are presented in table 5.13. Due to the importance of these estimates for the results of our model, these results are also presented visually, in figure 5.29. It is interesting to compare these estimates with estimates of fuel use of different modes made independently of this study, over 20 years ago (figure 5.30).

TABLE 5.13: Final estimates of the direct and indirect energy use of the eight most common modes of travel to work (10, including three car types), presented in MJ/pkm, under average occupancy rates for Great Britain (except for cars, which have units of MJ/vkm).

Mode	Ef	Efp	Ev	Eg	$Esys$
Bicycle	0.09	0.541	0.05	-	0.7
Bus (local)	2.1	0.85	0.15	0.30	3.4
Car (small)	2.5	0.99	0.57	0.30	4.3
Car (average)	3.0	1.21	0.67	0.30	5.2
Car (large)	3.9	1.58	0.87	0.30	6.7
Coach	0.43	0.17	0.08	0.30	1.0
Motorbike	1.7	0.70	0.33	0.30	3.1
Train	0.77	0.31	-	-	1.1
Tram	0.57	0.38	-	-	1.0
Walking	0.13	0.75	-	-	0.9

These values provide the EI values by mode that are fed into the model to calculate energy costs by trip. Although the larger system level energy costs are deemed more realistic, the majority of the analysis presented in chapter 6 to chapter 8 include only direct energy costs. This decision was made because the direct energy costs are more certain, come from official data sources and currently coincide with the UK’s reporting of transport emissions. Direct energy use should thus be more relevant to transport planners needing to meet energy and climate targets in the short-term.⁴⁸ Longer-term scenarios are less constrained by such reporting conventions, so the scenarios presented in chapter 8 use system level energy use estimates. Overall, the impact estimating energy

⁴⁸In the UK and the European Union as a whole, this legislation comes primarily from the EU’s 20/20/20 targets: 20% reduction in emissions, 20% of final energy delivered from renewable sources and a 20% increase in energy efficiency.

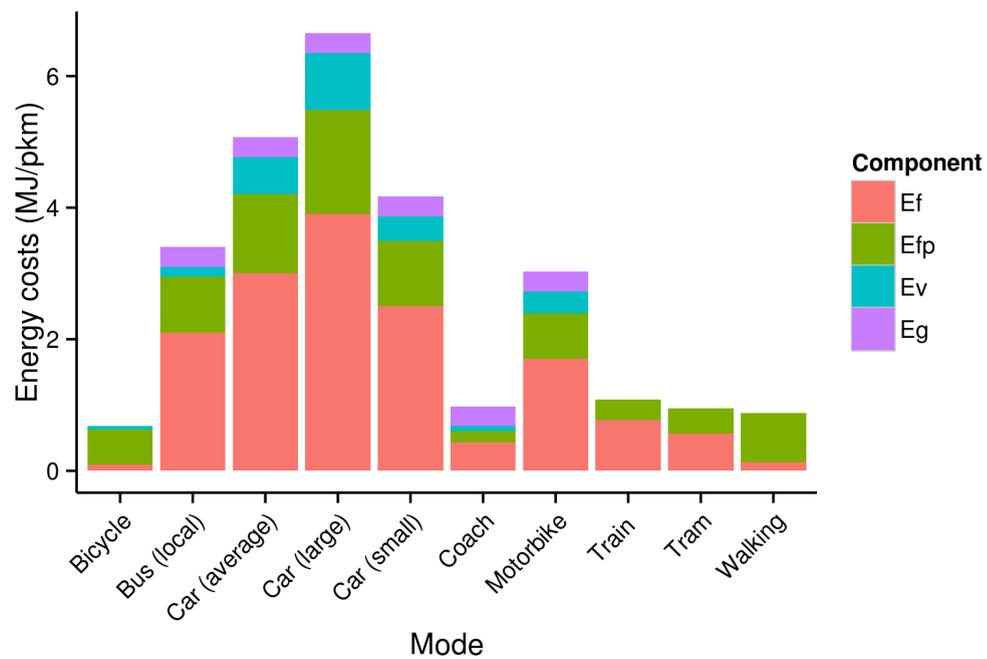


FIGURE 5.29: Final energy use estimates, from a range of sources.

use at the system level including system level on relative energy use is minor, as it scales proportionally with direct energy use for all modes of transport.

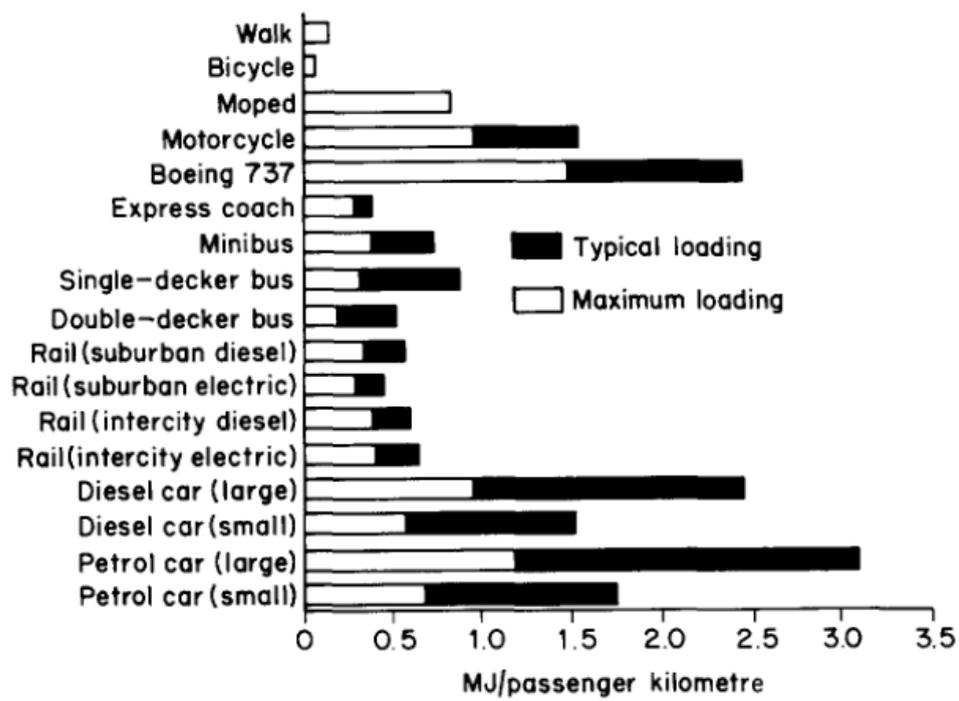


FIGURE 5.30: Estimated fuel energy use of UK transport modes, from Hughes (1991).

Chapter 6

The energy costs of commuting

The preceding two chapters have demonstrated that there are both detailed data (at various levels) on travel to work in the UK *and* methods that can be used to convert this information on behaviour into estimates of energy use. Based on these foundations, this chapter illustrates the main results, in terms of overall energy use. Estimates of energy use at national (section 6.1), regional (section 6.2) and in comparison with other sectors (section 6.3) levels are presented. The approach follows the principle of Occam's razor, whereby additional complexity is only added when necessary, in contrast to agent-based approaches, where complexity is inherent at the outset (Batty et al., 2012). Therefore the high level results are based on the simpler aggregate level methods. Results that emerge from spatial microsimulation (and which would be inaccessible using aggregate level methods alone) are presented later on, for a smaller case study region. South Yorkshire is used here as the case study region here and in subsequent chapters for consistency (section 6.4).¹ In this section the spatial distribution of energy use for commuting is illustrated at a low level. Indicators of how the energy use in each zone is distributed between different members of society are also presented. The international applicability of the methods for calculating the energy costs of work travel is tested in section 6.5, which compares the energy intensity of commuting in England and the Netherlands. In the final section the results are discussed with reference to the debate on energy use and urban form, introduced in section 2.3.

¹The reasons for choosing this case study area explained in section 6.4.1.

6.1 Commuter energy use at the national level

Based on the data and discussion of it presented until now, we are well-placed to perform a preliminary estimate of energy use at the aggregate level. This approach, starting simple to understand the fundamentals and most important factors influencing the system before later adding details, follows the recommendation of Batty (1976).

Having considered the limitations of the data, and weighed up the costs and benefits of complexity, it was decided to primarily calculate ET at the aggregate level, as a function of only two parameters: mode and distance travelled. (These are the cross-tabulated categorical variables provided as geographically aggregated count data at administrative levels down to ST Wards — see table 4.2). This can be expressed for any particular area as

$$ET = \sum_m \sum_d 2dR_{(d,m)} \times E_m \quad (6.1)$$

where ET is the total work-day energy costs for all commuter trips that happen in that area, d and m are distance and mode categories, dR is the mean average route distance inferred from the mode-distance combination and E an estimate of the energy cost per unit distance (direct or indirect), presented for each mode in table 5.13.

An alternative way to express this would be based on commuter flow data. If one know the approximate origins (i) and destinations (j) of every commuter trip, this can be expressed in a different way:

$$Et_i = \sum_j \sum_m n_{(i,j)} \times 2Q \times dE_{(i,j)} \times Ef_m \quad (6.2)$$

where Q is the circuitry factor which translates the Euclidean distance between two places into an approximation of the network distance, defined by equation (5.14). Summing Et for all the origin areas in the region of interest would provide an overall estimate of energy costs.

Clearly, neither equation (6.1) nor equation (6.2) tell the entire story, as they omit frequency of travel: how many days per week people travel to work (this is covered in section 5.4.1). They also omit a number of other complicating factors that are discussed in the previous chapter. However, they are enough to begin with, to create maps that capture the spatial variability of energy costs of commuting at a coarse geographical resolution. The approach summarised by equation (6.1) is used, because the input data is much simpler, smaller and easier to manage. (Equation (6.2) could be used to verify the estimates.)

The input variable into equation (6.1) that has not yet been quantified is dR . Route distance by mode and distance band is needed to account for the fact that Census data on distance is presented in categories (with breaks at 2, 5, 10, 20, 30, 40 and 60 km), whereas distance itself is continuous. The simplest way around this problem would be to assume that route distance sits in the centre of the bins (i.e. 1, 3.5, 7.5, ... km). However, this would be a very gross simplification because the route distance is certain to be greater than the Euclidean distances calculated from home-work postcode pairs. Also, because each mode has a different distance-frequency distribution, it is safe to say that the average route distance will also vary depending on the mode of travel.² To take this into account, distance data from Understanding Society was used. First, the values were converted into estimates of Euclidean distance and split into the Census bands. Next, these were re-converted into the original route distances, and the average was taken for each distance band/mode combination. The results, which are presented in table 6.1 and visualised in figure 6.1 and figure 6.2 for motorised and non-motorised modes, provide strong evidence of inter-mode variation in distance travelled within the same distance band. However, these results are problematic due to the low quality of the input data ($n = 5,000$ but less than 5 individuals were present for unusual categories such as people walking more than 5 km to work) and were not entirely as expected. The anomalies are summarised as follows:

- Bus journeys appear to be longer than the equivalent journeys by train, which was expected to be associated with the longest trips (although train journeys are in second place).
- The average bicycle trip was expected to be longer than walking trips in all cases. This did apply in the 0-2 and 2-5 km categories, but after that the trend reversed. This can be explained by sample size: a few unusual people walk far to work, whereas cyclists, as expected, tend to cluster around the lower ends of the 5-10 and 10-20 km bins.
- The ‘inverse U’ shape of the bottom graphs in both cases were unexpected. This could be explained by the tendency of people to round to 10: the average distance travelled in the 30-40 km bin was the closest to the upper bound in all cases, perhaps a result of people rounding to 25 miles for many trip distances in the 20s (just under 40 km in Euclidean distance).

²One would, for example, expect people who walk 2 to 5 km in Euclidean distance to travel on average less far than those who drive between 2 to 5 km, as ‘impedance’ of walking rises rapidly after the first kilometre whereas the additional personal effort of driving an extra kilometre or two is much lower (Iacono et al., 2010), discussed in chapter 2.

It would be desirable to corroborate these findings with other individual level data on travel to work. For the purposes of assessing the relative energy costs of commuting in different areas, however, these estimates suffice: the concepts and code behind the estimates would produce slightly different values given different input data, but, at present, this is not our concern. With evidence-based estimates of $dR_{(d,m)}$ in place, we can proceed to estimate the relative energy costs of commuting in different places.

TABLE 6.1: Average distance travelled by mode and distance band (km), from USd data.

Upper limit	2.0	5.0	10.0	20.0	30.0	40.0	60.0	250.0
Car driver	1.6	3.9	7.9	15.0	26.0	35.8	50.3	102.6
Car passenger	1.5	3.9	7.9	15.2	26.5	36.4	48.0	95.0
Motorbike	1.4	4.1	7.0	15.2	23.5	36.0	NA	NA
Bus	1.8	3.8	7.7	13.9	27.7	40.0	56.0	110.5
Train	1.5	4.2	8.1	15.1	26.4	37.6	53.2	98.8
Metro	1.7	4.0	8.1	14.7	25.8	NA	NA	65.0
Cycle	1.5	3.9	7.5	11.5	NA	NA	NA	NA
Walk	1.2	3.5	8.0	13.7	25.0	NA	NA	NA
Other	1.0	4.3	7.6	13.5	27.8	37.5	42.0	130.0
Taxi	1.7	3.0	9.0	12.0	NA	NA	NA	NA

Based on these categories, and the values of E_f reported in the previous section, the 99 distance-mode variables of the cross-tabulated census table ST121 can each be allocated an average energy costs. Originally the energy cost associated with the number of people in each distance/mode category was calculated using the LibreOffice Calc spreadsheet software. However, this soon became unwieldy so the analysis was transferred into R. The main script file used to convert the raw count data (figure 6.6) into energy estimates is available in the [thesis-reproducible](#) folder associated with this thesis.³ The benefit of this script is that it can take input data of the type displayed in figure 6.6, regardless of the number or scale of the geographic units.

At the national level, the distribution of trips by mode and distance is displayed in figure 6.3. This graph shows the dominance of car drivers for all trip distances, except for the 0-2 km bin. As expected, bicycle and walking trips are dominant in the lowest distance categories and tail off to essentially zero after the 20 km mark. Another result that was expected was the tendency of train journeys to be longer, probably due to the possibility of working on the train and the use of this mode by high-income workers travelling to London.

³Code and output were also embedded in RMarkdown, to show the output from R. Every step of this process is illustrated on the author's Rpubs website (rpubs.com/robinlovelace).

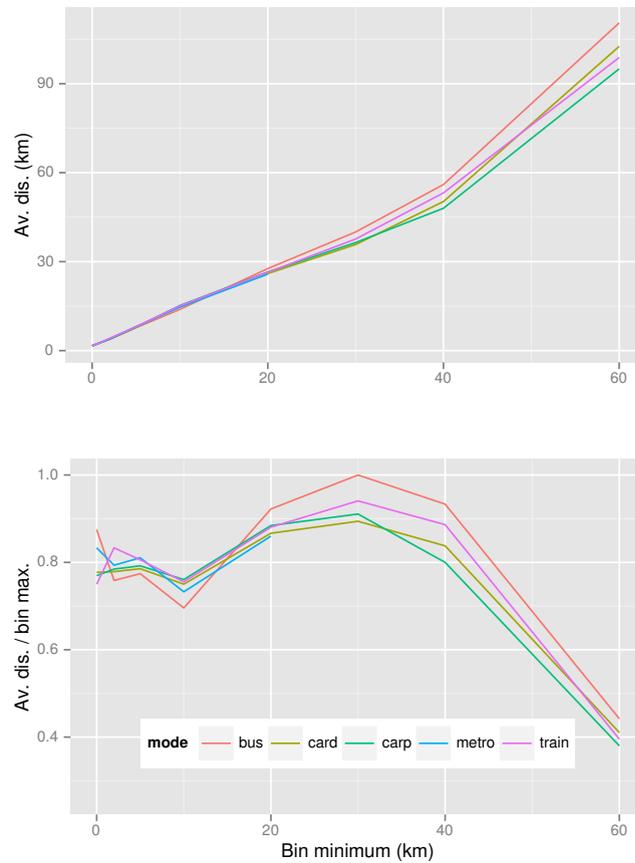


FIGURE 6.1: Distance bands and average distance travelled for motorised modes, expressed as the relationship between lower bound and average distance (top) and that between lower bound and the ratio of upper bound to average distance (below), from Understanding Society data. ‘card’ and ‘carp’ refer to car driver and car passenger respectively.

According to the methodology described above, this data was translated into energy costs at the national level of Wales and England (the data table “ST121” is unavailable for Scotland and Northern Ireland). As illustrated in figure 6.4, the energy costs of commuting in Wales are higher per trip, by 10% (34.5 MJ in England, 38.0 in Wales). In practice, it is probably not worth plotting this information geographically, as there is very little geographical information to report: the values are aggregated over a very wide area, so a choropleth map of the results makes little sense. However, the purpose of figure 6.4 is primarily to introduce the subsequent geographical plots, which are of increasingly small geographic zones.

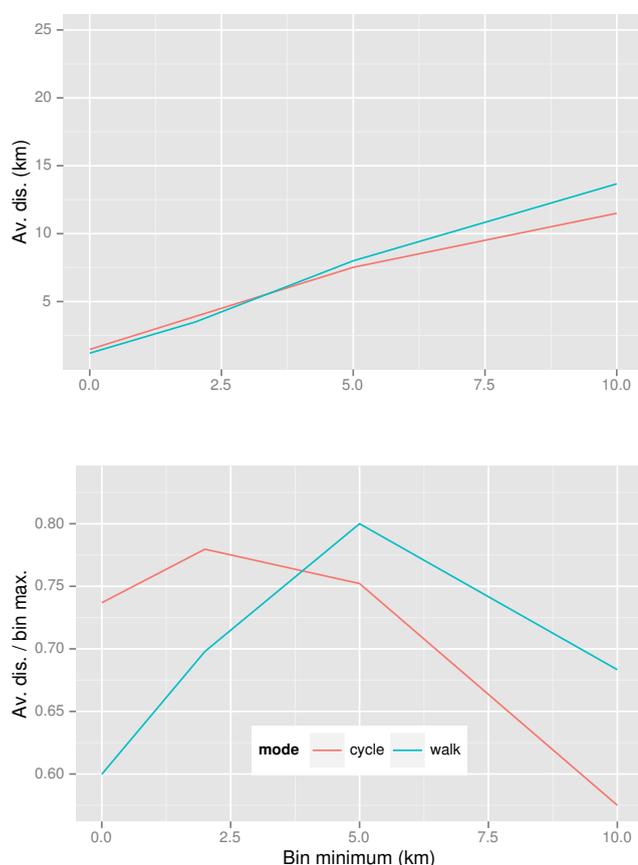


FIGURE 6.2: Distance bands and average distance travelled for non-motorised modes, expressed as the relationship between lower bound and average distance (top) and that between lower bound and the ratio of upper bound to average distance (below).

6.2 Regional and sub-regional patterns

The average energy costs of commuter trips in England are illustrated at the regional level in figure 6.5, to provide an overall impression of its spatial variability at the coarsest geography. The high degree of geographical aggregation masks much of the variability, yet there is still a substantial difference between regions. As expected, London is the region with the lowest energy costs per commute at 20.8 MJ per one-way trip or 40% below the average for all regions. Excluding London, energy costs were lowest in the North West and highest in the East of England (closely followed by the South East). The variability between these regions was less noticeable: they were 10% below and 12% below the national average respectively.

To gain more insight into the spatial pattern of commuter energy costs, the same data

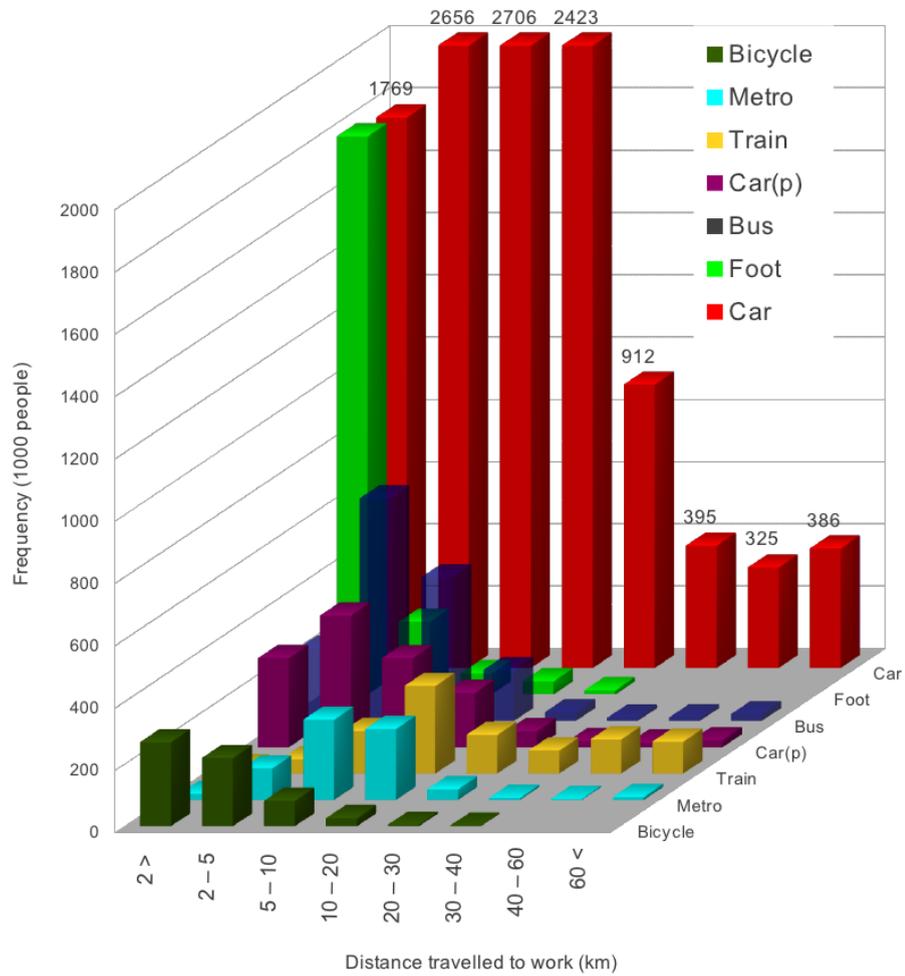


FIGURE 6.3: Mode and distance categories of commuter trips in England, 2001.

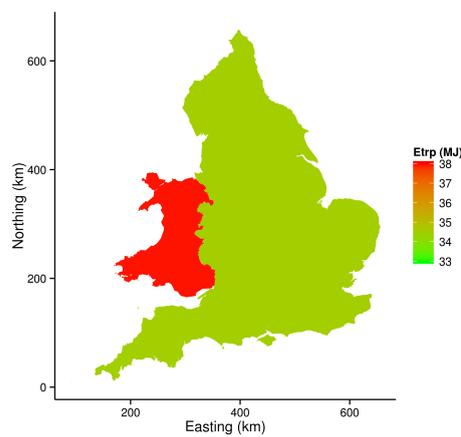


FIGURE 6.4: Comparison of commute energy costs between England and Wales.

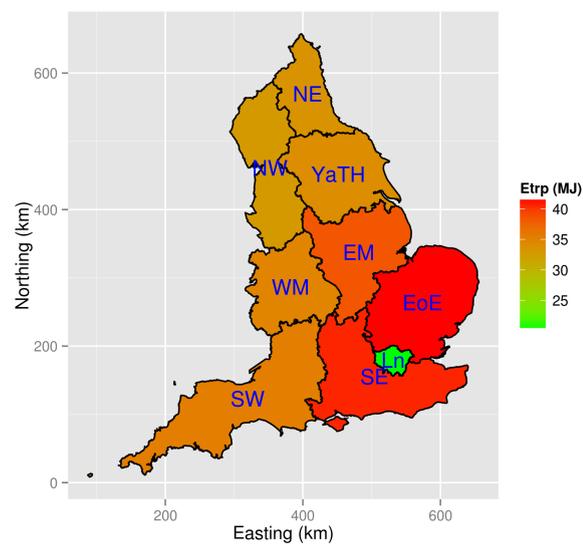


FIGURE 6.5: Average energy use per trip (Etrp, in MJ) in English regions, based on cross-tabulated distance/mode geographically aggregated count data.

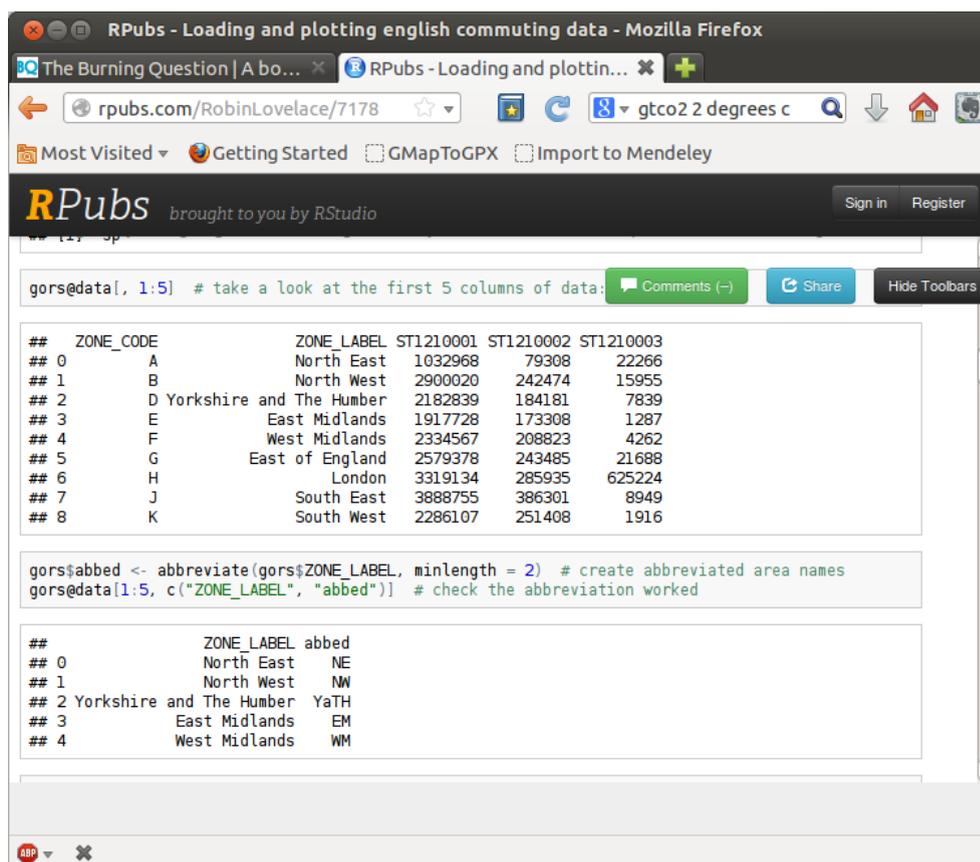


FIGURE 6.6: Raw count data of commuters by mode and distance, the first 5 columns of regional level data, from Casweb table ST121. Data displayed in RMarkdown format, illustrating the reproducibility of the results (see www.RPubs.com).

was re-plotted at lower geographical scales, down to the ward level for the nation. Figure 6.7 shows the distribution of energy costs at the county level, constituting 88 polygons (42 counties and an additional 46 Local Authorities to make-up areas not covered by counties). This is a useful level for identifying case study cities and areas that have unusually high or low levels of energy use, given their surroundings. As a general pattern, large and high-density urban areas tend to have lower energy use, with the three largest built-up areas in England (Inner London, Greater Manchester and the West Midlands built-up area) all having average commuter energy costs below 30 MJ (the mean is 36). Another pattern that emerges is the relationship between the very low energy costs of commuting in London, and the relatively high costs of areas within a ~ 100 km radius surrounding the centre: commuters in Bedford, Essex and Kent, all of which contain 'commuter belts' feeding London, for example, use on average 45 MJ per trip to work. The highest and lowest (outside London) values are found in Rutland (the geographic centroid of which is located 109 km from central London, and which was the last county in England to have a direct trainline to London) and the City of Kingston upon Hull, respectively. Comparison of these two counties could make an interesting case study to explore the reasons for underlying reasons behind high and low energy costs of commuting in England.

The results for districts, of which there are 308 in England, are presented in figure 6.8. As is apparent from the large and relatively homogeneous area of bright green in London (and knowing its high population density), the districts with the lowest commuter energy costs are found in the capital. In fact, 9 out of 10 of the districts with the lowest energy costs per commuter trip are located in London (the lowest is found in the Isles of Scilly, with an average of 7.6 MJ/trip). The district with the highest energy use per commuter trip (60 MJ/trip, 10% more than the second highest zone) is South Northamptonshire, visible in figure 6.8 as the red zone in the far south corner of the East Midlands. The standard deviation of average energy use per trip at this level of geographic aggregation was 9.0 MJ, 50% higher than the 6.0 MJ/trip standard deviation observed at the regional level.

The same results are presented in figure 6.9, at the ward level. Here, much greater variability is apparent (note the increased range of values represented in the colour scale). The standard deviation is 11.6 and values range all the way from 5.1 to 88 MJ per trip. It is interesting to note where these extreme values are found: the former is located in the central London ward of Portsoken, where walking is the most common mode of travel to work, followed closely by catching the tram. The latter was found in Park Farm North, a suburban ward located in the far South East of England, just south of Ashford, where car drivers account for 68% of all commutes. The complex patchwork of average commuter energy costs displayed in figure 6.9 suggests that regional

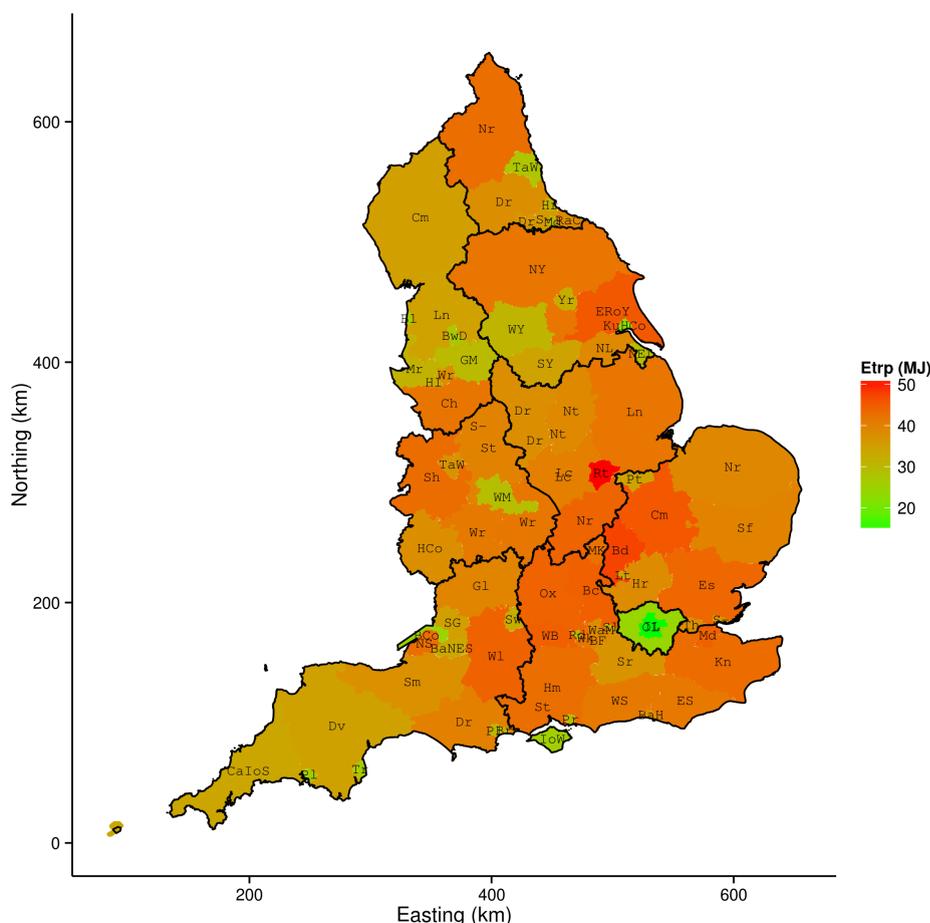


FIGURE 6.7: Average energy use per commuter trip at the county level. The letter strings are abbreviations of the full county names (e.g. Dv is Devon).

level assessments, such as those presented in figure 6.5, are not able to capture the full geographical variability of the variable at all well: there is much more variability within zones than between them. One pattern that stands out from the ward level analysis is the tendency of settlements to be directly surrounded by green areas associated with low energy costs. Although only large cities (those with populations in excess of 100,000) are displayed in figure 6.9, it seems that many towns and cities are immediately surrounded by areas of low commuter energy costs. Haverhill (located in the East of England, roughly half-way between Cambridge and Chelmsford), Hereford (in the south-west of the West Midlands) and a number of coastal towns such as Sheringham (~ 40 km north of Norwich) and Scarborough (in Yorkshire and the Humber) are examples of this.

The method used to calculate energy costs creates estimates that are disaggregated by mode and distance. This allows the aggregate energy use result in each area to be

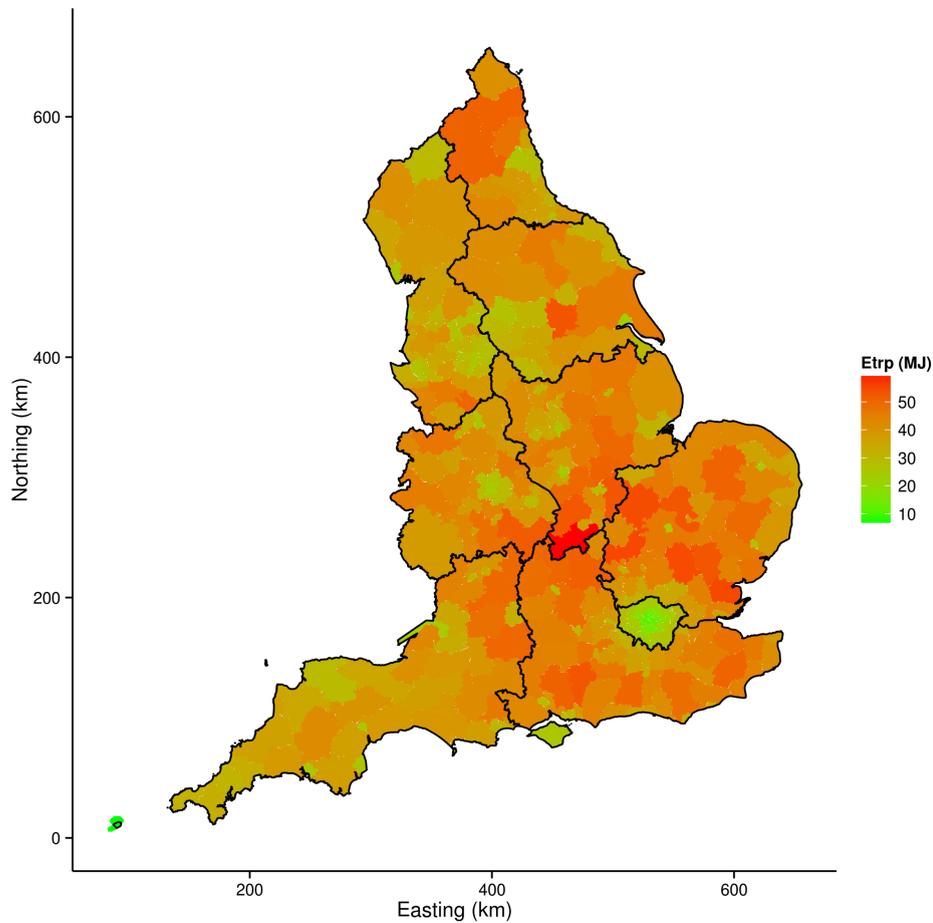


FIGURE 6.8: Average energy use per commuter trip at the district level.

subdivided. A policy-relevant example of this would be those areas in which short-distance car journey constitute a large proportion of the energy costs of work travel (these areas may benefit from improved walking and cycling infrastructure). Another example is the proportion of commuter trip energy use in each area used by trains. The result is interesting in itself, and provides confidence that the calculations are working correctly: it is clear from figure 6.10 that there is a tendency for areas located close to railways to be associated with a high proportion of per trip energy use to be composed of rail travel. Also as expected, areas with fast rail connections to London seem to have high energy use for this mode of travel.

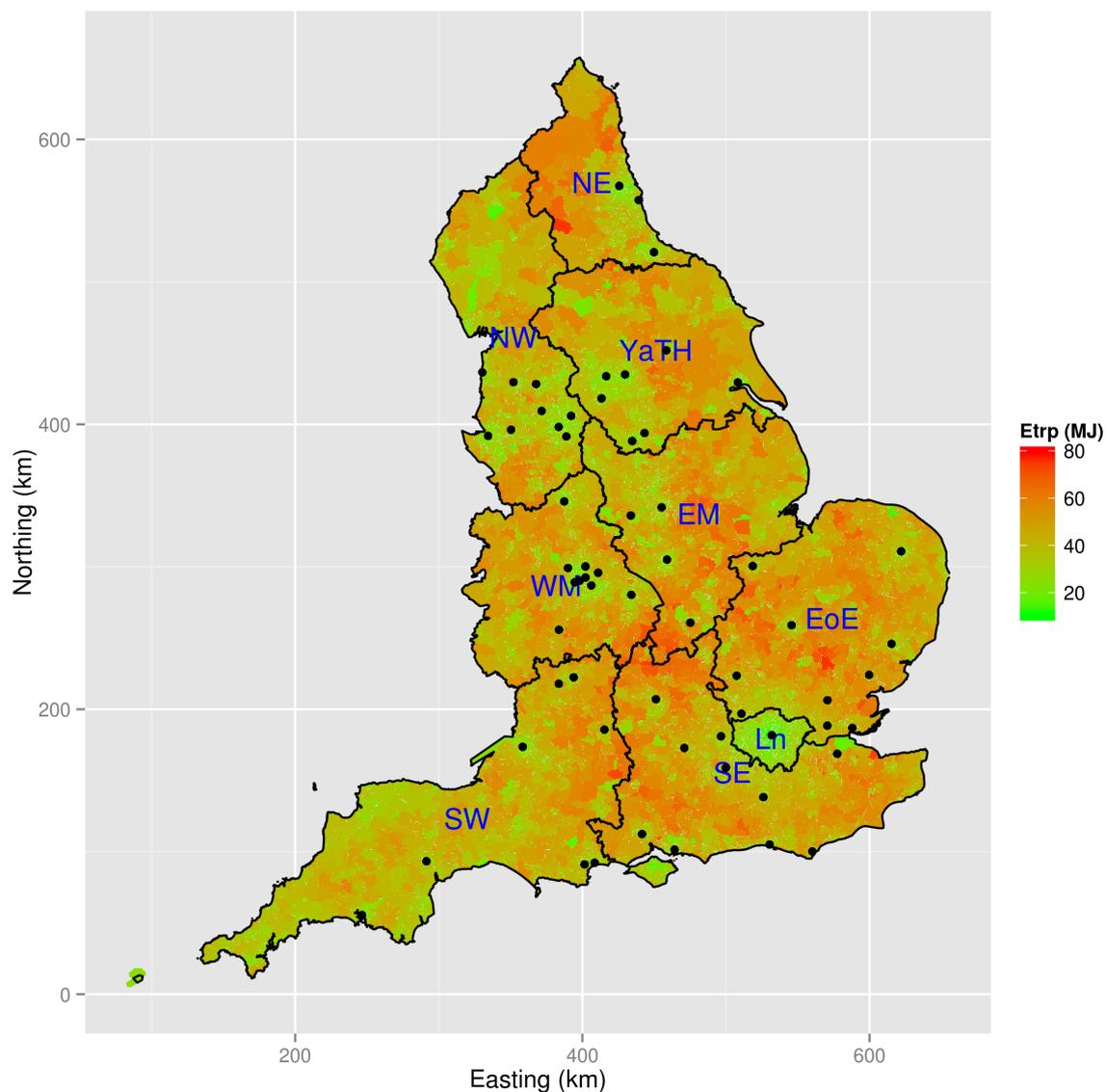


FIGURE 6.9: Average energy use per trip (Etrp, in MJ) in English wards. The black dots are large (100,000 people or more) cities (from Brownrigg (2013)).

6.3 Total commuting energy use and comparisons with other sectors

In chapter 5, reasons and methods for calculating commuter energy use on an annual level were laid out. In this section, total energy use for commuting is presented, based on the average frequency counts presented in table 5.7 and the assumption that people work on average for 44 weeks per year. As acknowledged in section 5.4.1, these are quite crude assumptions that could be updated if the true distribution of part and full time jobs in each area were known and using spatial microdata. However, geographical

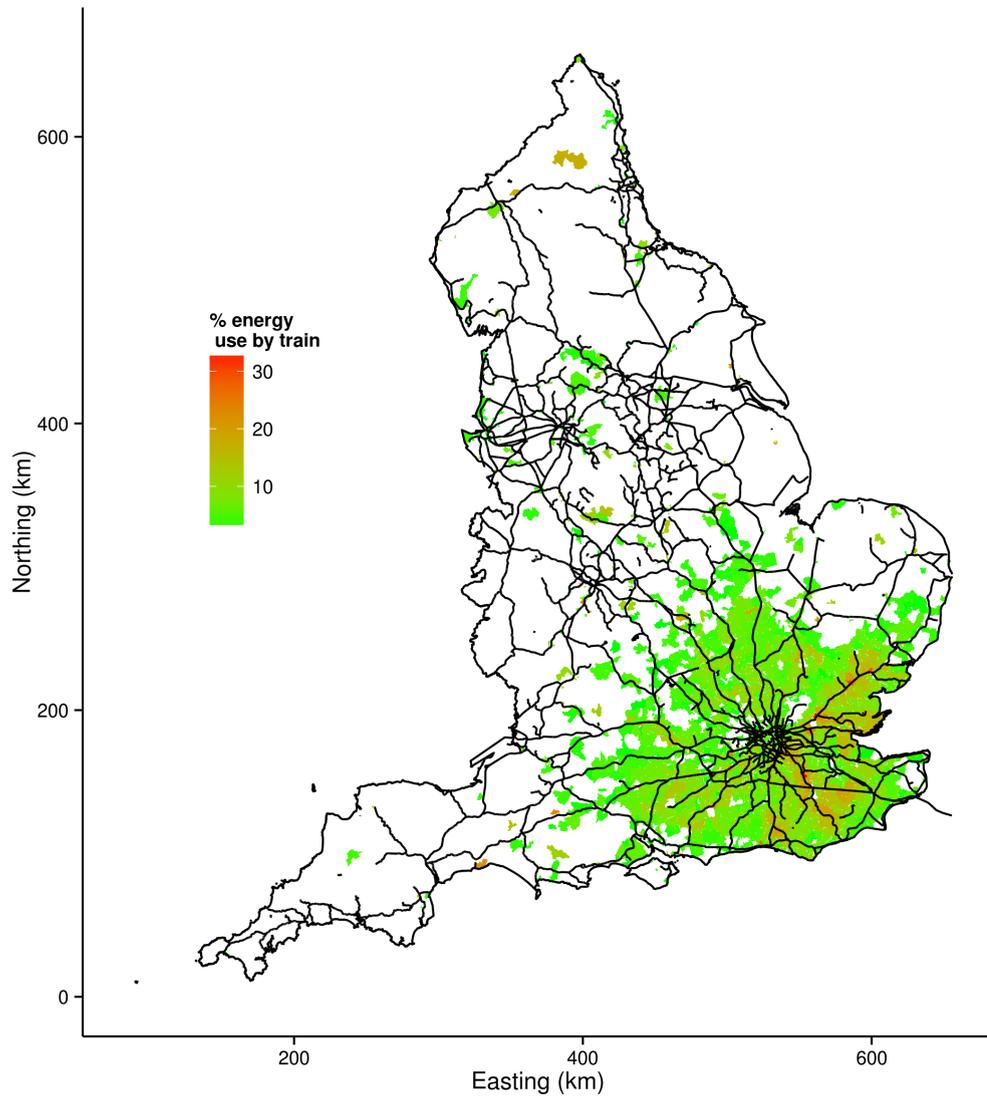


FIGURE 6.10: Proportion of energy use caused by train trips, plotted alongside the rail network (black lines). Only areas above the national average (3%) are plotted.

breakdowns of energy use from other sectors are provided only at coarse levels of aggregation, so using the spatial microsimulation approach in this case seemed unnecessary. Moreover, total energy use for commuting is something that would be useful to estimate at the national level, something which the spatial microsimulation methods described in chapter 4 cannot handle.⁴

Using the script file 'districten-yr', the total energy costs of commuting across all of England in 2001 was estimated to be 220 PJ, or 61 TWh. To put these large numbers into context, total electricity usage in the UK (not just England) is 400 TWh (Mackay,

⁴If small samples of the spatial microdata were used (e.g. a 1% sample), a spatial microsimulation model would be possible for the whole of England, although the loss of information from sampling may negate the benefits.

2009). Overall, this represented 4.1% of total energy in England from all sectors and 14.4% of total transport energy use, based on the DECC's 2003 NUTS level 4 estimates.⁵ As expected, commuting was found to be a large energy user.

Because commuter energy use scales with population, it was decided to represent total energy use not in absolute terms, but relative to total energy use, in each area. Figure 6.11 illustrates the spatial distribution of the proportion of energy use across England. It shows that although the average is just over 4%, in some areas it approaches 10%. Four areas were identified in which commuter energy use accounted for over 9% of total energy use: Castle Point (a wealthy area in South Essex),⁶ Maldon (another wealthy zone in Essex), Rushmore (East Hampshire) and Tamworth (an urban area on the Northern outskirts of Birmingham). Whether or not these areas can be classified as 'commuter belts' or if there are other reasons for their high energy use was not explored and remains an interesting question for future research. The only two Local Authorities in which commuting was found to account for less than 1% of total energy use were both in Central London. A similar picture is painted when the proportion of total transport energy use consumed by commuting is plotted (figure 6.12). It inspires confidence that when total transport energy use was plotted against commuter energy use, there was a strong positive correlation ($r = 0.75$). This correlation was slightly higher than when the simpler energy use per trip (Etrp) metric was used. This correlation increased slightly when compared with total road energy use. Surprisingly, the correlation was even greater between total commuting energy use and total energy use ($r = 0.82$). No explanation for this finding could be found.

It is also interesting to compare the energy use estimates presented in the previous section with official emission data, which have recently been released as 2005 estimates (the closest to 2001 available) at the Local Authority level.⁷ It was found that the total per trip costs were closely correlated to the official estimate of total transport energy ($r = 0.78$) and that emissions from minor roads were most closely correlated (table 6.2). It is interesting to note that the variable most highly correlated with per person energy commuter energy costs was transport emissions from motorways. This can be explained by considering that areas near to motorways tend to have longer commutes. There was

⁵This dataset is available from <https://www.gov.uk/government/statistical-data-sets/> and includes breakdowns of energy use by sector (industry & commercial, domestic and transport) and primary energy source (from coal to renewables). Because the national level commuting dataset I was using operated at the Local Authority level, while the DECC data was presented as NUT 4 zones, which are slightly different. Joining by zone name, 16 of the 354 Local Authorities were left blank, as shown in figure 6.11.

⁶Hints to its high commuter energy use, relative to its total can be found on its Wikipedia page: "Levels of home and car ownership in Hadleigh and Canvey are very high, social deprivation is relatively low." 'Commuters' are also identified as a major economic group in the area ([see wikipedia link embedded in pdf](#)).

⁷These datasets can be accessed from <https://www.gov.uk/government/publications>.

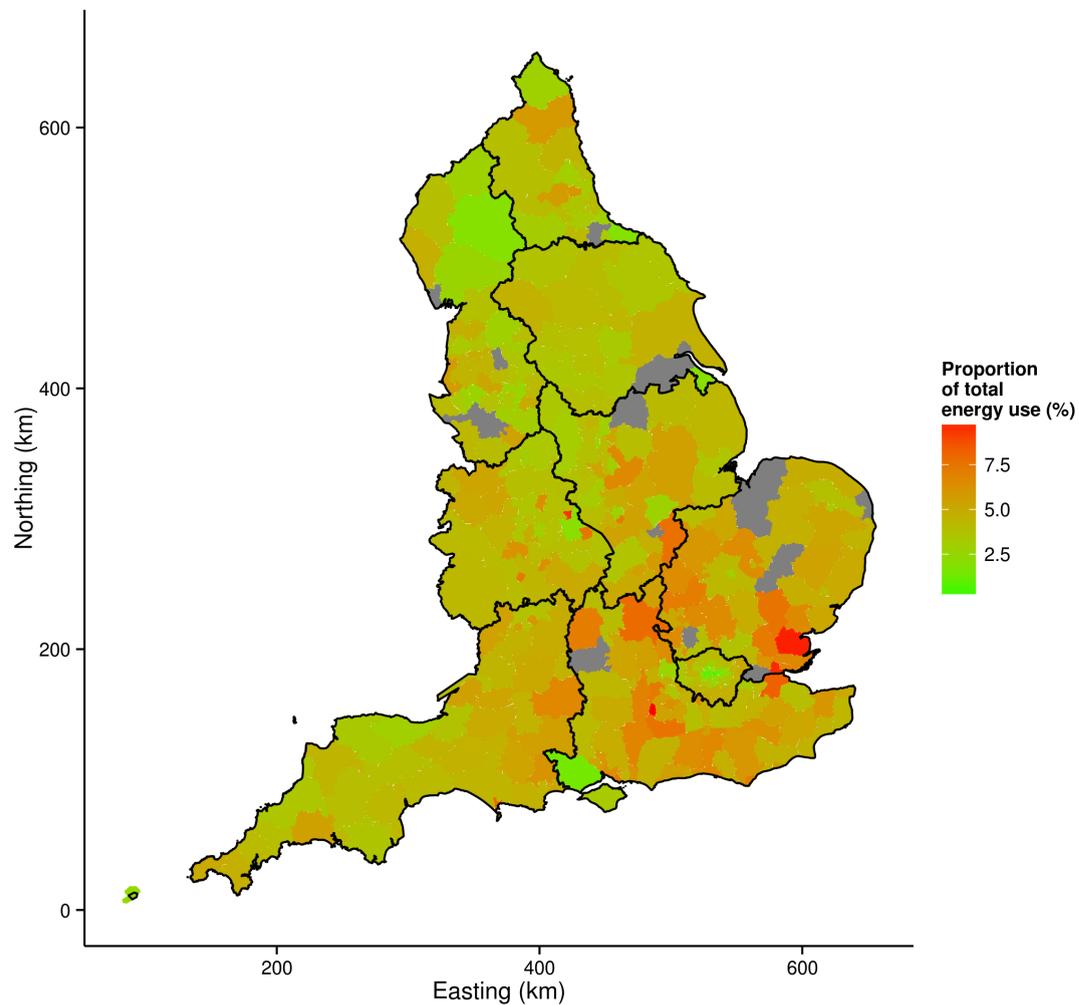


FIGURE 6.11: Proportion of total energy use in the UK consumed by commuting. Grey areas represent zones for which the DECC 'NUTS 4' level did not coincide with Local Authorities from the census.

also a fairly strong positive correlation ($r = 0.48$) between per capita commuter energy use and per capita transport use.

In the policy context, commuter energy use has been quantified at the national level and disaggregated by Local Authority. It appears to be closely correlated with official data on transport energy use and emissions. In the intuitive units recommended by Mackay (2009), commuting has been found to use, on average, 7.9 kWh/p/d for each commuter or 3.7 kWh/p/d for every man, woman and child living in England. In terms of the total energy use figures developed by David MacKay (which includes embodied energy and services such as defence), this equates to only 1.9% of per capita energy use. (The system boundaries in the DECC analysis are far narrower, accounting for the differences

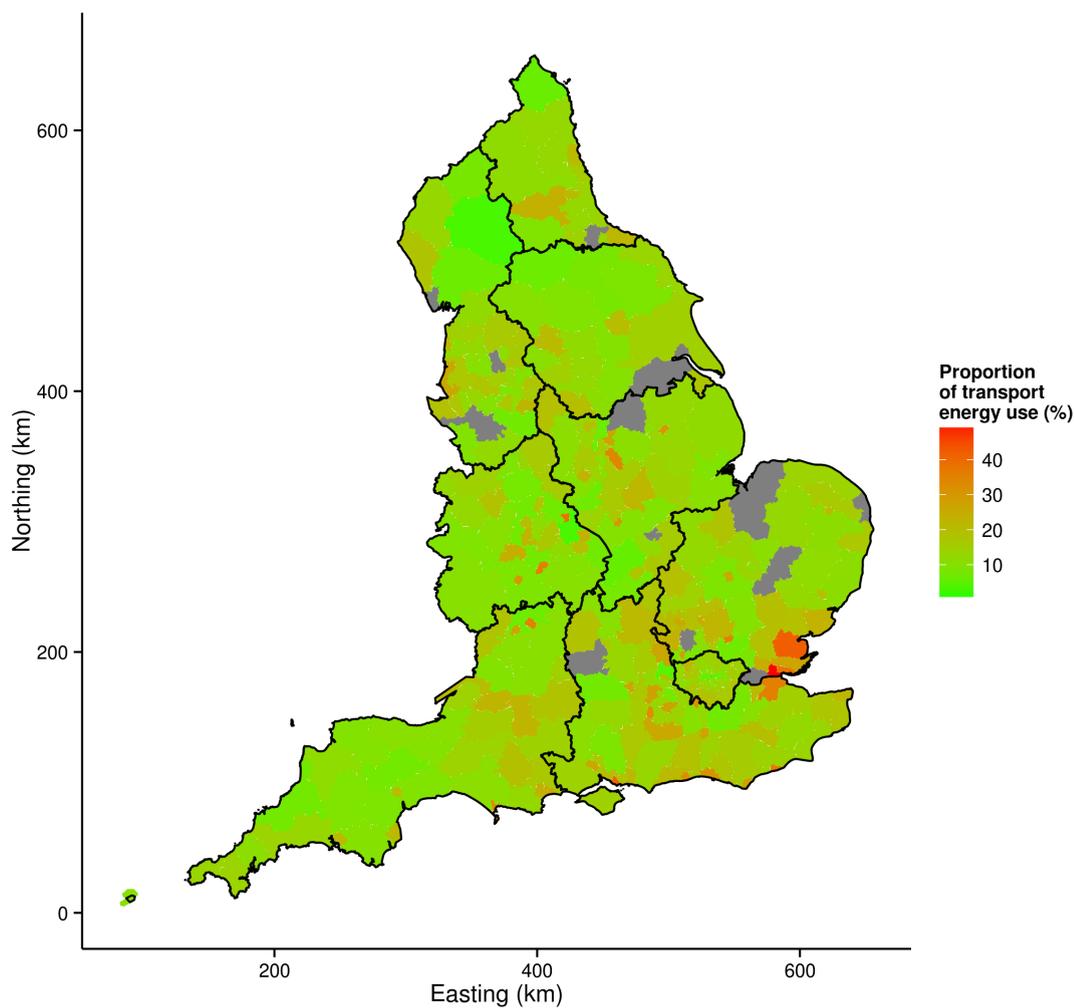


FIGURE 6.12: Proportion of transport energy use in the UK consumed by commuting.

TABLE 6.2: Correlation matrix of energy use for commuting and emissions at the Local Authority level in England. ET and EAV are total and per capita commuter energy costs, respectively.

	ET	EAV	A roads	M ways	Minor roads	Trans. Total
ET	1					
ETrp	0.06	1				
A roads	0.62	0.13	1			
M ways	0.36	0.25	0.16	1		
Minor roads	0.85	-0.08	0.55	0.25	1	
Trans. Total	0.78	0.18	0.71	0.74	0.74	1

between MacKay's figures and theirs.) Even without including the system level energy costs of commuting described in chapter 5, this is a large energy user for something that is so integral to a functioning society as getting to work. However, the aggregate level is limited, and masks the large differences that exist within statistical zones. For this reason, the next section investigates the variability of commuter energy costs at the individual level.

6.4 Local and individual level variability

As with any research in which geographical zones are the unit of analysis, the maps of energy use presented above mask individual level variability within zones. If interpreted incorrectly, conclusions resulting from such analyses may be 'ecological fallacies', where knowledge generated at one level of understanding is incorrectly applied to another. To provide an example, the strength of the correlation between wealth and the energy costs of work travel at the ward level is unlikely to be the same as the strength of the correlation at the level of individuals. The process of geographic aggregation smooths relationships, often making correlations seem greater and simpler than they really are (Openshaw, 1983).

Spatial microsimulation can also be used to generate estimates of geographically aggregated variables such as income, hence the use of the term 'small area estimation' used to describe some spatial microsimulation models (see chapter 3). Regarding the energy use of travel to work, spatial microsimulation can help overcome a major data constraint at some geographical levels: energy use is roughly a function of mode and distance of travel, yet in some cases no cross tabulations on this matter are provided. Even if average distances of travel to work are provided, it may be impossible to know which modes of travel are responsible for high values. When distance band and mode of travel are known but no cross-tabulations are provided between them (as is the case with Super Output Area administrative geographical levels from the data portal Casweb), spatial microsimulation can be used to 'fill in the gaps'.

A final potential issue with the ward level analysis of the entire nation, as presented above, is the assumption that relationships are constant over space. In many cases this assumption may be justified (e.g. for the relationship between population density and travel-to-work distance, which can be assumed to be more-or-less universal), but sometimes relationships vary substantially from place to place. This is a central motivation behind geographically weighted regression (Fotheringham et al., 2002).

6.4.1 A case study from South Yorkshire

To illustrate the results of the spatial microsimulation model in terms of energy use, a case study of South Yorkshire is used. This county case study is used rather than the entirety of England because processing time and memory demands were found to be problematic for larger areas.⁸ The reasons for selecting South Yorkshire over other counties included the clearly defined cities of Sheffield and Barnsley, as well as the region between Sheffield, Rotherham and Doncaster that may be described as the ‘South Yorkshire conurbation’ (Barker et al., 1978) — it has a diverse range of settlements from rural to urban and suburban. In addition, social inequalities are quite clearly inbuilt into South Yorkshire’s geography. One can see, for example, where traits associated with wealthy (to the west of Sheffield city centre, bordering the Peak District) and more deprived (in the South-East of Sheffield, for example) are located by visual inspection. The final reason is that the author is well-acquainted with this area of England, although a different case study region could equally have been used: the purpose is to show the kinds of result that the spatial microsimulation method can generate. For continuity, South Yorkshire is also used as a case study region in the subsequent chapters.

After running the spatial microsimulation model outlined in chapter 4, constraining by age/sex, mode, distance of commute and social class, an R object called a list is created. The list is a collection of data tables, one for each administrative zone; each contains a number of rows corresponding to the number of commuters in the area of interest. The results for the first six individual in the first MSOA area in South Yorkshire in the list (“Barnsley 001”) are displayed in table 6.3.

TABLE 6.3: Sample of the spatial microsimulation model output for South Yorkshire. The table was saved as a comma-delimited file with the command “`intall[[1]]`”, which refers to the data table corresponding to the first zone in Sheffield. In total, the R object “`intall`” contains 532,130 individuals from 176 MSOA zones.

	a_hidp	a_pno	pidp	sex	age	dis	mode	nssec8	urb	ncars
18	68041483	2	68041491	male	35	71	Car (d)	Other	rural	2
18	68041483	2	68041491	male	35	71	Car (d)	Other	rural	2
200	68303283	1	68303287	male	41	125	Car (d)	Other	urban	1
200	68303283	1	68303287	male	41	125	Car (d)	Other	urban	1
219	68323003	1	68323007	male	53	71	Car (d)	Other	urban	1
219	68323003	1	68323007	male	53	71	Car (d)	Other	urban	1

From the household and personal ids (a_hidp and a_pidp) can be joined a wide range of additional variables (table 6.4). Binding the information representing in table 6.3 for all

⁸The model was run for Yorkshire and the Humber, which contains just over 2 million commuters. Results were generated (as shown in section 8.4), but the time between IPF iterations, and the tendency of the computer to lock-up after all available RAM had been used — on a computer with 12 Gb — led to a smaller case study region being selected.

176 zones (using the command `do.call()`) results in a single table representing all five hundred thousand commuters in South Yorkshire. From here, energy use data can be produced for each individual, using the same technique described for the calculation of aggregate energy use. The additional refinement added at this individual level was the size of car: large cars were allocated a higher value (3.9 MJ/km) than small cars (2.5 MJ/km).⁹

TABLE 6.4: Sample of individual level microsimulation output. The number of cars in the individuals' household and the engine size of their primary car are extracted using the `merge()` function applied to the ID codes, that are also present in table 6.3

	a_hidp	a_pno	pidp	N. cars	Engine size	Et
18	68041483	2	68041491	2 Sheffield	medium engine - 1.4 - 1.9999	312.3
18	68041483	2	68041491	2	small engine - 1.0 - 1.3999	268.3
200	68303283	1	68303287	1	inapplicable	743.8
200	68303283	1	68303287	1	small engine - 1.0 - 1.3999	471.7
219	68323003	1	68323007	1	inapplicable	423.0
219	68323003	1	68323007	1	medium engine - 1.4 - 1.9999	312.3

The impact of car engine size on the relative average energy use of each zone was found to be very small and the correlation between values calculated that did not take car size into account and values that did was very high ($r = 0.9985$). The resulting spatial distribution of energy costs of commuting at the MSOA level is plotted in figure 6.13. This illustrates how spatial microsimulation can be used to create estimates of energy use at the aggregate level when cross-tabulated distance/mode datasets are unavailable. At the individual level, the standard deviation in per trip energy use is much greater than at the geographical level in this case study: 95 MJ between individuals compared with only 11 MJ between MSOA areas. This reflects the impact of geographical smoothing and also provides an indication of the high level of inequality in energy use for work travel between commuters living in the same area.

The individual level results are well-illustrated by plotting the proportion of energy use consumed by different groups. The example plotted in figure 6.14 represents the proportion of energy use for commuting consumed by the 20% most energy-intensive commuters, which is also a proxy for inequality. This plot shows a very clear spatial pattern, with city centres being associated with the most unequal distribution of commuter energy costs. We will return to this point in the subsequent chapter — for now suffice to say it is an interesting result. To illustrate the method's ability to disaggregate by socio-economic categories, figure 6.15 shows the ratio of energy used for commuting

⁹13.6% of responses to this question were “inapplicable” or some other ‘NA’ value, even amongst those who drove a car. In these cases the energy costs were set equal to those of a medium-sized car.

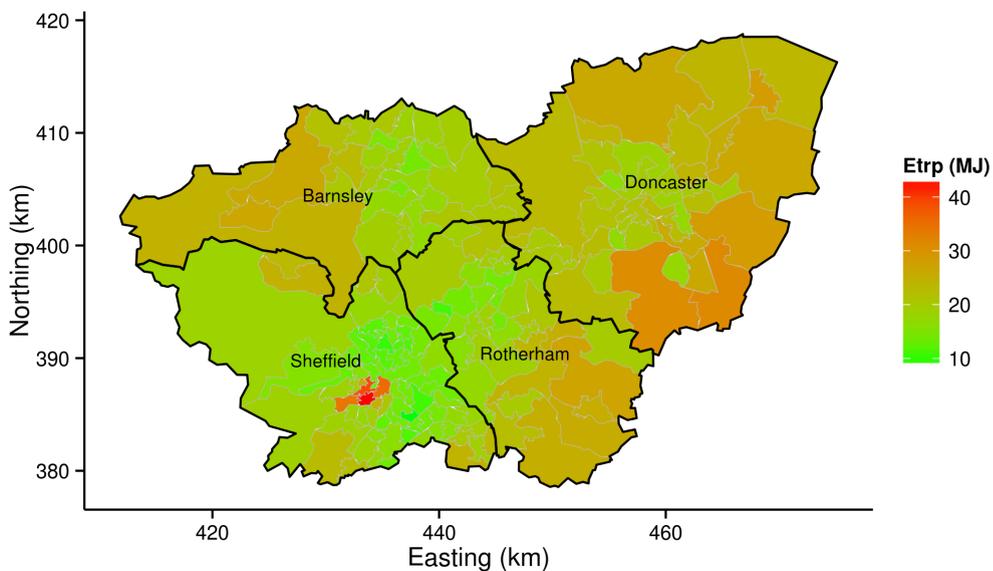


FIGURE 6.13: Energy use (direct and indirect) per commuter trip at the MSOA level in South Yorkshire.

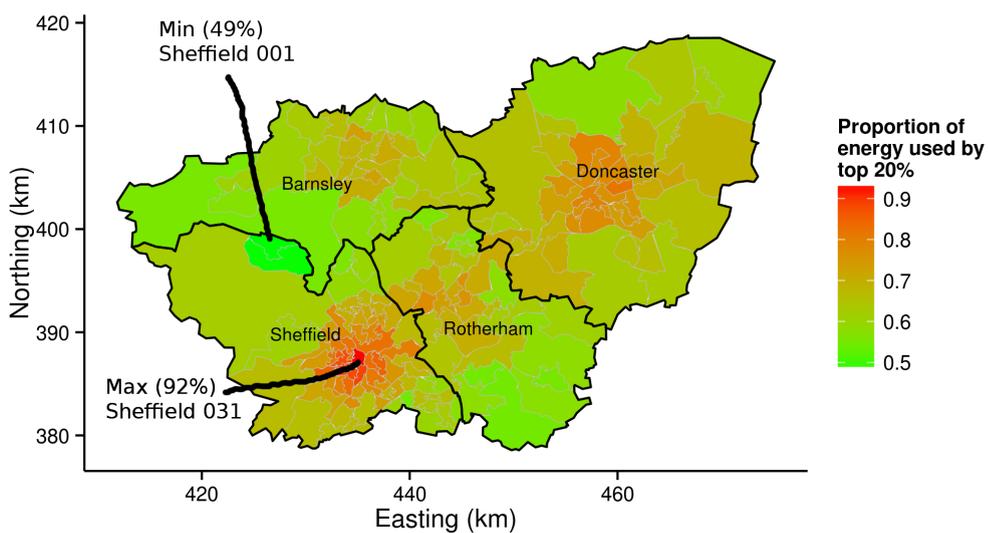


FIGURE 6.14: Proportion of energy used for commuting by the top 20% of commuters. Highest and lowest areas labelled for future reference.

by the top social classes (1.1 and 1.2) compared with the average energy cost per commute in each area. It is interesting to note that in all areas the value is above 1.4, reaching more than 3 times the average in some areas.

In fact, one can use the simulated spatial microdata to cross-tabulate any combination of variables within any area. This is illustrated in table 6.5, which shows the link between socio-economic class and commuter energy use for 3 geographical zones: South Yorkshire overall, as well as the same relationships in the most and least unequal areas, defined in figure 6.14. The results indicate that in the centre of Sheffield ('Sheffield 031'), the lowest classes tend to work closer to home, on average, than the averages for their class overall and that distance travelled is highly unequally distributed. In North Stocksbridge ('Sheffield 001'), by contrast, there is much less difference between different classes. It is also interesting to note that the average energy intensity of trips in the city centre is lower for all classes than in Stocksbridge. This can be explained by the proximity to tram and rail stations and the higher proportion of walking and cycling. We build on these insights in chapter 7 to further explore the inequalities in commuting and commuter energy use in the study region.

TABLE 6.5: Average commuter energy use (MJ/trip), distance (km) and energy intensity (MJ/km) in South Yorkshire (SOYO) by socio-economic class. The three areas are SOYO and the most and least unequal zones in terms of the distribution of individual energy use (see figure 6.14)

Area → Employment class	SOYO			Shef 031			Shef 001		
	Etrp	Dis	EI	Etrp	Dis	EI	Etrp	Dis	EI
large employers	111	27.5	4.1	141	39.6	3.6	119	28.4	4.2
higher professional	73	17.8	4.1	102	27.3	3.7	86	19.9	4.3
lower management	56	14.5	3.8	66	21.9	3.0	59	16.3	3.6
intermediate	29	8.1	3.6	17	7.5	2.3	47	12.1	3.9
lower supervisory	39	10.5	3.7	16	8.8	1.9	58	14.8	3.9
semi-routine	20	8.4	2.4	10	11.1	0.9	28	13.7	2.0
routine	26	8.1	3.2	9	5.8	1.6	42	12.7	3.3

More detailed analysis at the individual level is presented in chapter 7. The results presented in this section demonstrate that individual level variability in commuter energy use is important and in some cases potentially more so than inter-zone variation.

6.5 A comparison of commuter energy use in England and the Netherlands

In order to demonstrate that the methods can be used internationally, this section provides a short case study, comparing the energy costs of home-work travel in England

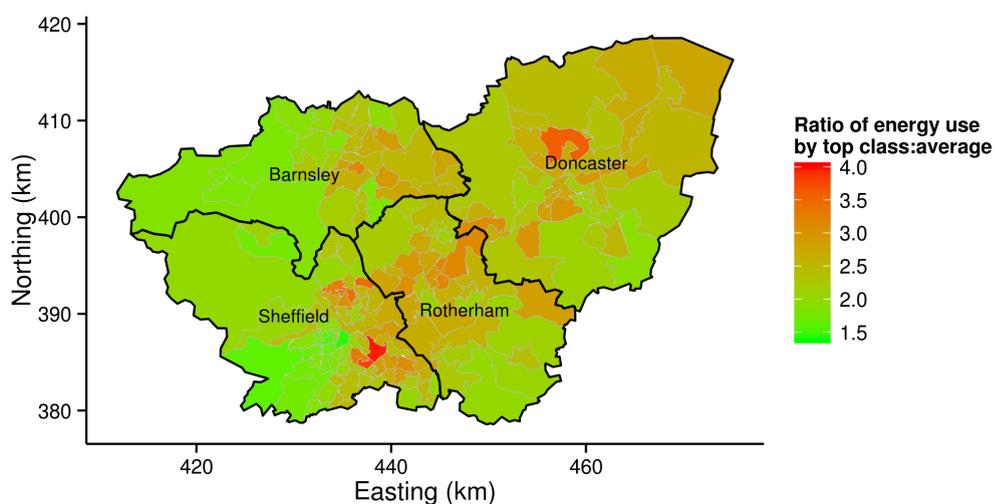


FIGURE 6.15: Relative energy use by top social classes in South Yorkshire.

and the Netherlands. These countries were chosen for the following reasons:

- Geographically aggregated data could be found for both.
- There are reasons to expect the Netherlands to have commuting energy costs substantially different from those in England. The working hypothesis we set out to test was that the Netherlands would have lower energy costs, primarily due to the high uptake of cycling, for which the nation is famous.
- The countries are similar ‘on paper’, in terms of population density, GDP per capita and culture.

The final point is illustrated in table 6.6, which shows the extent to which England and the Netherlands are similar according to a handful of basic measures. One major difference between the two countries is in terms of income inequality, with England being substantially more unequal. If only table 6.6 were considered, one would assume that the energy costs of commuting would be roughly the same in the two countries. However, a couple of factors led to the hypothesis that commuting in the Netherlands would be less energy-intensive: its relative size (42,000 km² vs 130,000 km² for England) and its famously high rate of cycling, which account for 27% of trips nationwide and above 50% of trips in some cities (Pucher and Buehler, 2008).

TABLE 6.6: Comparison of basic national attributes in England and the Netherlands

Attribute	England	Netherlands	Units
Population density	407	406	ppl/km ²
GDP	50000	46000	\$/capita
Income inequality	34 (UK)	31	Gini Index
Wellbeing	0.875 (UK)	0.921	UN HDI

6.5.1 Data, method and results

The input dataset for the Netherlands came in a different form from that of England. The English data, downloaded from the Census, provided 88 key columns from which energy values were generated: 8 distance bins for 11 modes of transport. Based on average route distances estimated for each of the 8 Euclidean distance bins for the 8 modes whose energy costs are described in section 5.7, the energy costs per one-way trip were calculated for each cell in all of the 88 columns. The values in each of the cells of the English data are people counts, constraining the number of people in each distance/mode category. The Dutch dataset, on the other hand, provided proportions, average distances and average times for 8 modes of transport in a wide format (table 6.7). The first challenge upon receiving this dataset was to understand the table’s structure and translate the column headings into English. Another issue was finding geographical data for Dutch provinces and their populations (this allowed for the energy costs per province to be weighted, to provide an accurate estimate of average energy costs per commuter trips nationwide). This data was provided by the open-data initiative Natural Earth.¹⁰

Finally, the commuting dataset was matched to the geographical shapefile data in R.¹¹ Despite these data preparation issues, the Dutch dataset was in fact easier to convert into average energy costs per trip than the UK data, as it was simply the product of mode efficiency (Ef), average route distance (dR) and modal split (p) for each mode:

$$Etrp = \sum_m p_m \times Ef_m \times \bar{dR}_m \quad (6.3)$$

¹⁰<http://www.naturalearthdata.com/>

¹¹Initially this stage was problematic, as was discovered when the regions were plotted with their name codes highlighted: the names were not associated with the correct geographical areas. The R code used was reviewed at each stage and it was discovered that the error was introduced through the “merge()” function, which allocated the tabular data to the geographical data by matching the zone codes. It was found that the default (silent) default argument of “merge()” is “sort=TRUE”. This meant that the function was re-ordering the geographical data alphabetically. Adding “sort=F” into the command solved the problem.

TABLE 6.7: Sample of the first 4 columns of the raw Dutch commuting data. A further 54 columns on the proportions travelling by and average time and distances of trips by 9 modes of transport are not shown.

Perioden	2010	2010	2010
Vervoerwijzen	Totaal	Auto (bestuurder)	Auto (passagier)
Regio's	aantal	aantal	aantal
Nederland	0.48	0.25	0.03
Groningen (PV)	0.44	0.22	0.03
Friesland (PV)	0.45	0.24	0.02
Drenthe (PV)	0.46	0.29	0.03
Overijssel (PV)	0.48	0.26	0.03
Flevoland (PV)	0.51	0.28	0.04
Gelderland (PV)	0.47	0.26	0.03
Utrecht (PV)	0.5	0.23	0.03
Noord-Holland (PV)	0.48	0.22	0.03
Zuid-Holland (PV)	0.49	0.23	0.03
Zeeland (PV)	0.47	0.27	0.03
Noord-Brabant (PV)	0.47	0.28	0.04
Limburg (PV)	0.46	0.28	0.03

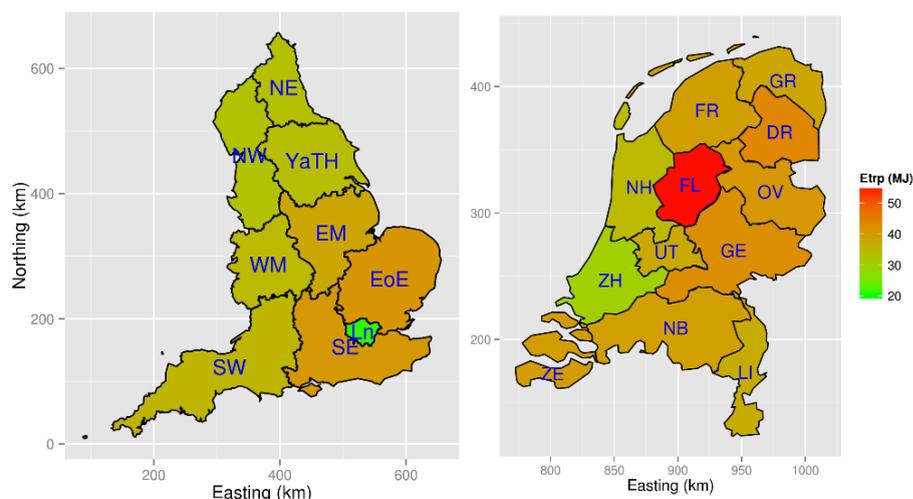


FIGURE 6.16: Comparison of commuter energy use in England and the Netherlands.

This formula was applied to Dutch regional data, and aggregate energy costs were calculated for England using the method described in section 6.1. The results, illustrated in figure 6.16, came as a surprise: energy use for commuting is *higher* in the Netherlands, which is relatively small, bicycle-friendly and has a low GDP, than in England. The difference is not as great as that represented in figure 6.16 (a 14% difference, when energy use per trip is averaged across all zones), because the zones are not of equal population or size. When commuter energy costs are weighted by population, the overall average energy cost per commuter trip is still higher in the Netherlands, but less so — 8%: 37.5 MJ/trip in the Netherlands against 34.5 MJ/trip in England.

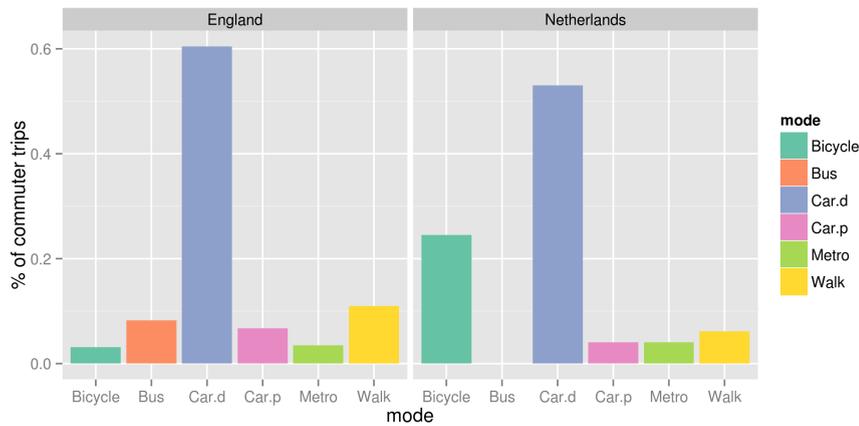


FIGURE 6.17: Modal split of commuter trips in England and the Netherlands.

6.5.2 Explaining Dutch commuter energy use

To explore this non-intuitive result, the first stage was to look at the modal split of commuting in England and the Netherlands (figure 6.17). As expected, Dutch commuters are far more likely to travel to work by bicycle. However, they are also less likely to travel to work by walking, as a car passenger or by metro (due primarily to the London Underground) — all low-energy modes — than UK commuters. The proportion of people travelling by car, the most energy-intensive personal travel mode, is only slightly lower in the Netherlands (57%) than in England (60%) despite the 27% of trips made by bicycle. Modal split cannot account for unexpectedly high Dutch commuter energy costs.

The next variable explored was distance. The average Dutch commute for the major forms of transport is 1 km further than the English average at 15.5 km, from the data. This may seem like a small amount, yet it is almost 7% further, accounting for most of the variability in energy use. When we break this figure down by mode, as in figure 6.18, it becomes clear that car trips are the reason for the increased distance of travel to work in the Netherlands: all other modes are associated with shorter trip distances, whereas the average commuter trip by car, the most energy intensive transport mode, is 30% further than in England (24.6 km in the Netherlands, compared with 18.7 km). It therefore seems that the prevalence of one particular trip type — long car trips — explains why commuter energy use in the Netherlands is greater, per person, than in the UK.

To explore the underlying reason for these high-distance car commutes, the length of motorway in each country was found. In the Netherlands there are 2631 km of motorways whereas in the England there are 3673 (Eurostat, 2013, via the UK Data Service). These values equate to roughly 150 km of motorway per million people in the Netherlands,

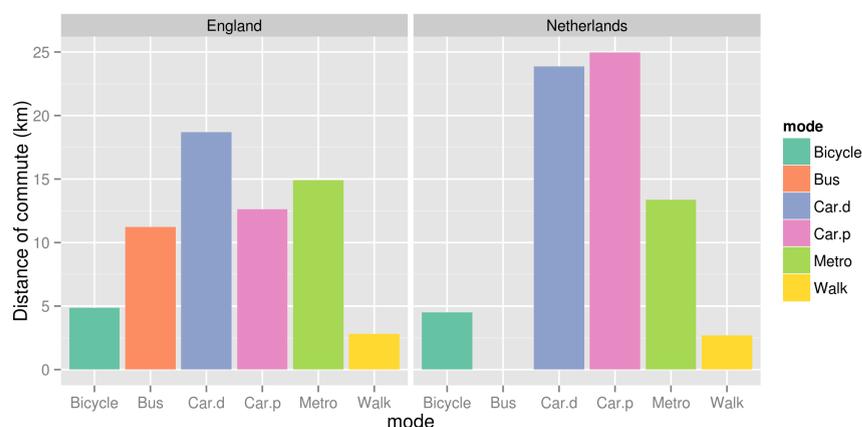


FIGURE 6.18: Average distance of commuter trip by mode in England and the Netherlands.

compared with only 70 km per million in England, less than half. Despite this advanced road network, and the bicycle infrastructure for which Holland is famous, road congestion is a known problem (OECD, 2010). The average time for commutes in the Netherlands is longer than for any other nation in the Organisation for Economic Cooperation and Development, something that has been attributed to high population density and a rigid housing market: “more than just transport policies are required to solve these problems” (OECD, 2010, p. 8).

Regarding the spatial distribution of energy-intensive commuting, there is no clear pattern at this coarse level of geographical aggregation. A pattern does emerge when energy use is plotted against population density (figure 6.19), which shows a strong negative correlation ($r = -0.7$, $p < 0.001$) between the two variables. The two clear outliers in terms of energy use are London (20.8 MJ/trip) and Flevoland (54.8 MJ/trip), which are also on opposite ends of the population density scale. Figure 6.19 is also useful as it shows there is a large amount of overlap in commuter energy between the two countries, even at this high level of geographical aggregation. Three English regions (the South East, East of England and the East Midlands) have average commuter energy costs above the Dutch national average; interestingly each of these zones is quite wealthy, with strong links to London (implying commuting to London may be a cause of high energy use here). The only Dutch province with average commuter energy costs below the English average is Zuid (meaning South) Holland. This area has a very high population density and includes large cities including the Hague and Rotterdam.

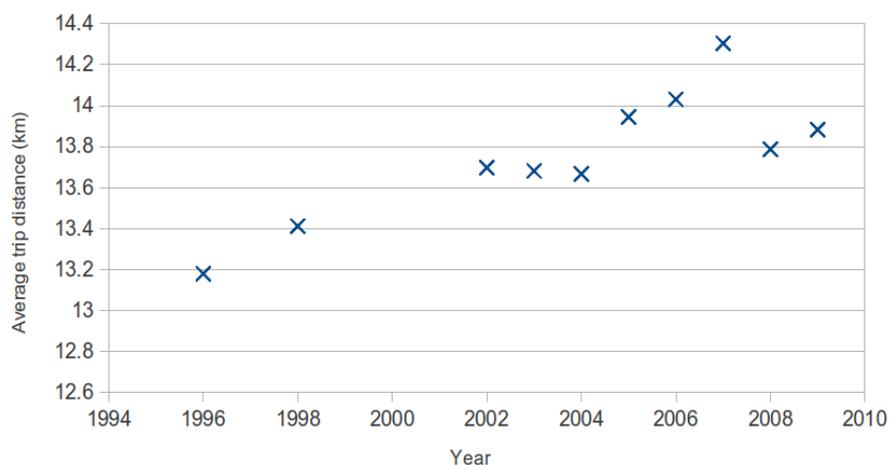


FIGURE 6.20: Average commuter trip distance over time in Great Britain. Data from DfT (2011a, table 9), $n > 15,000$ for every year.

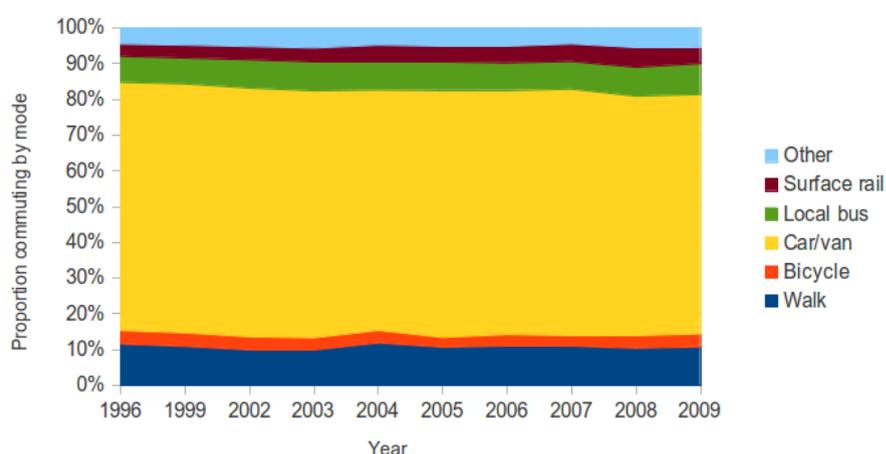


FIGURE 6.21: Modal split of commuter trips, Great Britain 1995 - 2009. Data from DfT (2011a, table 9), $n > 15,000$ for every year.

is possible. Further, average distances were not provided for all modes of transport in all areas, in which case the mode's average figure for the areas that were reported were used to fill in the gap. Finally, the figures for the proportion of people travelling by train seemed very low, given that the Netherlands has an advanced rail network. As outlined in chapter 4, there are also issues with the UK dataset. The translation of Euclidean distance categories into average route distances is a particularly risky activity and may introduce error in excess of the difference between Dutch and English average commuter trip energy costs reported above.

In light of these caveats, it is concluded that a more robust dataset from the Netherlands is needed to resolve the enigma of high Dutch commuter energy use. The basic method used to calculate energy costs has been shown to be applicable to another country, although more refinements (e.g. alterations in the average energy intensity of Dutch

cars) will be needed if this result is to be seen as robust. If it holds up to further investigation, it is an interesting and policy relevant result: it would illustrate that promotion of urban cycling alone is not enough to reduce the overall energy costs of personal transport nationwide.

6.6 Discussion

In this chapter the methods and data presented in chapter 4 have been combined with the estimates of energy use by mode presented in chapter 5 to calculate the energy costs of commuting at a range of scales. The main unit of measurement used to present these results is energy use per one-way commuter trip. This is a useful measure, as it is robust to variations in the employment rate and makes no assumptions about frequency of trip. If the aim is to compare commuting with other energy-using activities, however, the results would be more usefully presented as energy costs per person per day. This approach was undertaken by Boussauw and Witlox (2009), which would allow direct comparisons between commuter energy use and other ‘essential’ energy costs such as electricity and gas use in the house and (depending on data availability), other travel costs.

Despite these limitations, the findings are still useful in their own right. From inspection of the district and ward level maps, it is clear that dense urban areas tend to have lower average commuting costs than the countryside. London is the extreme manifestation of this tendency, and has achieved commuting energy costs below the national average throughout most of its wards. However, many of the areas within roughly 100 km but outside Greater London have unusually high average energy costs per commute. This is likely to be due to long-distance commuters and ‘commuter belts’ which serve London’s vast service sector. It is concluded from this pattern that citywide personal transport costs should not be evaluated only in terms of the internal flows within them: flows from the surrounding areas should also be considered.

The results presented in this chapter provide much scope for further research. The pattern of London as a centre of relative commuting sustainability surrounded by a ring of high energy costs, for example, raises the following question: are cities, overall, associated with lower commuting energy costs than rural settlements, once long-distance commuting has been taken into account? This question feeds into the ongoing debate about compact cities and urban forms that are conducive to reduced energy use (Levinson, 2012). Moreover, the descriptive results require explanation. Is there a model that can successfully explain the variability in energy use observed, based solely on population distribution and infrastructure? If so, this would have implications for planning

policy, as the energy impacts of new settlements (e.g. housing estates) and transport infrastructure could be predicted.

This potential for policy relevance leads on to the tentative finding that Dutch commuter trips are, on average, more energy intensive than English ones. This, if it was confirmed, would strongly suggest that simply trying to emulate the Netherlands in terms of rates of urban cycling would not guarantee environmental and other benefits of lowered energy use. The finding supports the conclusion of Boussauw and Witlox (2009), that interventions aiming to reduce the distance between home and work may be more effective than those aimed at changing modal split.

Before exploring some of these broad policy-relevant questions in chapter 8, the next chapter zooms-in, to a single case-study area. This is to illustrate the ability of the spatial microsimulation approach to explore local commuting patterns and evaluate specific transport interventions.

Chapter 7

Social and spatial inequalities in commuter energy use

There are many options open for manipulation of the transportation system, and many impacts on different groups which must be considered. Prediction of the impacts associated with a particular set of options requires prediction of the corresponding pattern of flows which will occur in the multimodal transportation network, using a complex system of models.

(Manheim et al., 1968)

7.1 The importance of distributional impacts in transport studies

At the sub-national level, the relative costs and benefits of climate change-related policies are highly uneven. It has been calculated, for example that the bottom 10% of households by income will benefit least from the government's domestic energy policies such as those contained in the Green Deal (Preston et al., 2013). This, the authors point out, is unfair on three levels: poor people are least able to deal with the impacts of climate change; they pay proportionally more for the mitigation strategies; yet they have contributed least to the problem: the top 10% emit 3 times more emissions than the bottom 10%, excluding indirect emissions caused by the products and services they consume.

At the aggregate level, literature shows that behaviour varies depending on a range of factors including distance to employment centres, transport infrastructure and the

number of local employment opportunities. Social characteristics are also closely linked with commuting behaviour, as illustrated by DfT data on the average distance travelled to work by mode, cross tabulated by household income (figure 7.1). Transport modelling, and especially the related discipline of transport engineering, have tended to be ‘hard’ subjects, focussed only on the technological performance of transport interventions. However, as implied by the quote that begins this chapter, *all* transport interventions will have some kind of distributional impacts, either favouring certain places more than others or certain groups of people.

The dangers of omitting such social considerations from the analysis were recognised early in the history of transport and urban modelling. In fact, ignorance of distributional impacts was implicated as one of the reasons for the perceived failure of the first generation of urban models in the 1960s: “disillusionment with technology began to grow as planners and politicians began to realise that long-term planning of transportation and land use [which the models focussed on] had little or nothing to do with more immediate problems of poverty and inequality” (Batty, 1976, p 10). This problem continues today (see Tribby and Zandbergen, 2012 for one example), providing a strong remit for this chapter and its focus on including social factors in the evaluation of travel patterns and future interventions. Before moving on to the core results of this chapter — a case study of inequalities in commuting patterns and energy used in South Yorkshire — it is worth considering a few national statistics on the relationship between socio-economic variables and transport to work, for context.

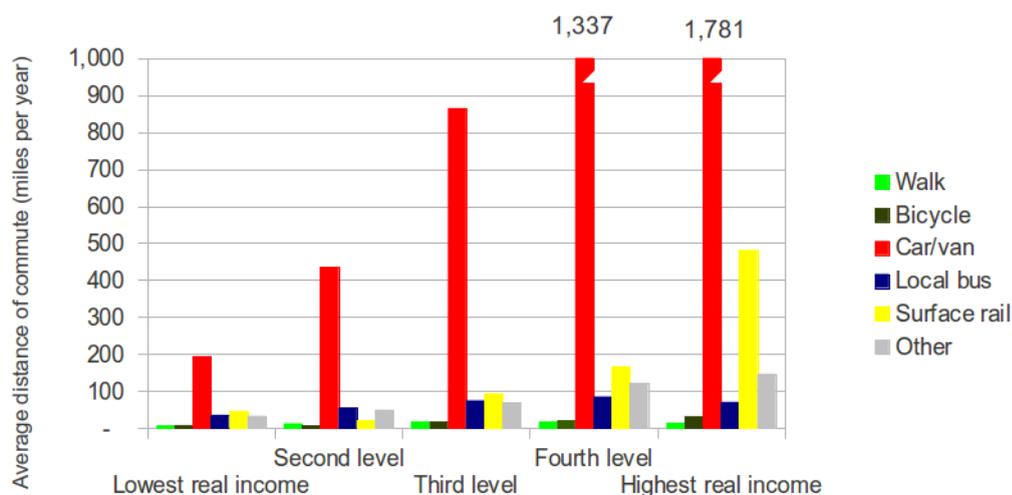


FIGURE 7.1: Average distance of commute by mode by income quintiles in Great Britain in 2009. Data: (DfT, 2011a, Table 6).

Figure 7.1 illustrates that social inequalities are manifested not only in income and material goods but also in terms of the daily trip to work. Workers in the top 20% of households by income commuted on average 8 times further during 2009 than those from the bottom 20%. From one income quintile to the next, average distance almost doubles in every case, with the difference slowing only slightly towards the top quintiles.¹ It is notable from figure 7.1 that wealthier people also tend to use more energy-intensive modes. However, the variability in mode of transport is far lower than the variability in distance (figure 7.2).

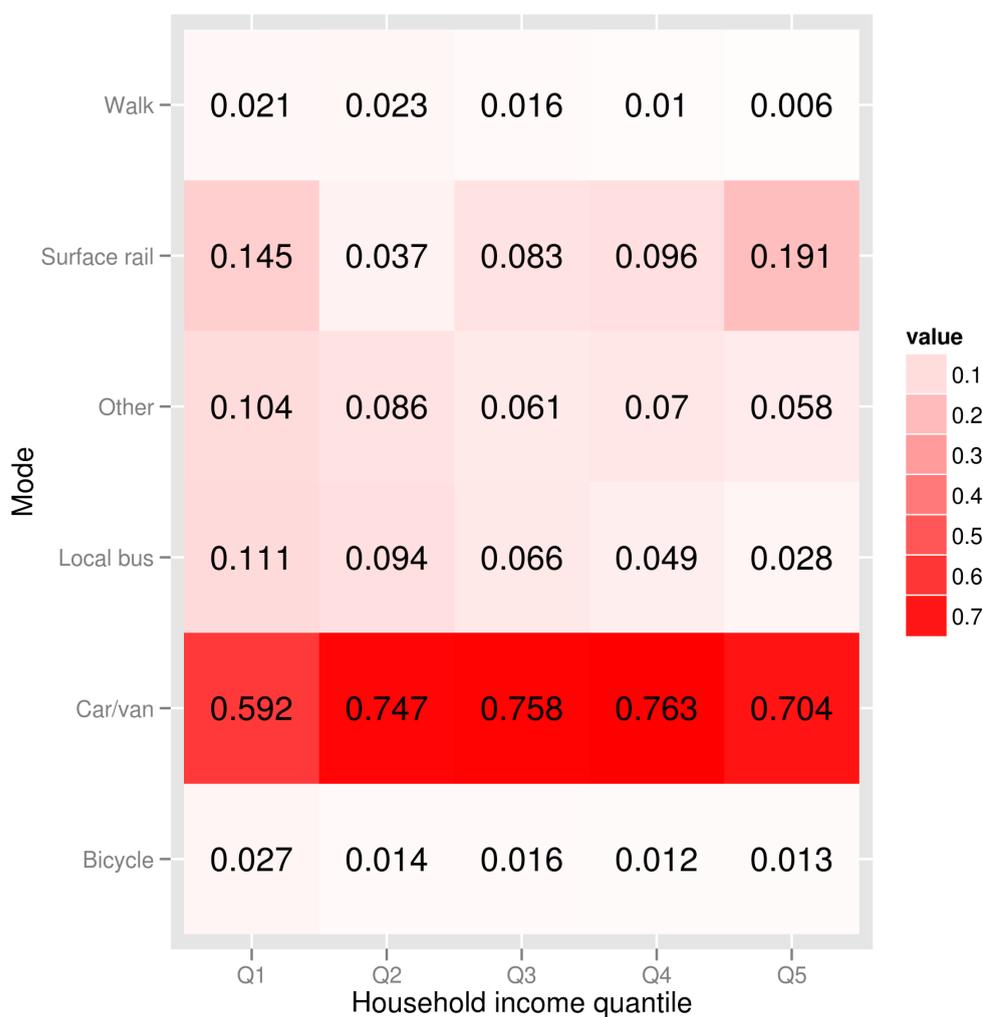


FIGURE 7.2: Proportions of trips made by mode of transport in Great Britain, 2009. Data: (DfT, 2011a, Table 6).

These overall findings provide a strong message to policy makers: policies encouraging behavioural change may be most effective if they target particular groups of commuters. This differs from blanket policies such as efficiency-related tax bands which inherently

¹Distance travelled to work increased by a factor of 1.8, 2.0, 1.5 and 1.4 between Q1 and Q2 in the first instance to Q4 and Q5 in the last.

assume commuter patterns are homogeneous. At sub-national level, such variability depending on socio-economic status should also be taken into account by local planners. However, in many cases, the data or analysis capabilities are not available to target particular groups living in particular areas.

With these motivations, the present chapter builds on the kind of breakdowns in commuter behaviour by socio-economic variables illustrated in figure 7.1, but at lower levels. This is where the simulated individuals provided by spatial microsimulation really come into their own, as aggregate data tell us little about the socio-economic attributes of the individuals that make up aggregate commuter patterns.

The following presents results which tackle these issues. Because the spatial microsimulation model assigns characteristics to every single working person in the study area, the analysis becomes unwieldy when applied to very large areas. (The IPF model took 30 minutes per iteration when applied to the 2 million commuters of Yorkshire and the Humber on an Intel i5 ‘Sandy Bridge’ computer with 12 Gb RAM). Age/sex, mode, distance and social class categories were used as the constraints, from which a wide range of simulated results were generated.

As noted in chapters 1 and 2, commuting is a major reason for personal travel, and a broad research area within transport geography. In many cases zonally aggregated census statistics — often the most reliable source of information about spatial variation in commuter patterns — form the basis of geographical commuting research (Horner and Murray, 2002; Titheridge and Hall, 2006). Advances in data availability and computational methods have facilitated the analysis at the individual level, as outlined in chapter 4. This trend — towards micro level social and spatial analysis — has several potential benefits for decision makers. It is the aim of this section to highlight these benefits and provide useful insights into the link between socio-economic attributes and commuter behaviour. The case study region of South Yorkshire is the same as that used in chapter 6, for continuity. The results showcase the potential benefits of spatial microsimulation:

- the ability to target specific *types* of commuters
- the possibility of modelling the impacts of small scale interventions (e.g. a new bicycle path or bus lane) on individuals living in the local area
- higher spatial resolution than is provided by aggregate data for certain cross-tabulated variables (e.g. mode and distance). This could provide insight into the impacts of change on network usage (e.g. identify likely points of congestion)
- a foundation for agent-based and dynamic microsimulation models.

The shift towards micro level analysis also has some potential disadvantages. These limitations, and strategies to overcome them, can be summarised as follows:

- The individual level results are simulated, and are unlikely to be totally representative of the zones in question. We can have confidence in the constrained variables (although large bin sizes for continuous attributes such as age may not fully capture unusual distributions),² but the target variables are simply the result of their relationship with constraint variables at the national level. This can be tackled through validation methods (see Edwards and Clarke, 2009, and below) or, in the long run, through increased access to real spatially disaggregated microdata.³ In fact, awareness of the policy insights offered to researchers by spatial microdata could encourage the release of real geographically disaggregated microdata (see (Lee, 2009)).
- Lack of accurate distance travelled estimates in the main model (currently broad distance categories are used). This could be overcome by creating more accurate origin-destination pairs for individuals. Lower level commuter flow data (compared with the data presented in Fig. 7.5) is available to do this.⁴ Also, undertaking network analysis of roads, railways, and walkways (see Fig. 7.6 for an example) for all individuals could allow more accurate estimates of route distance. However, this is computationally challenging, although increasing feasible (Gao et al., 2010).
- Omission of explanatory variables such as car parks, the quality of paths, and even the provision of showers for cyclists at work destinations. These variables can be included by appropriate survey questions (Buehler, 2012) or analysis of environmental variables (Rietveld, 2004).

Each issue presents a major methodological challenge, but none of them invalidates spatial microsimulation as a modelling tool to better understand travel behaviour. These issues are partly tackled in Section 7.4 and their implications discussed in the final section of this case study.

²The distance bins presented in Table 7.1, for example, are quite widely spaced. In a situation where many people travelled a distance close to the edges of one of these bins — for example due to a factory located 11 km from an employment centre — the results, which would represent an even distribution of all individuals in the sample who 10 to 20 km to work, would be inaccurate.

³For example, a dataset of geo-coded individuals and their workplaces provided by Finnish government allows destination/origin analysis and insights into the directions of flow (Helminen and Ristimäki, 2007)

⁴Commuter flow datasets of the type presented in Fig. 7.5 are available at the much smaller Output Area level (from the Office of National Statistics). However, the data are available only on a DVD, with the following proviso: “analysis [of the Output Area commuter flow data] requires the use of specialist software, which is not supplied with the product, but which is available from intermediary organisations (for more information contact Census Customer Services).”

These include greatly increased computational requirements for analysis, lack of available software or expertise, and the pitfalls of overcomplexity. As chapter 3 shows, new techniques for spatial microsimulation, which model individual characteristics and behaviour, can overcome the majority of these problems. A more fundamental barrier preventing the use of micro level methods in many contexts is that accurate, geocoded microdata are simply unavailable. In the UK, for example, census-derived microdata are made available only as a Sample of Anonymised Records (SARs) at coarse geographical levels (Dale and Teague, 2002).⁵ More specific surveys (such as the UK's National Travel Survey) can provide further insight into travel patterns at the individual level but these also omit high resolution geographical information to protect participants' anonymity.

The more practical aim of this section is to bring micro level analysis within reach for transport planners and researchers already acquainted with aggregated census data on commuting. Detailed non-geographical microdatasets on commuting already exist, but many analyses for evaluating the impact of commuting policies require *spatial* microdata. As indicated above, there are a number of reasons why such spatial microdata may be needed: planning for more sustainable commuting is a complex problem that operates on a range of scales, including that of individuals (Vega, 2012; Verhetsel and Vanelslander, 2010). In the words of Li et al. (2012, p. 313), “a more spatially disaggregated method is needed”. To summarise the research problem, tools to aid the design and evaluation of policies affecting commuters are needed. These tools should be flexible, able to operate at a range of levels and shed light on various issues, from the potential of telecommuting (where internet access facilitates working from home, saving transport fuel) to levels of access to public transport, walkways and cycle paths.

7.2 Model implementation

The method requires both aggregate and individual level datasets described in chapter 4 to share at least one ‘linking variable’. These linking (or constraint) variables, described in Table 7.1, preferentially sampled representative individuals, in this case via IPF, which was introduced in chapter 3. The target variables (Table 4.3) are thus simulated.

The mathematics (Fienberg, 1970) and code (Lovelace and Ballas, 2013, Supplementary Information) used to implement IPF are described in detail in chapter 4. To ensure the model is working, the simulated micro-data are aggregated and then compared with census data. Total absolute error (TAE), a simple and effective goodness-of-fit metric

⁵The SARs are divided into two parts: the 2% SAR, which allocates each individual to a geographic region with a population size of at least 120,000 (narrowing-down the results to one or more Local Authorities), and the 1% sample, which allocates each individual to countries (Dale and Teague, 2002).

TABLE 7.1: The four constraint variables and their associated categories used as the aggregate level inputs into the spatial microsimulation model. The category notation for numeric variables follows the International Organization for Standardization (ISO) 80000-2:2009: Square brackets indicate that the endpoint is not included in the set, curved brackets indicate that the endpoint is included.

Variable	N.	Categories/bin breaks	Comments
Age/sex	12	(16,20] (20,25] (25,35] (35,55] (55,100]	Female and male categories, in employment (excludes full-time students)
Mode	11	mfh metro train bus moto car.d car.p taxi cycle walk other	Main mode of travel to work (no data on variability of mode choice)
Distance	8	(0,2] (2,5] (5,10] (10,20] (20,30] (30,40] (40,60] (60,250]	Euclidean distance between respondents' home postcode and their main place of work (does not capture multiple work destinations)
NS-SEC	9	NS-SEC 1.1, 1.2 2, 3, 4, 5, 6, 7 and other	Classes range from higher managerial (NS-SEC 1.1) to routine occupations (NS-SEC 7) — see (Chandola and Jenkinson, 2000) and on the ONS website (www.ons.gov.uk)

(Williamson et al., 1998; Voas and Williamson, 2001), was calculated after constraining for linking variable and after each complete iteration (Fig. 7.3). Further validation tests are described in section 7.4.

The weighted data provided by IPF-based spatial microsimulation is bulky (containing rows even for individuals who contribute very little: whose weight is close to zero), making many types of analysis more difficult (e.g. contingency tables and Gini Lorenz curves). To tackle this problem, and provide a single dataset for analysis using various techniques (e.g. individual level, geographic, or agent-based methods), the ‘truncate, replicate, sample’ method of integerisation was used Lovelace and Ballas (2013). Still, the final output dataset contained 532,130 rows, representing every commuter in South Yorkshire.

7.3 Assigning work location

The spatial microsimulation model results in a large dataset containing hundreds of individuals for each zone under investigation. For micro level spatial analysis, origin-destination pairs are needed: simulated places of home and work need to be geotagged.

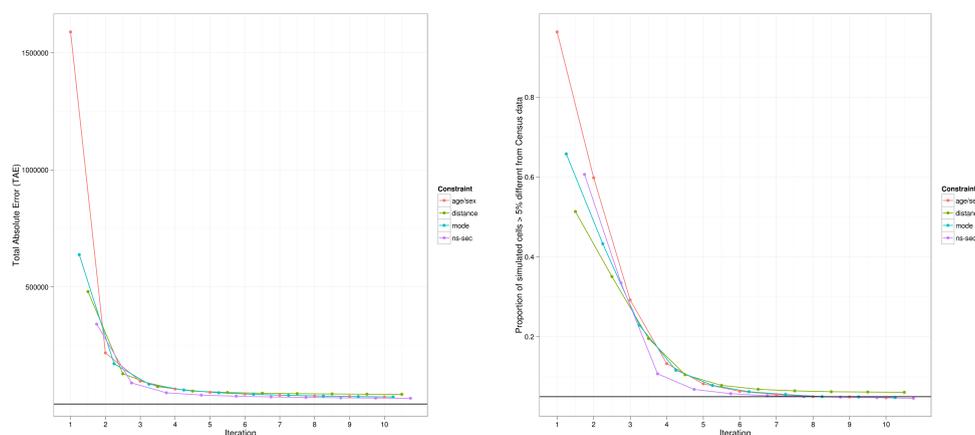


FIGURE 7.3: Improving fit between simulated and census data across all 4 constraint variables outlined in chapter 4, as illustrated by decreasing values of the total absolute error (TAE) (left) and decreases in the proportion of simulated aggregate cell values that differ from census data by more than 5% (right) after each constraint and iteration.

The horizontal black lines represent 0 error and 5% of cell values, respectively.

The simplest solution to this problem is to allocate all individuals in each zone home coordinates corresponding to the zone's population-weighted centroid. Likewise, work coordinates can be set to the nearest employment centre. This method allows for simple analyses such as the proxy for geographic isolation presented in Fig. 7.12.

Rather than assuming that work centres are always located in the city centre, a more realistic approach is to acknowledge that a variety of employment centres exist, and that the relative importance of each varies from place to place. This is illustrated in Fig. 7.5, a ward level flow diagram of the work locations of commuters based on the outskirts of Sheffield. Although Barnsley is the closest city centre to Stocksbridge (see Fig. 7.12), this analysis makes it clear that Sheffield is the primary non-home workplace.

At an even finer geographical level, it is possible to discern the localities within each city and ward where people are most likely to work based on UK census data. This is illustrated in Fig. 7.4. Although this level of geographic detail was not used in the final results due to aggregation issues,⁶ it demonstrates the potential for highly localised work allocation based on census-derived flow data.

The analyses presented in both Fig. 7.12 and Fig. 7.5 both greatly oversimplify trip routes. The straight lines underestimate travel distance, completely ignoring the transport network. A more realistic method is to randomly allocate each individual to a unique home location based on population density (or, potentially, local area classification) and estimate the route taken using shortest trip algorithms dependent on the

⁶The Output Area flow data presented in 7.4 is difficult to work with for individuals allocated to specific zones, because any number between 1 and 4 is randomly set as either 0 or 3. This makes the flow data essentially probabilistic for single Output Area pairs, hence our limitation to aggregate level analysis of this dataset here.

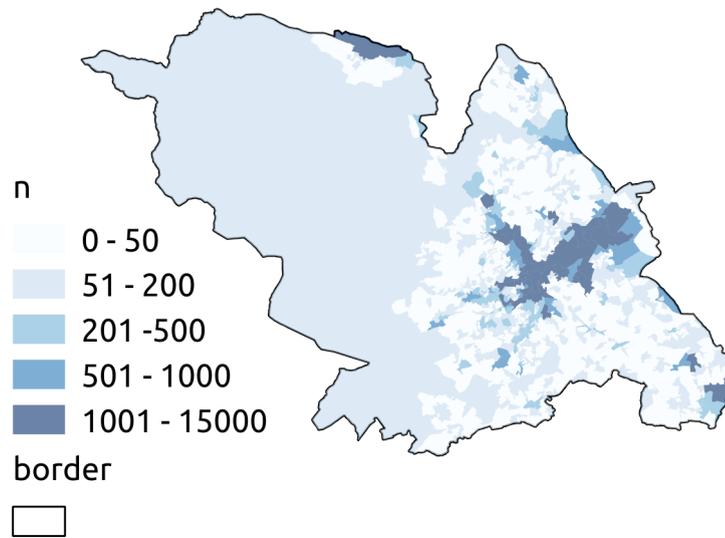


FIGURE 7.4: Employment density at the local level in Sheffield (n is the number of employees registered to each zone). These results were generated by summing all incoming flows to all of Sheffield's 1,744 Output Area (OA) administrative zones. Data provided on a CD, on request from <http://www.nomisweb.co.uk/>.



FIGURE 7.5: Flow diagram illustrating popular commuter destinations for citizens of Stocksbridge. The thickness of the lines is proportional to the number of people who travel there (for reference, 661 people travel to the centre of Sheffield — illustrated by the thickest line — and 2036 people work in Stocksbridge — illustrated by the dot from which all lines radiate. $n = 6,338$).

mode of transport used (Fig. 7.6). This latter method allows for the calculation of route distances by mode, but is more complex and difficult to implement over large areas.

TABLE 7.2: Contingency table illustrating the link between 2nd most common mode of TTW in an area and average values for other variables.

2nd mode	N. zones	Total (%)	\bar{D} (km)	\bar{P}_{car} (%)	\bar{Dens} (People/km ²)
MFH	18	10	17.0	68	31
Tram	4	2	10.8	53	179
Bus	95	55	11.2	54	106
Car (p)	10	6	13.5	63	40
Foot	46	27	13.2	53	112

These methods of spatial analysis provide great insight into the meaning of aggregate statistics for groups of individuals at the city level of policy intervention. However, to gain insight into the impacts of schemes on individuals and local communities, agent based models may be needed. In particular, there is great potential to link the work presented here with relevant agent-based simulation work in the social sciences (e.g. Gilbert and Troitzsch, 2005; Gilbert, 2007) and attempts to add a geographical dimension to this work (see Wu et al., 2008).

To this end Fig. 7.6 presents the simulated route choice of the 18 commuters selected from the spatial microsimulation model, and contains both socio-demographic and geographic detail.⁷

The distances travelled along the transport network are clearly substantially further than represented by simple straight lines. This concept can be defined formally as *circuity*, the ratio of straight-line distance to route distance (Ballou et al., 2002). Fig. 7.7 illustrates the impact of the road network on distance travelled. Overall, the route distance represented in Fig. 7.6 is 223 km, 24% further than the straight-line distance (179 km) for the 17 commutes. As in previous studies, circuity tends to decrease approximately logarithmically as a function of distance (Levinson and El-Geneidy, 2009). The spatial microsimulation method holds great potential for investigating the impact of the travel network, especially when combined with new tools for batch-processing of shortest-route algorithms.⁸

⁷For example, the simulated car passenger who commutes to central Sheffield in Fig. 7.6 is 16 years old, is classified as class ‘other’, and lives in a family that has access to 5 cars. These, and further simulated details such as income, could, once validated, contribute towards transport interventions targeting specific commuter groups.

⁸The analysis conducted one trip at a time, using the QGIS plugin “Road Path” for a simple solution with a user-friendly interface. (<http://plugins.qgis.org/>). To automate the process, Routino (<http://www.routino.org/>), PGRouting (<http://pgrouting.org/>) or the recently released R package osmar (<http://cran.r-project.org/web/packages/osmar>) could be used. The rapid evolution of transport network data and software provides avenues for methodological advance.

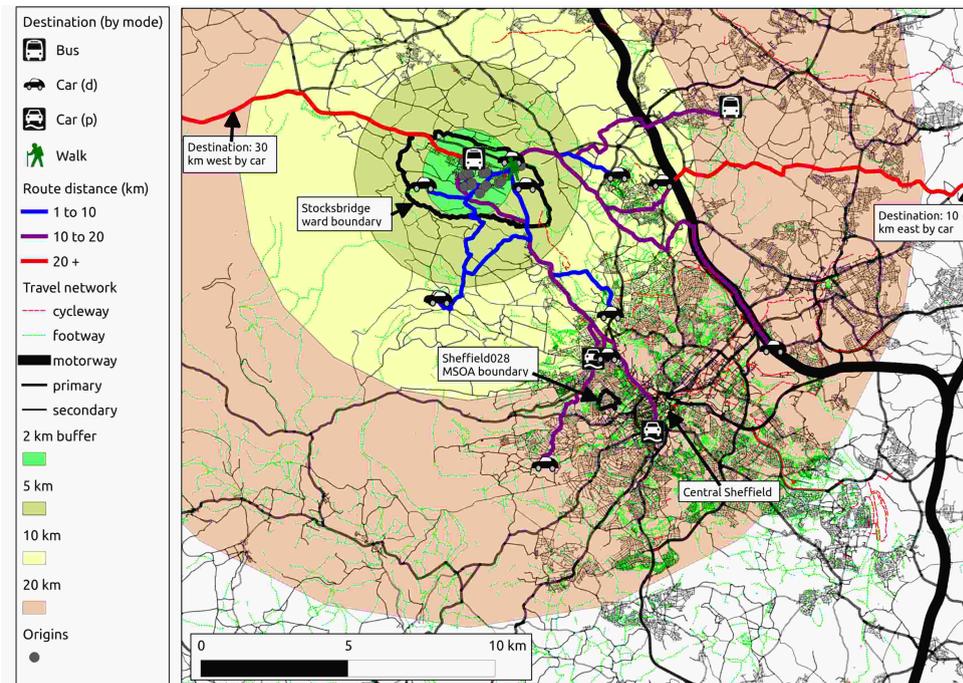


FIGURE 7.6: Simulated route choice for 20 randomly selected individuals from the spatial simulation model. Destinations were determined by 1) subsetting destination wards by distance from Stocksbridge centre, 2) assigning probabilities of working in each ward for each distance band (based on flow data presented in Fig. 7.5) and 3) randomly selecting points within the resulting destination wards. (Workplaces of 3 people who work from home are not mapped).

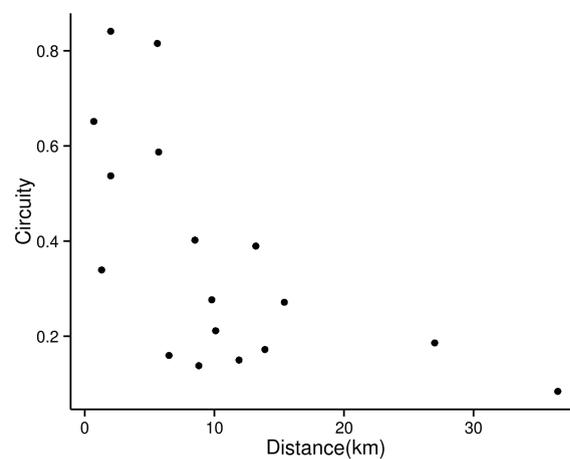


FIGURE 7.7: The circuitry of the route distance as a function of the straight-line distance for 17 commuter trips modelled in Stocksbridge.

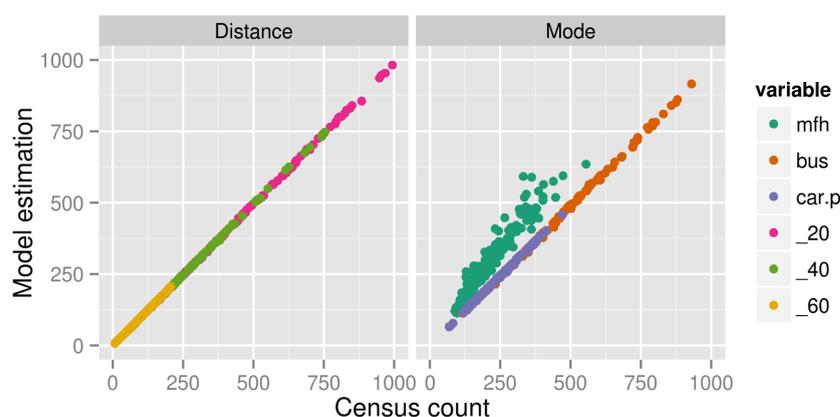


FIGURE 7.8: Comparison of census and simulated results at the aggregate level for a selection of six categories from the mode and distance constraints. The 20 category, for example, refers to the number of people travelling 10 to 20 km to work.

7.4 Model validation

Due to the dangers of using incorrect model data to inform policy, the importance of validation has been emphasised repeatedly in the spatial microsimulation literature (Clarke and Holm, 1987; Chin and Harding, 2006; Smith et al., 2009; Edwards et al., 2010; Ballas et al., 2012). Because the outputs of spatial microsimulation are by nature detailed and provided at the individual level, validation is challenging: “such detailed information is virtually never available at the disaggregate level for an entire region” (Ravulaparthi and Goulias, 2011, p. 37). In fact, one could argue that if individual microdata were made available at the small area level, spatial microsimulation would be obsolete.

Researchers using spatial microsimulation have been innovative at overcoming this ‘catch 22’ situation, using a variety of methods. In broad terms, there are two types of strategy available: internal and external validation (Edwards and Tanton, 2013). The first of this is relatively straightforward: the aggregated constraint variables are compared with the aggregated results of the spatial microsimulation model for the same variables. In our model, the results of this test were reassuring: the correlation between the aggregate counts from the census and those generated in our spatial microsimulation were 0.9989 overall for all 6,920 data points (40 categories by 173 zones). However, the quality of the fit was better for some constraint variables than for others: the r^2 values for the distance and mode variables were 0.9993 and 0.9983, primarily due to the inaccuracy or our estimates of individuals who work mainly from home (mfh) (Fig. 7.8).

This internal validation result is less impressive when one considers that IPF always converges towards the optimal result for known constraint variables: it is the unknown cross-tabulations and target variables that are the most useful result, so external validation should, in many cases, be the focus (Morrissey et al., 2008; Edwards and Tanton, 2013). Four methods of corroborating spatial microsimulation results with external data were identified:

- Compare simulation results with real spatial microdata.⁹
- Collect primary data from specific areas against which the simulated results can be tested.¹⁰
- Compare simulation results at the aggregate level with estimates from a dataset external to the model (Morrissey and ODonoghue, 2013).
- Aggregate-up the small area estimates provided by spatial microsimulation to compare the results with real data that *is* provided at higher geographies (Edwards and Clarke, 2009).

Each of these options was considered for our case study, but data constraints meant that only one, comparison of aggregate data on a target variable with a reliable external dataset, was deemed viable. The target variable chosen for this was income; Neighbourhood Statistics provides estimates of this at the MSOA level, allowing for direct comparison with our results (Fig. 7.9). The results show high levels of correlation ($r^2 = 0.93$) between simulated incomes and official estimates, although the spread of the values resulting from spatial microsimulation underestimated the true level of inter-zone variation in average incomes.

7.5 Results

The results show that, at the aggregate level, South Yorkshire's commuting behaviour is comparable to the national average. Nevertheless, the microdata illustrate substantial inter- and intra- zone variability. Table 7.3 illustrates the cross-tabulations (contingency tables) that are made possible when spatial microdata are used. Univariate statistics are available on mode of transport, age and number of cars but the interaction between these variables remains hidden in aggregated Census data.

⁹Income, for example, is collected by the Census, but is not disseminated at aggregate levels, let alone the individual level geocoded data required to validate the individual level results of the spatial microsimulation model. Access to such sensitive real microdata limits the applicability of this method.

¹⁰In some cases (e.g. environmental attitudes) this may be the only reliable validation option, as the information is simply not collected in geo-coded surveys.

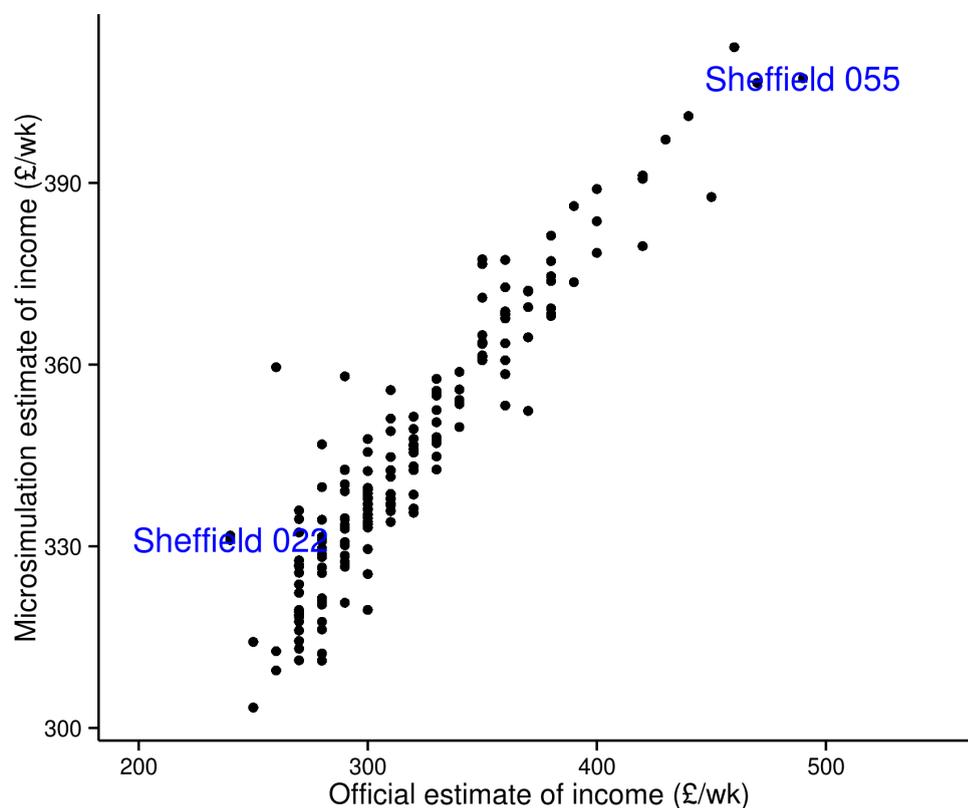


FIGURE 7.9: Scatter graph of mean equivalised household income produced as an output from the spatial microsimulation model (y axis) and official estimates from the Office of National Statistics for the 173 Medium Super Output Areas of South Yorkshire. Maximum and minimum official estimates labelled in blue.

Beyond illustrating the capability of spatial microsimulation to provide estimated cross-tabulations of aggregate level data, Table 7.3 also provides substantive information about commuting patterns that could be applied to transport policy:

- Cars dominate travel to work in South Yorkshire, to an even greater extent than in England as a whole.
- The dominance of cars is even greater when measuring travel to work in terms of distance travelled: car commuters travel on average further than all other types of commuters bar those who commute by train.
- There are also substantial differences in the age profiles of different commuting modes: walking, which is often associated with older members of society, appears to be more prevalent amongst the young. Bicycle commuters, who are sometimes stereotyped as young (Daley and Rissel, 2011), are not much younger than the average. Car drivers and home workers tend to be slightly older.

TABLE 7.3: Summary statistics of the commuting behaviour of individuals in South Yorkshire disaggregated by mode. (Motorbike, taxi, metro and ‘other’ modes have been removed for brevity).

Mode	N.	%	% National	Age	Distance (km)	Ncars
Bus	31486	7.2	7.4	38.3	7.5	0.5
Car (d)	268496	61.1	54.6	40.1	14.3	1.9
Car (p)	38233	8.7	5.9	33.5	14.5	1.5
Cyc	4498	1.0	2.6	38.3	5.0	1.1
MFH	45326	10.3	9.3	40.0	0.0	1.9
Train	5709	1.3	4.6	36.9	24.6	1.2
Walk	38406	8.7	9.7	36.6	3.1	0.8
Average	-	-	-	39.0	11.3	1.6

- Car ownership, which is seldom factored into transport policy assessments, (Kay et al., 2011) varies with the mode of travel to work. Those who catch the bus or walk are least likely to own a car, while those who drive to work or work from home own on average almost 2 cars per household.

As in England as a whole, it is clear that cars, in round numbers, constitute 70% of trips (61% of commuters drive to work; 9% are passengers in other peoples’ cars). The utility of the individual level results is illustrated at this aggregate level by observing differences in average age and distance of commute between modes: car drivers and bus passengers are on average older than those who walk to work. Unsurprisingly there are also differences in the average distance travelled. Train passengers travel 13 km further than average; those travelling by bus or non-motorised modes tend to live closer to home. A predictable, yet rarely investigated, result from Table 7.3, is the high variability in the average number of cars in households of different types of commuters: bus passengers appear to have the fewest cars per household of all modes. Each model result has the potential to inform policy. The final one, for example, provides support for the argument that public transport policies are currently failing to “lure car users out of the car” (Davison and Knowles, 2006, p. 193).¹¹

From this, total distance travelled and energy use by mode per year can be calculated. Fig. 7.10 presents these model results (of which distance is most robust, as it is constrained by Census data) for the average and range for all 694 MSOA zones in Yorkshire and the Humber.

The proportion of energy used by cars for transport to work is 95.6%: *this is more than 20 times the energy costs of all other modes of transport put together.*

¹¹As with the other non-constrained variables target variables described in Table 4.3, this model result should be validated by additional data before strong conclusions are drawn.

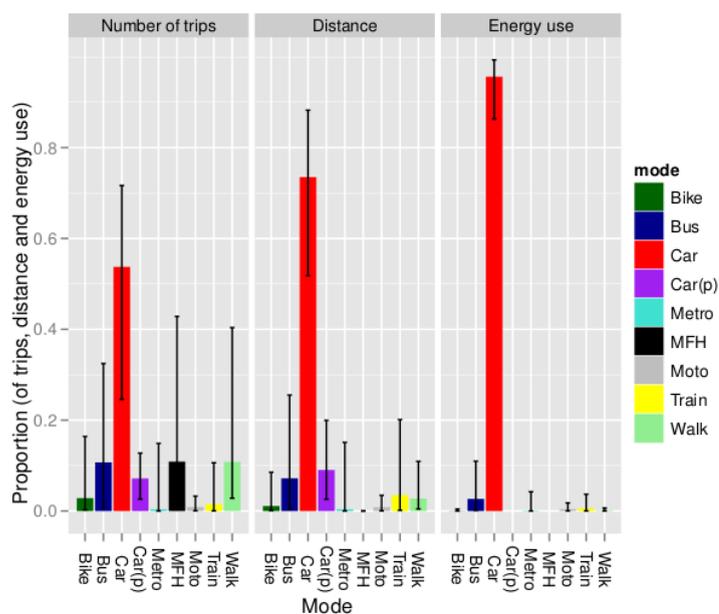


FIGURE 7.10: Proportion of trips, distance, and energy use accounted for by different commuter modes. The error bars represent the range of values within MSOA areas in Yorkshire and the Humber.

An illustration of the increasing dominance of cars as one moves from trip number, through distance travelled, and then energy use metrics, is provided in Fig. 7.10. Note that in some regions car drivers account for less than a third of all commuter trips. Yet in terms of energy use, cars consume more than 85% of all energy consumed for getting people to work and back.

The results show a strong relationship between location and distance travelled. The role of location, and distance to employment centres more specifically as a cause of distant commutes was explored using travel to work (TTW) zones, defined by the Office for National Statistics at the wider regional level of Yorkshire and the Humber (Fig. 7.11).¹² Fig. 7.11 shows that MSOA areas located in and around the conurbations surrounding Bradford, Sheffield and Hull tend to have low average commuter distances, while rural locations such as the North York Moors are associated with long average commutes. This result differs from that of suburban USA (where urban sprawl accounts for high commuting costs even within major conurbations), but it is hardly new or surprising (Marshall, 2008; Sexton et al., 2012). An unexpected result is the tendency of city centres to be associated with high average commuter distances. This can be seen in red patches surrounded by a sea of green in the centres of Bradford, Leeds, Scarborough

¹²The wider regional level of analysis of Yorkshire and the Humber (see Fig. 4.3) was used in this case because TTW zones are large: only 3 are found in South Yorkshire (Fig. 7.12), so a larger area is useful to see the overall pattern. Travel to work zones are defined as “zones with a self- containment of at least 75% (which is to say that less than 25% of those who work in an area live outside it, and less than 25% of the employed residents of that area commute to workplaces outside the same area)” (Coombes and Openshaw, 1982).

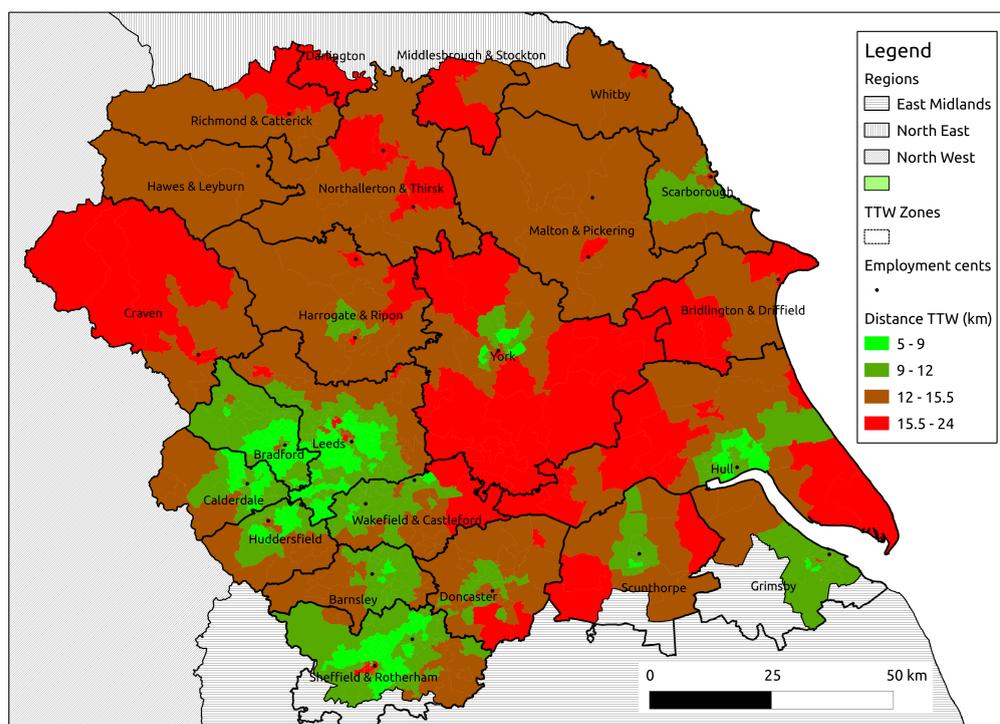


FIGURE 7.11: Average distance travelled to work in Yorkshire and the Humber by MSOA zone. Black lines represent TTW zones.

and Sheffield. (One hypothesis to explain this is as follows: some city centres attract wealthy individuals, who tend to commute further, often by train.) Energy costs are directly proportional to distance travelled for all modes. It is therefore unsurprising that average energy cost of commuter trips in each area are closely related to the distance of commute ($r = 0.97$). Distance is the most important driver of energy costs at the MSOA level within Yorkshire and the Humber; the correlation between average distance and average energy use per commuter trip is 0.97. The geographical causes of energy intensive commuting are therefore the same as the causes of high average commuter distances at the MSOA level.

To explore this link further, the average distance from employment centre was calculated (7.12) and plotted against the average energy cost of transport to work in each MSOA, see dots in Fig. 7.13. The reversal of slope in the tick-shaped curve of the relationship between distance to employment centre and energy use suggests that the link between these variables is not as simple as one might expect: other factors are at play, possibly linked to individual level variables such as income.

Spatial microsimulation allows one to ‘drill down’ to the individual level, target specific groups and model who (in addition to where) is most likely to benefit from specific interventions. Table 7.4, for example, shows simulated differences in commuting patterns

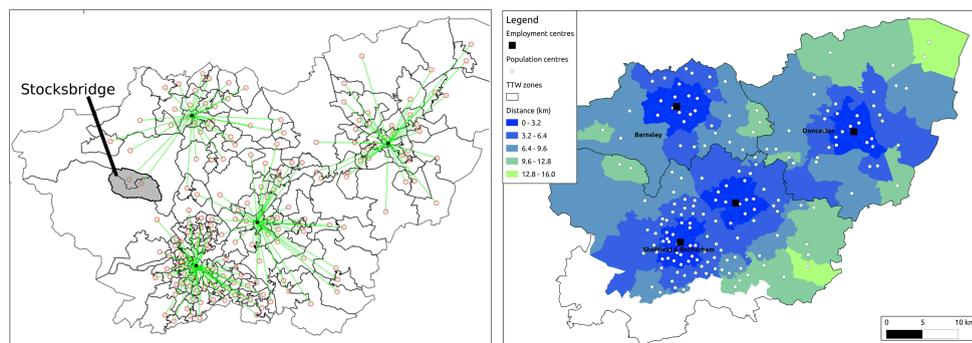


FIGURE 7.12: Average distance to employment centre in South Yorkshire. The left-hand map illustrates how distance was calculated (using the command `nncross()` in the R package ‘`spatstat`’). The right-hand map illustrates the results — Sheffield and Rotherham are grouped together in the same travel to work zone.

between high and low income citizens in South Yorkshire as a whole.¹³ Because the individual microdata are also geocoded, the same analyses could be conducted for specific zones. Table 7.5 illustrates how the results of spatial microsimulation allow inter- and intra-zone analysis to be combined. Table 7.5 indicates that Sheffield028 (an MSOA zone) is more unequal in terms of income and distance travelled to work than Stocksbridge (a statistical Ward) (see Fig. 7.6 to see their respective locations). These results, which can be compared with the regional data presented in Table 7.4, or re-calculated for smaller zones, are thus (to the extent that administrative boundaries allow) ‘frame independent’ (Horner and Murray, 2002).

To further explore differences in intra-zone inequality, commuter work travel distances were plotted as Lorenz curves (Fig. 7.14b). These provide further insight into commuter patterns in each of the zones described in Table 7.5, and illustrate that a small proportion of the population living in Crookes accounts for a large part of the average trip distance. Stocksbridge, by contrast, has a more even distribution of commuter patterns.

Regarding the categorical target variables described in Table 4.3, the results imply that wealthy commuters in South Yorkshire drive larger cars, use the internet more frequently, and may be less likely to want to move than those with low incomes (Fig. 7.14a).

7.6 Discussion

This chapter has demonstrated how spatial microsimulation can be used to model commuter patterns in concrete case study. Whole individuals from a detailed national survey

¹³The categories “very poor” to “affluent” used here are defined in (Ballas et al., 2005d). Statistical bins are defined as proportions of the median income, with breaks at 50%, 75%, 100% and 125% of the median (Ballas et al., 2005d, p. 91).

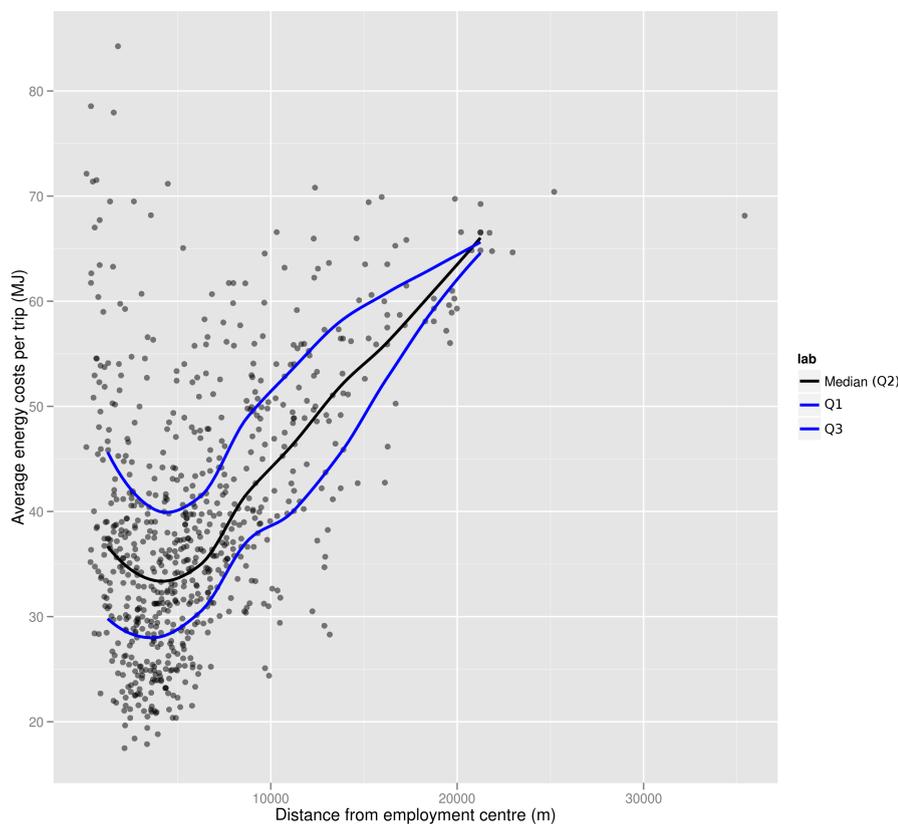


FIGURE 7.13: The relationship between distance to employment centre and average energy costs of commute for MSOAs in Yorkshire and the Humber. The blue and black lines are smoothed moving quantiles (Q1 and Q3 represent the 25th and 75th percentiles respectively), which indicate central tendency and heteroscedasticity.

TABLE 7.4: Contingency table of average values for continuous variables related to commuting, cross-tabulated by income bands, based on the spatial microsimulation model for South Yorkshire (n = 531,282).

Income group	Proportion	Age	Dis (km)	N.cars	Income (£/yr)	N.child
v.poor	10%	38	5.8	1.2	5519	0.9
poor	18%	39	8.1	1.2	10158	1.0
below.av	22%	39	8.3	1.4	13974	0.8
above.av	18%	39	8.9	1.6	17902	0.6
affluent	32%	40	16.5	1.9	29448	0.5

were allocated to geographic zones at various levels; this provided further insight into intra-zone variability of commuting than is available from the use of aggregated census data alone. In addition, the careful selection of target variables not included in the census provided insight into the relationships between commuting behaviour and a variety of ‘target variables’ such as income, internet use, desire to move home, type of car and number of children.

TABLE 7.5: Contingency table of average values for continuous variables related to commuting, cross-tabulated by income bands, based on the spatial microsimulation model for the Ward of Stocksbridge (n = 6,338) and MSOA Sheffield028, which corresponds to Crookes (n = 2,470).

Income group	Proportion	Age	Dis (km)	N.cars	Income (£/yr)	N.child
Stocksbridge (13 km from centre)						
v.poor	10%	39	9.5	1.2	5886	1.0
poor	21%	38	12.3	1.0	10571	0.9
below.av	19%	39	12.3	1.5	14560	0.7
above.av	20%	39	12.9	1.8	18513	0.5
affluent	30%	40	17.1	2.0	29198	0.5
Crookes (2 km from centre)						
v.poor	10%	32	4.0	1.1	5208	0.8
poor	16%	33	5.7	0.9	9972	0.9
below.av	23%	31	7.4	1.1	14145	0.5
above.av	14%	34	8.7	1.5	17914	0.5
affluent	37%	36	25.0	1.8	29932	0.4

From the perspective of data-constrained policy makers, these results are attractive: they provide a level of detail that is inaccessible for analyses based on geographically aggregated census data alone. The ability to explore the commuter behaviour of subsets of individuals based on age, distance travelled and class (constraint variables) or other variables including size of car or income (target variables) will be useful in various applications: being able to simulate the *characteristics* of commuters who are most likely to benefit from certain interventions and identifying *where* these people live and work clearly has huge potential for transport planning and policy. To illustrate the point, the distribution of low-income households reliant on buses can be simulated and mapped at the county level to help inform the location of new bus routes (Fig. 7.15). For example, if this type of analysis had been properly conducted and validated during the planning stages of the recently implemented rapid bus routes in Albuquerque mentioned in Tribby and Zandbergen (2012), the system could have been designed such that low income residents benefited from faster access to the city centre. In fact, relatively wealthy households (who probably have more transport options already) benefited most from the scheme (Tribby and Zandbergen, 2012). This illustrates the importance of considering not only aggregate level impacts, but also taking into account the local and micro level distributional effects of intervention.

The spatial microsimulation approach to modelling commuter patterns outlined in this section provides a foundation for investigating such effects. In addition, it has been

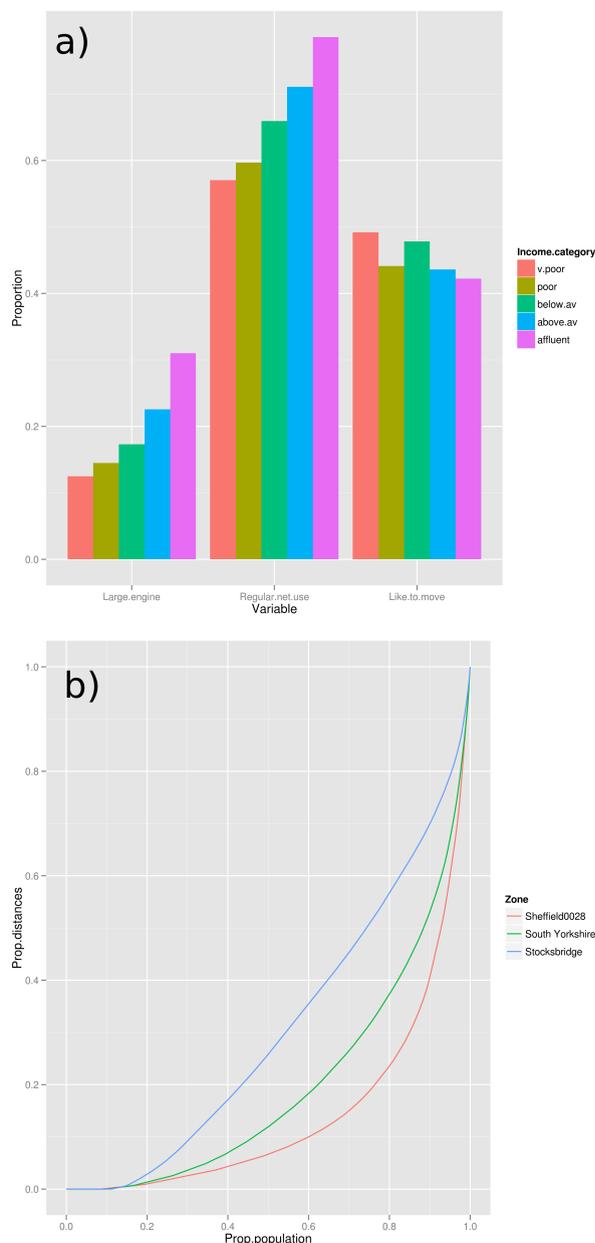


FIGURE 7.14: **a)** Variability of vehicles (proportion of primary cars in household whose engine size is 2.0 litres or more), internet use (proportion of commuters who use the internet daily or weekly) and desire to move home depending on equivalised income. These categorical target variables are described in Table 4.3. **b)** Lorenz curves illustrating the individual level variability in commuter distances for 3 zones. The Gini indices associated with these curves are 0.278, 0.294 and 0.305 for Stocksbridge, South Yorkshire and Sheffield0028 respectively.

shown that spatial microsimulation methods can enrich transport models with policy relevant socio-economic variables at individual and small-area levels.

Despite these possibilities, it is important to remember that the results are *simulated*. Consequently, linking variables — these are constrained by known census aggregates and are therefore trustworthy — must be distinguished from target variables, which are

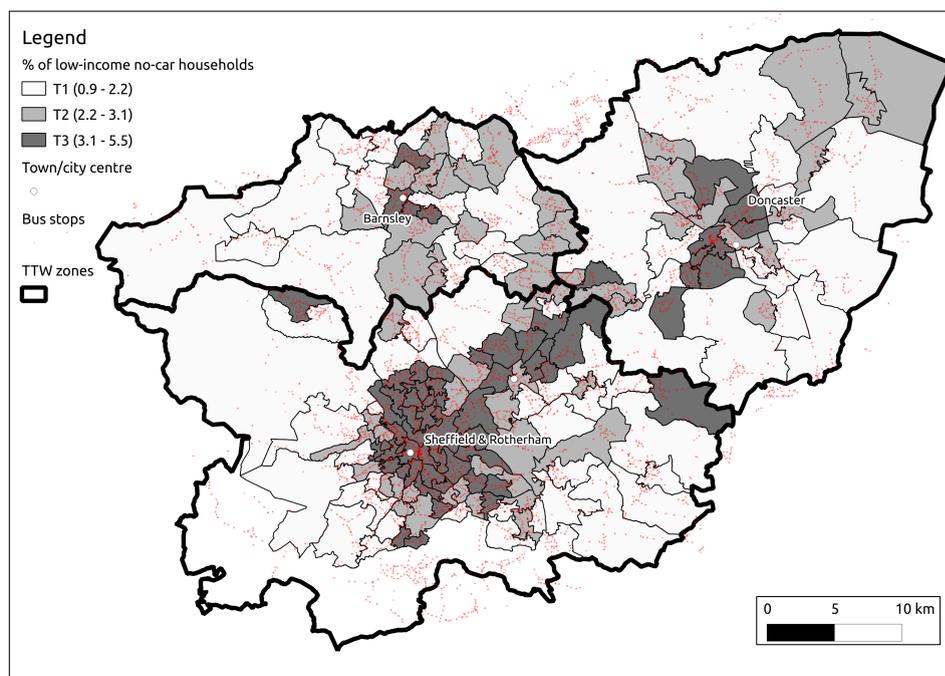


FIGURE 7.15: Proportion of population which earns less than 50% of South Yorkshire’s median income *and* lives in a car free household within the 173 MSOA boundaries of the metropolitan county, according to the spatial microsimulation model. Translucent red dots represent bus stops (data from data.gov.uk/dataset/nptdr).

more tentative estimates based on correlations between target and linking variables at the national level. Target variable estimates rely on an often unstated assumption: that the relationships between variables at the national level (e.g. between distance travelled to work and income) tend to remain at local levels. This assumption cannot be expected to hold everywhere, so results arising from target variables are expected to underplay the true level of spatial variability. Where possible, target variable results should be corroborated against independent datasets (Edwards and Clarke, 2009).

Many transport interventions have wide-ranging impacts on commuters. These depend on geographical *and* individual level factors, and the importance of the latter especially is often overlooked in transport policy (e.g. Tribby and Zandbergen, 2012). The micro level methods presented in this chapter therefore have great potential, to enable researchers and transport planners to better model and predict the impacts arising from various interventions. With the current focus on energy and sustainability in transport (Chapman, 2007), there is a risk that distributional impacts continue to receive little or no attention. Spatial microsimulation has the potential to address this issue, by helping decision makers to design sustainable transport measures that are both effective and fair.

Chapter 8

Scenarios of change

“In the 1970s, I used to wait for a break in the lines of car-plant workers cycling to work on their bikes so that I could cross the road to get to school. Today, there are almost no workers employed by that factory any more; much of the work is done by robots ... So much has changed so quickly”

Dorling (2013, p. 106)

“There is no certainty where one can neither apply any of the mathematical sciences nor any of those that are based on the mathematical sciences”

Leonardo da Vinci, *Manuscript G*, quoted in (Rosci, 1978, p. 13)

The preceding sections focus on understanding the energy costs of commuting currently (based primarily on the 2001 Census, which may be considered out of date). The analysis so far has a number of important policy implications in the present, but transport systems are constantly evolving. It is the evaluation of change that make transport models so useful to policy-makers. This chapter therefore investigates the impacts of change on commuting systems. More specifically, the focus is on evaluating the effects of changed *behaviour* on commuter energy use. Behaviour was chosen in preference to other types of change, such improved efficiency of vehicles due to new technology or new infrastructure (which in itself can be an agent of change), for two main reasons. The first is policy-related: behavioural change is at the top of the ‘sustainable transport hierarchy’ (in the form of demand reduction and modal shift) proposed by the Sustainable Development Commission (figure 2.1, chapter 2). Changed behaviour can be brought about quickly at low cost, whereas technological and infrastructural interventions tend to take

longer. Despite these advantages, which are reinforced in a time of fiscal constraint, the energy impacts of behavioural shifts have received little attention, relative to the energy impacts of new technologies such as electric cars. Second, the impact of new policies on behaviour is itself subject to a high degree of uncertainty: taking behaviour change as a given and building on this (without worrying about how that change is brought about) thus simplifies the modelling process and reduces the number of assumptions on which it is based.

In developing the scenarios of change, the aim is not to create the most likely scenarios possible, or even the optimal ones, but the most *informative* ones. The task is twofold: to inform about the likely energy impacts of specific types of behaviour change (modal shift, telecommuting and localisation of economic activity) and, secondly, to inform about *how* spatial microdata can be harnessed, in general terms, for policy evaluation in relation to commuting. The scenarios are presented as idealised cases of what *could* happen, not what *will* or *should* happen. Consideration of how these changes are brought about and which interventions most likely happen are omitted: it is assumed that these details can best be provided by policy makers well-acquainted with their plans or by researchers modelling the various factors that determine commuting behaviour (section 2.2).

A basic concept in modelling, embodied in the principle of parsimony often referred to as ‘Occam’s razor’, is to use the simplest explanation wherever possible. This implies modellers should start simply, only adding further complexity when necessary (Batty, 1976). It is vital when using mathematical models to investigate complex systems to remember the following point, that recurs in the literature (Wilson, 1970; Smil, 1993; Mackay, 2009): the purpose of the exercise is not to capture the totality of the system (this is impossible in a truly complex system), but to enhance *understanding* of the processes being modelled. The real world is heterogeneous, so “one size fits all” models, with no critical interpretation, are of little use. Models that are “black boxes”, and not set up for the particular (and often unique) problem that they are designed to solve may even hinder understanding, by letting the computer provide an answer with no insight into how or why it arrived at the answer. “In some senses, every application of a model is unique and requires special adaptation to the problem in hand, and thus there is an element of hypothesis testing in every predictive model design” (Batty, 1976, p. 4). It is when the focus shifts away from testing, experimentation and understanding and towards “generating the ‘right’ result” that models can become dangerous and politicised.

For this reason, this chapter is structured so that the simplest scenarios are presented first, to ensure maximum transparency and understanding. There are five subsections. The first two are named after the nations which inspired the scenarios contained within: ‘going Dutch’ for modal shift to cycling; ‘going Finnish’ for uptake of telecommuting.

‘Going Dutch’ is implemented both at aggregate and individual levels, to highlight the advantages of each approach: the aggregate level scenario allows energy savings to be calculated nationwide, while the individual level implementation allows more sophisticated determination of the chances of switching mode based on continuous age and distance variables, rather than the simple dependence on distance bands assumed in the aggregate level version. The code used to generate and analyse these scenarios is provided, for reproducibility and transparency, in the ‘scenarios’ folder of the ‘thesis-reproducible’ repository published alongside the thesis.¹ Section 8.3 is concerned with a more complex scenario which raises the issue of the limits to the spatial microsimulation approach and modelling more generally. Section 8.4 explores another use of the model: for evaluating the extent to which commuters are vulnerable to oil price shocks. Finally, in section 8.5, the policy relevant findings from the chapter are summarised and the limitations of the approach as a decision making tool are discussed in the context of future uncertainty.

8.1 Modal shift: ‘going Dutch’

”I’ve got three ways of getting to work. The bus, the car and the bike. If I go by car I know that if I leave between about 7:15 and 9 O’clock I’ll get stuck in a jam and there’s no way round it. And then I’ve got to find somewhere to park. If I go by bus, well the bus runs every 30 minutes and it gets stuck in the same jams, except for the bit with the bus lane. But if I go by bike it takes about the same time as the car for seven miles, I get exercise, I don’t have to wait anywhere and, I know I shouldn’t, but I get this smug feeling when I overtake all the cars in the traffic jams. You talk about the car as a symbol of freedom and independence - for me that’s my bike, not the car!”

(Anonymous commuter, Goodwin et al., 1991, p. 61).

The quote above demonstrates that the individual benefits of modal shift to bicycles can be large, even before any of the direct and indirect energy savings are considered. Perhaps because of these highly tangible benefits, modal shift is seen by many as one of the main ways to tackle energy intensive commuting. The recent announcement of £148 million (77 for 8 cycling cities, 71 distributed by local authorities) in cycling expenditure by David Cameron underlines the perceived benefits increased cycling.

¹This is available [online](#) from github and can be found by searching for ‘thesis-reproducible’ on the github.com website.

Returning briefly to the basic comparison between the Netherlands and England presented in table 6.6, it is clear that the two countries are relatively similar, at least on paper. Using the former's famously high cycling rate of 25% for all commutes, it would be possible to set this as a long-term goal for UK cities. Section 6.5 shows that a high rate of cycling does not lead, on its own, to low overall commuter energy costs. Yet it does provide an empirical basis for a what-if scenario of modal shift to cycling in England.

8.1.1 An aggregate level model of modal shift

Starting at the national level, let us make assumptions about the people who transfer to cycling from other modes in a very high cycling uptake scenario, for each Euclidean distance band. Because cars are the main culprit of energy intensive commuting, and for the sake of simplicity, only the car-bike shift is considered, after Lovelace et al. (2011):²

- a 50% shift for car journeys between 0 and 2 km
- 30% shift for trips between 2 and 5 km
- 5% of car commuters in the 5 to 10 km band shift, and
- just 1% of car commuters in the 10 to 20 km band shift³

These numbers are based on a loose interpretation of Dutch data: 43.6% of all trips between 1 and 2.5 km, and 33.3% of trips up to 7.5 km were made by bicycle in the Netherlands in the year 2000 (Rietveld, 2004). Still, in the British context it is acknowledged that these values are quite arbitrary and ambitious: peoples' uptake of cycling may be different in England. 50% value for the shortest trips is certainly possible physically in most areas, but would take a transformation in travel to work habits for the 8% of commuters who travel 2 km or less by car (20% of commuters travel this distance to work overall). Evidence from the Netherlands and Denmark show that it is possible for more than 30% of *all trips* (not just those less than 2 km) can be made by bicycle

²In reality, it is likely that cycling would have an equally high tendency to replace the other common modes of short-distance travel — bus Dorling (2013) and walking trips. The former is due to the financial savings to be made, the latter due to the increased speed of cycling over walking. It could be argued that neither of these shifts would have substantial energy implications compared to the car-bike shift, however: bus use and walking both constitute a lower share of commuting, even for short trips than car trips; both are less energy intensive than driving (in the case of walking, greatly so); and even if bus trips *were* replaced by bicycle trips for shorter trips, the energy savings that result would be highly uncertain due to the top-down nature of bus service planning — it is largely elderly citizens who are least able to cycle who most depend on bus services.

³This number is so low because, knowing long-distance (7 miles plus, each way), bicycle commuters, the trip is usually only taken by bike a few times per week at most. In addition, this is far beyond the capabilities of the majority of the population, so is still a very optimistic assumption.

in some cities (Groningen, Munster, Copenhagen, for example), provided the correct policies are in place (Rietveld, 2004; Pucher et al., 2010). In addition, an EU report concluded that 30-50% of car trips below 5 km could be replaced by walking and cycling combined.⁴ Beyond 5 km the drop-off is expected to be steep: cycling 6 miles of route distance (roughly in the centre of the 5-10 km Euclidean distance bin) each way each day requires a level of fitness and commitment held only by a few. Cycle-commuting further than 10 km each day requires exceptional levels of fitness, but is not unheard of, even in the current low-cycling context.⁵ Based on these assumptions it is possible to calculate the energy savings from a modal shift to cycling:

$$\Delta E_{trp} = \sum_b p_b \times \overline{EI}_{car,b} \overline{dR}_{car,b} \times N_{car,b} - p_b \times \overline{EI}_{bike,b} \times \overline{dR}_{bike,b} \times N_{car,b} \quad (8.1)$$

where b are distance bands (in this case from 0-2 to 10 to 20 km), p is the proportion of car trips replaced by bicycle trips, EI is the energy intensity of travel (MJ/km, from chapter 5), dR is the route distance and N is the number of people travelling by that particular mode-distance combination.

Applied across England (simplifying to assume EI remains constant over all distance bands considered), this analysis suggests that the average energy costs of commuter trips could be reduced by 3.2% nationwide. Clearly, these are optimistic assumptions about uptake of cycling, so the true figure offered by modal-shift to bicycles in the short-term is likely to be lower. However, because the majority (60%) of commuters travel over 5 km, beyond which only a handful of drivers will switch to bikes, the proportion of all trips is not as high in this scenario as might have been expected: it increases from 2.1% currently to 10.1% in the high cycling scenario — still far less than the 25% figure for Dutch cycle commuters, and well below the rate of cycle commuting in the most cycle-friendly areas of the UK. In the ward of Romsey, just east of central Cambridge, for example, over 30% of commuters cycle to work.

Geographically, the energy savings of this what-if scenario vary considerably. At the regional level, savings would be highest in the Northwest and lowest in the East of England (3.7 and 2.5% respectively). At a lower levels, a clear geographical pattern

⁴“There is a considerable potential of car trips of less than 5 km that could be done by walking and cycling. The analysis carried out allows us to establish that it lies between 30% and 50% in European countries” (Gnavi and Bonanni, 1999, p. 60).

⁵The following comments were taken from the online forum <http://singletrackworld.com> in response to the question “how far is too far to commute by bicycle each day?”: “I found that doing 20 miles a day (10 each way) for 5-6 days meant I was knackered for any weekend riding.” “I do 23 miles each way but only twice a week. I don’t think I could do 5 days a week!” “when I was very fit, I found 19 miles each way 5days a week fairly hard going though I’ve never been any good at just cruising along.” “I’ve done 13 miles each way every day through London (so lots of start stop) and that was ok most of the time. Done a [sic] asymmetric 17.5 miles there 13 miles back and that started to feel bit of a drag in terms of time and effort. I think for me 15 miles each way would be my limit for 5 days a week. Although at the moment I’m very lazy and drive 8 miles to work 3 days a week and ride 2days a week!”

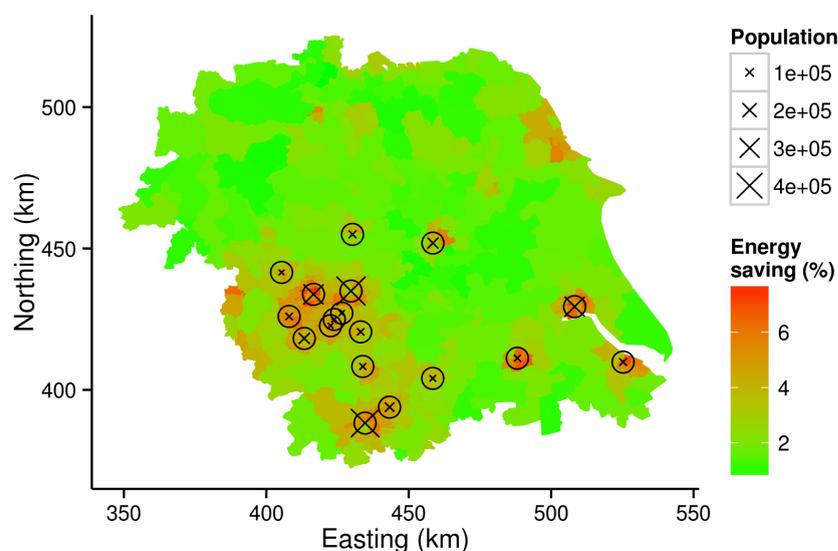


FIGURE 8.1: Estimated energy savings from car-bicycle modal shift in Yorkshire and the Humber at the Ward level. Size of x points represent size of settlements with over 30,000 people, rings illustrate circle 5 km from city centres.

emerges: the potential energy savings of replacing car commutes with bicycles tend to be greatest in the urban areas directly surrounding town and city centres. Beyond around 5 miles from city centres, the potential energy savings drop rapidly to below the national average. Potential energy savings in central wards tend to be slightly lower than this ring of between around 1 and 5 km from the city centre. This pattern is clearly present in figure 8.1, which shows the results in the region of Yorkshire and the Humber. From the perspective of transport planning, this result could be extremely useful for allocating cycling investments to areas where it would have most impact. In general, the results seem to support the prioritisation of routes into city centres from the outskirts. It would be an interesting exercise to assess the extent to which current bicycle path geography reflects areas of highest potential energy savings.

The above results are based on crude assumptions and simple back-of-the-envelope calculations. They take no account of the characteristics of the people in each zone (young people, for example are more likely to be willing to take up cycling), infrastructure or terrain. A number of refinements could be made, based on simulated spatial microdata and information about the environment in each zone. Based on the literature, socio-demographic, infrastructural and environmental factors all play a role in determining

the cycling rate. Thus, using the spatial microsimulation approach, the shift to cycling could be modelled at the individual level, as a function of individual and geographical factors, for example: route distances (for cars and bicycles), topography, climate, age, sex, the price of driving and perceived attractiveness of cycling.

8.1.2 A spatial microsimulation implementation

The simplistic assumption that a fixed proportion of car commuters will shift to bicycle for each distance band in all areas is clearly flawed. As mentioned above, a range of factors conspire to influence the number of people cycling in any given area. The physical ability to ride a bike has a strong age dependence and it is well-known that the current wave of cycling uptake is driven largely by the young.⁶ Some areas will have a higher proportion of older commuters, who would be less likely to be able, physically, to cycle a long distance to work. An additional problem with the aggregate level model is that it depends on distance/mode cross-tabulations, which are not available at all geographic levels.

It is precisely this context, of multiple and interacting variables affecting an output, operating on individual to regional levels, that spatial microsimulation becomes useful. In this implementation, the outputs of the spatial microsimulation technique set out in chapter 4 are used to create an individual level model of modal shift. To take the age-dependence into account, the individual level implementation of the ‘Going Dutch’ was undertaken as follows:

- The probability of switch to bicycle depends on figure 2.2 set out in equation (2.1). The “cycle to work” parameters from Iacono et al. (2010) were used: $\alpha = 0.402$; $\beta = 0.203$.
- The age dependence of the shift was estimated based on the National Travel Survey data: the relationship between variable i272 (“Ridden a bicycle in the last 12 months”) was determined as a linear function of age (see figure 8.2) and this simple linear model was used to normalize the previous probability estimates by age.
- The sample size was set equal to the modal shift resulting from the aggregate level implementation of the ‘go Dutch’ scenario, with the probability of switch depending on age and distance, as described in the previous bullet points.

⁶Sex may also impact the probability of bicycle uptake: “Gender may be an issue when women have to consider the social risks of travelling by bike during the evening” (Rietveld, 2004, p. 532), but this reasoning is not deemed strong enough to merit a gender dependence here.

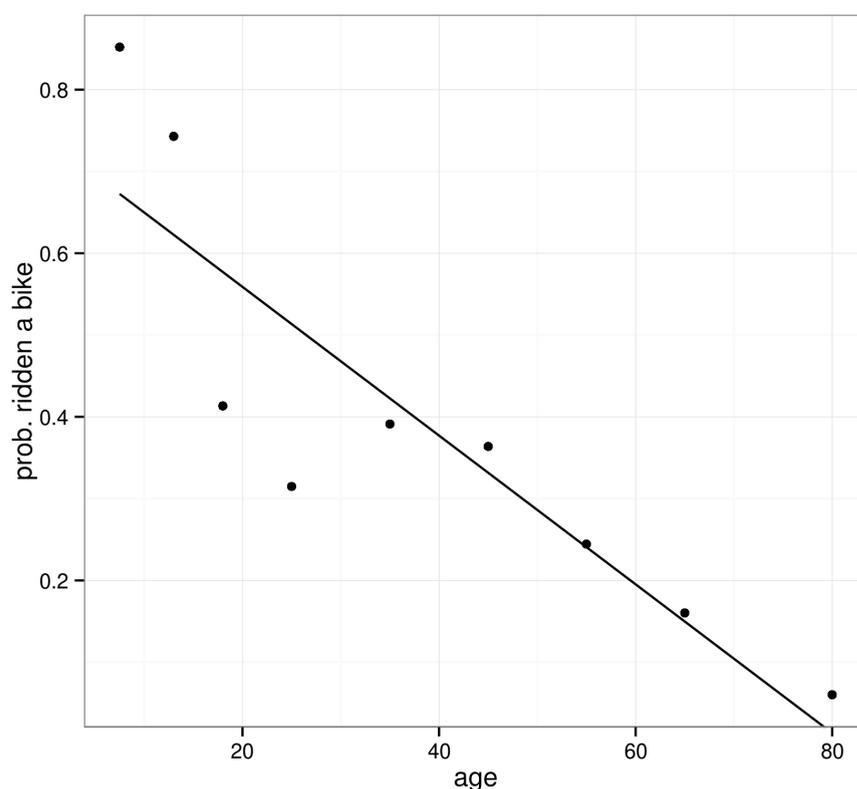


FIGURE 8.2: The relationship between age and bicycle use, from the National Travel Survey. Ordinary Least Squares regression was used to find how the probability of having cycled in the past year (y axis) related with age — it was assumed to be linear after visual inspection. The resulting formula was $p = 0.74 - 0.0091 \times age$.

- The energy savings of a switch were calculated and aggregated for each zone.

Applied to South Yorkshire overall, the energy savings resulting from this scenario were 4.0% of total energy use, slightly above the national average. As with the national level figures, the savings vary geographically: the lowest energy savings were found in the city centres (most notably Sheffield's), where cars are rarely used for short distance trips (walking and public transport options are already popular). The areas of highest energy savings tended to be found in annuli (rings) surrounding urban centres, with inner and outer bounds approximately 2 and 5 km from the centres respectively (figure 8.3) .

Across the region as a whole, the difference between the individual level implementation (with age dependency) and the simplistic implementation (without age dependency and probability bands, not a continuous probability variable dependent on distance) was small: energy savings were 4.4% in the simplistic model, 0.4% percentage points greater. This can be explained by the range of distances within distance bands: in the individual level implementation a 9 km trip is less likely to switch to bicycle than a 6 km trip

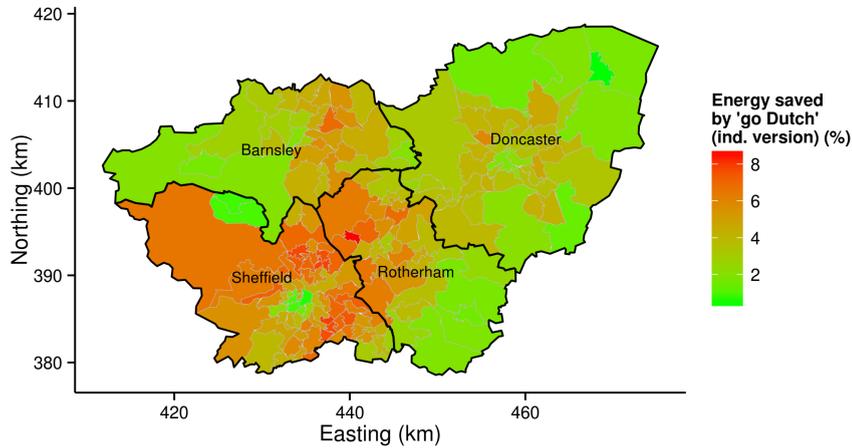


FIGURE 8.3: Energy savings from car-bike modal shift in South Yorkshire, from the individual level implementation of the ‘go Dutch’ scenario.

whereas in the aggregate level model the probability is the same. The spatial distribution of the differences between the estimated energy savings in the individual level and aggregate level implementations are shown in figure 8.4. Note that the individual level savings were substantially lower in Stocksbridge (Northwest Sheffield).

An interesting feature of the ‘go Dutch’ scenario is that more energy is saved in areas with below-average commuter energy costs than in areas where commuter energy costs are high. (In the individual level implementation displayed in figure 8.3, the correlation between current commuter energy use and predicted savings was -0.20 , a statistically significant result). This can be explained in terms of distance: areas with the highest energy costs will tend to be too far from commuter centres for cycling.

8.1.3 Taking the scenario further

Using methods akin to the binomial regression model presented in Schoner et al. (2013), the probability of a car-driving commuter switching to bicycles could be calculated. Proxies for the more ambiguous quantitative concepts such as ‘topography’ (e.g. the proportion of land area with a slope greater than more than 3% — see (Heinen et al., 2010)), climate variables (e.g. number of days of rain per year), could be constructed. The model could be calibrated based on existing data, and then used to evaluate specific what-if scenarios. A new bicycle path, for example, could alter both dR_{bike} and $bikepath$ variables; carbon taxes could increase the price of driving, whereas new cycle facilities

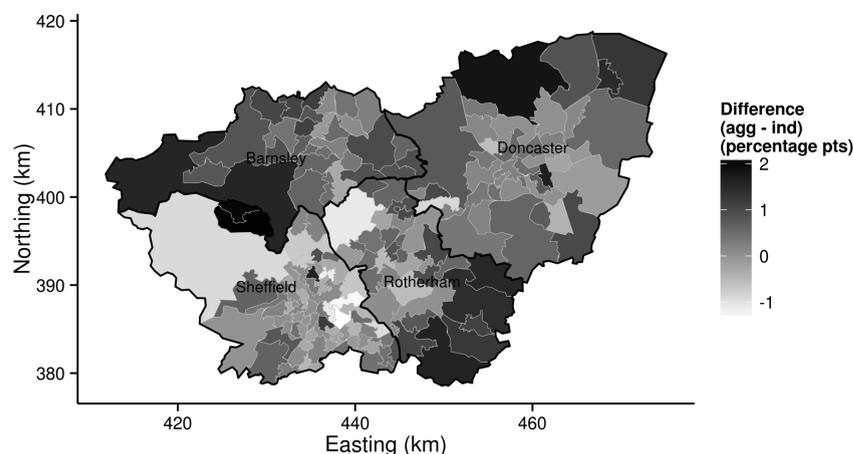


FIGURE 8.4: Differences between individual and aggregate level implementations of the ‘go Dutch’ scenario across the MSOA zones of South Yorkshire.

could increase the attractiveness of cycling, for any particular area. Buehler (2012) specified and ran such a logit model to investigate the impact of cyclist facilities on cycling in Washington. Such an approach, based on spatial microdata, would signify a major step forward in the sophistication of models of modal shift for policy evaluation from the city-wide population model used by Lovelace et al. (2011) to estimate the energy savings resulting from cycling uptake in Sheffield.

It is outside the scope of the thesis to design and implement this model. However, the approach has great potential for assessing individual schemes in terms of energy use and extending non-geographical work on modal shift (Lovelace et al., 2011). The main barrier to the implementation for practical transport planning purposes would be not so much the accessibility of data from which it could be tested and calibrated, but expertise and time to create suitable spatial microdata with origin-destination points and accurate zonal and individual level variables. Developing such a model would be an application of the spatial microsimulation approach to assessing the energy costs of commuting with important practical consequences. Indeed, a similar approach could also be used to investigate the reduction of home-work distance, another oft-cited strategy for reducing commuter energy use.

8.2 Reducing commute frequency: ‘going Finnish’

If modal shift to active modes has less impact than expected, perhaps trip frequency is key. With the spread of high-speed internet over the past two decades and the shift to service sectors over the past century, the need to be physically present at work *every day* for many people has diminished.⁷ This section therefore focusses on telecommuting. The energy implications are clear: Although the energy calculations made so far are on a per-trip basis, the overall energy costs of commuting depend on how frequency the trip is made. An individual who commutes 5 miles 200 times per year, for example, may use more energy than someone who makes a 10 mile trip on a part-time basis. These frequency estimates are not made in the model because the spatial microdataset is not constrained by hours of work (or even full-time/part-time status). However, it is still possible to estimate the distribution of energy savings resulting from telecommuting based on the obviously incorrect but analytically useful assumption that everyone travels to work the same number of times each year. This assumption can be made without a large impact on the results because the major factor determining energy savings from telecommuting will probably not be the prevalence of full/part time work, but the possibility and willingness of people living in each zone to work from home. This appears to be largely determined by distance to work⁸ and type of job. In Finland, for example, “teleworking was almost non-existent among employees with a low educational level and manual work,” whilst those with higher occupational positions were far more likely to telework (Helminen and Ristimäki, 2007, p. 336). Due to the lack of firm evidence about the determinants of telecommuting in the UK, this information is taken as the basis of the telecommuting scenario (which should certainly be updated as more evidence emerges). Using the South Yorkshire simulated spatial microdata described in chapter 7, a simple interpretation of Helminen and Ristimäki (2007) is used as the basis of energy savings. Thus, the scenario was as follows:

- Identify individuals in the highest socio-economic class, who are thought to be likely to be able to telecommute.

⁷To take one anecdotal line of evidence, my girlfriend Carlota works for Skype. They are totally free to work wherever they want: there is no obligation to be in the office each working day. The office is seen as a useful social hub than the basis of productivity. In this case it would be hard to argue that telecommuting reduces energy use (many of the staff spend time away from the office on international trips), but it at least shows the potential of large organisations to implement and even encourage long-distance work.

⁸Helminen and Ristimäki (2007) found that the probability of telecommuting increased roughly exponentially with increased distance, reaching a maximum of $p = 0.12$ for individuals travelling 150 km to work

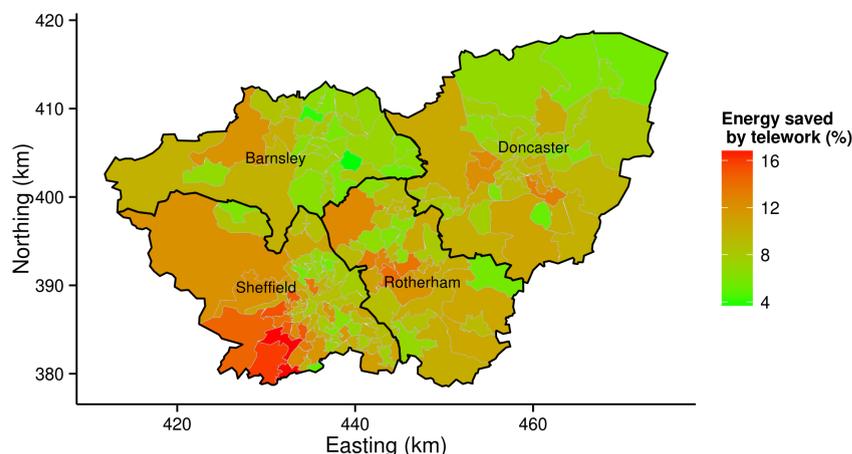


FIGURE 8.5: Energy savings from telecommuting scenario in South Yorkshire.

- Sub-sample from these, with the probability of selection set as $p = 1/e^{-y}$, where $y = 5.3 + 0.022 \times dR$ (measured in km) (see Helminen and Ristimäki, 2007) and the sample size proportional to the number of higher occupation workers.
- Create a new energy cost estimate for each area by subtracting the energy costs of the sampled individuals from the total.

This resulted in a 9.2% energy saving overall, with substantial variation between zones figure 8.5. What is fascinating about this result is the numbers involved: whilst approximately 8% of commuters were affected by the modal shift scenario developed in the previous sector (with energy savings of only 3%), the numbers are almost reversed in this scenario: altering the behaviour of only 2.7% of commuters could, in this case result in energy savings approaching 10%.

The spatial distribution of energy savings reflects the areas of high wealth (Dore in the West of Sheffield, for example is notoriously well off, and has large savings in this scenario), long commuting distances and a preponderance of higher occupations and managers. This is reflected in positive correlations between energy savings and average trip length ($r = 0.014$, not significant), proportion of managers and workers in higher occupations ($r = 0.79$, $p < 2.2e-16$) and mid-estimates of wealth for 2007-8 from the Office of National Statistics ($r = 0.63$, $p < 2.2e-16$). Unlike the modal shift scenario, the greatest energy savings tend to be made in areas with high average energy use for commuting, and affect the most energy intensive commuters rather than the least.

Another current trend that has large potential energy implications is the trend towards part-time work. Using similar methods as those presented above, individuals likely to go part-time could be identified, and energy savings could be calculated accordingly. Policies to promote this trend could include reducing taxes for part-time workers. However, if the end result is the same amount of work being done by more people, the energy savings could be negligible, as more trips would be made by newly employed people.

8.3 Reduction in commute distance: ‘eco-localisation’

The previous sections show that substantial energy savings can be made by building on already existing social trends: towards pro bicycle and active travel policies and telecommuting. However, savings of more than 12% are needed: the government has committed to reducing emissions by over 80% by 2050 and given the slow pace of technological change (Smil, 2010a), this probably means large reductions in energy use. Of course, it would be possible to develop more aggressive scenarios of modal shift and telecommuting for South Yorkshire, but this section focusses on the ‘elephant in the room’ regarding energy intensive commuting: distance. As already suggested in section 6.5 and emphasised by Boussauw and Witlox (2009), home-work distance is the most important driver of energy-intensive commutes. In the absence of nationwide high speed rail or even an international ‘hyperloop’,⁹ distance forces people to use the least efficient mode (cars) and use them a lot. There is also a strong equality argument to be made for focussing on distance: from the South Yorkshire case study, only 7% of commuters travel more than 30 km each day. Yet these individuals account for 41% of commuter energy use in the model. Failing very high rates of telecommuting (with attendant social impacts), this leads to the conclusion that home-work distances must be reduced to cut dramatically energy usage for commuting.

How can this be done? Or more specifically for this research, how can realistic scenarios of reduced commuter distances be created? In the current economic context, there are essentially only two options available to workers wanting a job closer to home. These are: 1) move job or 2) move house. The former depends on an adequate job being available closer to home, about which there is an extensive literature, based around the concept of ‘excess commuting’ (Buliung and Kanaroglou, 2002). The latter may not be feasible for financially constrained families, due to the tendency of house prices to increase towards city centre, where most jobs are to be found (Li et al., 2012),¹⁰ but would be an option

⁹The hyperloop was conceived by entrepreneur Elon Musk as a new mode of transport, located somewhere between rail and aviation, faster than the former yet much more energy efficient than the latter.

¹⁰Put in other terms, commuters are “trading off decreased house prices for longer commutes” (Li et al., 2012, p. 312).

for the wealthiest commuters, who use a disproportionate amount of total commuting energy use.

To realistically model this requires much information, including the spatial variability of house prices, its interaction with transport links and the availability of specific types of job. This data could be obtained, to varying degrees, and represented as part of an integrated land-use transport model. Spatial microdata could fit into this approach. Yet the complexity of data and modelling is beyond the scope of this project.

Instead, the focus of this section is shifted to more hypothetical ‘what if’ scenario founded on the idea of the localisation of economic activity (North, 2010). The premise of ‘intentional eco-localisation’ is that “responses to peak oil and resource constraint as a long term problem cannot be disconnected from the need to avoid catastrophic climate change” (North, 2010, p. 585) and its main features are as follows:

- Its proponents are not willing to wait for either new technologies or high oil prices to reduce energy use: lifestyles must change as part of an overall transition away from economic growth.
- Any economic activity that can be undertaken locally (e.g. food production) will become increasingly decentralised (meaning that jobs less concentrated in specific areas).
- Suburbia in its current form gradually vanishes, and communities will become “villagised’ so people could meet more of their needs from their neighbourhood without commuting” (North, 2010, p. 591).
- Second locally useful professions will become common, to supplement conventional jobs further from home.

Of course, translating such a broad vision into a quantitative scenario of change is highly challenging (Winther, 2013). This scenario exists not only far in the future, but also under the assumption that economic and social conditions will be very different from what they are today. The socio-economic traits of individuals in South Yorkshire will also have changed, reducing the relevance of the spatial microsimulation approach to this problem.

Based on these difficulties, and heeding the warnings from Vaclav Smil about the dangers of creating arbitrary quantitative scenarios about the future of complex non-linear systems (Smil, 2000, 2008), it was decided to not quantify this scenario. The costs of attempting to quantify energy savings of ‘eco-localistaion’ (the impression of simplicity

and certainty, when in reality the long-term future contains a vast array of possibilities) were deemed greater than the benefits (potential clarification of the mechanisms by which it is assumed that commuter energy costs would be reduced). The main benefit of quantitative scenarios are for policy evaluation: unlike modal shift or telecommuting, the ‘eco-localisation’ scenario cannot be reduced to a single policy or change.

All this is not to say that one cannot imagine what the commuting pattern would be under this scenario, or how much energy it would use. Because the major drivers for ‘intentional’ localisation (as opposed to forced localisation) are concern about climate change and resource depletion, very little fossil energy would be consumed in it. In terms of non-fossil energy (such as that consumed by electric cars and bicycles, and biofuel-powered vehicles), the amount of energy use depends on two factors: the state of technology in these areas, and the widespread availability of vehicles. The eco-localisation movement depicted by North (2010) is quite technologically pessimistic. Yet there is strong evidence for rapid change in the sector, with fleets of electric taxis and buses already being deployed in many countries.¹¹ Electric bicycles, a cheaper option, are also becoming more popular (Pierce et al., 2013). The impact these advancements could have on an eco-localisation scenario, and depend to a large extent on their affordability for the masses and the availability of cheap electricity for charging.

Regardless of the pace and direction of technological advance, commuter energy use in a more localised economy would certainly be much lower than its current level. Whether the localisation is confined to more material sectors of the economy (most likely, unless the internet collapses!) or applies to the information economy also would have an effect, as would myriad other assumptions about the future that cannot possibly be validated. This scenario is limited use to policy makers in need of tools to aid with the day-to-day tasks of evaluating different scenarios. Nevertheless, it could, in the right hands, be the most powerful as it highlights how commuting is bound up in the wider economy and illustrates the scale of changes needed to reduce energy use and emissions to a fraction of their current levels, as climate science suggests. The other reason why the eco-localisation scenario may be attractive is that it enables communities to reduce their reliance on imported oil, potentially increasing energy security and ‘oil vulnerability’. The next section investigates how the spatial microsimulation approach could contribute to understanding, and efforts attempt to measure, the likely impacts of high oil prices.

¹¹These include Colombia, Beijing and New York, according to contemporary news reports.

8.4 Oil vulnerability

In addition to greenhouse gas emissions, one of the most problematic features of modern transport systems in the long term is their high dependence on finite fossil fuels. This is well illustrated by the fuel tax protests of 2000, when a small group of protesting hauliers caused chaos in hundreds of petrol stations in the UK (Lyons and Chatterjee, 2002). The high vulnerability of transport systems to relatively minor perturbations in the supply of oil has not gone unnoticed by the research community. McKinnon (2006) investigated the impacts of a week-long cessation of fuel supplies to the UK's road distribution network and arrived at the worrying conclusion that it would lead rapidly to economic collapse. Based on a detailed analysis of the 2008 spike in high prices and subsequent collapse of the US housing market, Sexton et al. (2012) arrived at the conclusion that the latter (and much economic strife) was caused by the former, due primarily to high energy costs of commuting from low density suburbs.

These studies have provided strong evidence that modern transport systems are highly vulnerable by speculating on possible future outcomes based on historical precedents. However, few studies have sought to quantify the likely impacts or predict the people and places most likely to be affected. This section explores methods of measuring 'commuter oil vulnerability' based on spatial microdata of commuters in Yorkshire and the Humber, and generates results indicating which types of area, and people may most affected by another oil price spike.

8.4.1 Metrics of vulnerability: resources, jobs, money

Four metrics, which reflect economic, energetic and other perspectives on oil vulnerability, were developed, and calculated for zones in Yorkshire and the Humber. The inputs into the vulnerability metrics were supplied by the results of the spatial microsimulation model. These metrics are as follows:

- Economic vulnerability: defined as commuter fuel poverty (V_{cfp}), the proportion of people spending more than 10% of their income on work travel.
- Energy based metric 1: proportion of energy use expended on work travel (V_e)
- Energy based metric 2: proportion of individuals spending more than 10% of their 'energy budget' on work travel in each area (V_{ei}).
- Hybrid vulnerability index based on distance to employment centre, dominance of cars, and the average energy costs of commute (V_h).

It should be noted that two of these metrics, $V_{c_{fp}}$ and V_e , also operate at the individual level, allowing for the identification of characteristics associated with vulnerability to be assessed in each zone (see Section 8.4.3). Both financial and energy metrics of commuter vulnerability are used. The former has strong foundations in economics; the latter in systems ecology. Finally, a more complex hybrid vulnerability metric is presented.

8.4.1.1 Economic vulnerability — commuter fuel poverty

The total monetary costs per trip (C) can be estimated as a function of the value of time lost (c_s) and direct monetary expenditure (c_m) per unit distance (d) for each mode of transport (Ommeren, 2006). Due to methodological difficulties in measuring c_s (Mokhtarian and Salomon, 2001), we focus on the direct monetary costs:

$$C = c_m \times d \quad (8.2)$$

The standard definition of fuel poverty is spending more than 10% of disposable household income — specifically, equivalised income — on adequate home heating and cooking (Boardman, 2010). Thus, ‘commuter fuel poverty’ can be defined as spending more than 10% of one’s equivalised income on commuting. At the individual level, commuter vulnerability can thus be defined either as a continuous ($V_{c_{fp}}$, equation 8.3), or a binary ($V_{c_{fp}bin}$, equation 8.4b) variable. For zones, vulnerability can be defined simply as the proportion of people living in commuter fuel poverty ($V_{c_{fp}a}$, 8.5).

$$V_{c_{fp}} = C/I \quad (8.3)$$

$$V_{c_{fp}bin} = \begin{cases} 1, & \text{if } V_{c_{fp}} \geq 0.1 \\ 0, & \text{if } V_{c_{fp}} < 0.1 \end{cases} \quad (8.4a)$$

$$V_{c_{fp}a} = \frac{\sum V_{c_{fp}bin}}{n} \quad (8.5)$$

8.4.1.2 Energy-based metrics

An alternative approach is to take the ecological view that energy is the ‘master resource’ (Smil, 2006), and measure vulnerability accordingly.¹² The resulting metric would focus

¹²According to this view, a system’s performance can be assessed by the energy flows within it (Odum, 1971)

not on the monetary expenditure of transport to work, but on the energy costs. Using the data presented in chapter 5, energy costs per trip (E_T) can be calculated based on information on mode (m), distance (d), and energy consumption per kilometre (η):

$$E_T = \eta_m \times d \quad (8.6)$$

This estimate can be used as a self-standing marker of vulnerability, if one assumes that more energy intensive commuting patterns are inherently more vulnerable. Following the logic of fuel poverty measures, an alternative to monitoring absolute energy use in transport is the *proportion* of one's energy budget expended on commuting (P_{ET}):

$$P_{ET} = \frac{E_T \times T_{yr}}{E_{yr}} \quad (8.7)$$

where T_{yr} is the number of commuter trips made per year and E_{yr} is total energy use per year. These input values can be calculated at the individual level from the survey data. At the individual level, the resulting energy-based vulnerability metrics (V_{ei}) can therefore be calculated as continuous or binary individual level variables. For geographic zones, V_{ei} is defined as the proportion of commuters who spend more than 10% of their energy budget on work travel.

An alternative energy-based vulnerability metric that operates solely at the aggregate level (V_e) is calculated as the total energy expenditure on commuting in the area divided by total domestic energy use:

$$V_e = \frac{\sum E_T \times T_{yr}}{\sum E_{yr}} \quad (8.8)$$

8.4.1.3 Hybrid vulnerability metrics

A criticism of the aforementioned vulnerability indexes is their narrow focus, either on energy or money. They take no account of other quantifiable factors that influence vulnerability, such as geographical isolation from employment centres, level of community cohesion or the diversity of transport options in the area (Pickerill and Maxey, 2008; North, 2010; Steele and Gleeson, 2010; Newman et al., 2009). For this reason, a hybrid metric based on multiple risk factors may be more appropriate. The following is one example of a hybrid index that operates at the aggregate level:

$$V_h = (P_{ET} + \alpha) \times \sqrt{\beta D_c} \times P_{car} \quad (8.9)$$

where P_{ET} is the proportion of the individual's energy budget spent on commuting, D_c is distance to employment centre, P_{car} is the proportion of work trips made by car in the zone in question, and α and β are parameters to be set.

V_h acknowledges that the vulnerability of commuting patterns to high oil prices is complex, and caused by multiple, self reinforcing factors. By changing the values of the predefined parameters (or by modifying the equation) it is possible to increase or decrease the importance allocated to certain factors. Increasing the value of α , for example makes the result far less sensitive to the proportion of energy used for commuting. Perhaps isolation is seen as a more important determinant. In this case the value of β could be increased.¹³

Each of these metrics has its limitations, not least the reliance on aggregate cost and energy estimates that may vary significantly from place to place and person to person. These limitations are further discussed in Section 4.7.3. For now the assumption is that they are useful proxies of commuter oil vulnerability and, after exploring aggregate level findings based on census data, investigate the results of each formulae in turn.

8.4.2 Results: trips, distance and energy use

The spatial microsimulation model allows cross-tabulations of commuter patterns by a range of variables. Table 8.1 illustrates the importance of the three most popular modes in terms of fundamental features: proportion of trips, distance, and energy use. The dominance of the car is striking. Drivers (excluding car passengers) account for 55% of trips, 75% of distance travelled and 96% of energy use. This result is predictable as the region's transport infrastructure is focussed on the car, and coincides with other findings from the UK (Brand et al., 2013).¹⁴ Overall, cars consume more than 20 times more energy than all other forms of transport to work put together whilst providing transport for 62% of the workers.

An additional inequality surrounds distance: trips of more than 10 km account for 76% of the distance travelled and 80% of the energy costs of transport to work, yet are made by just 31% of employees. The results suggest that very long trips to work consume a disproportionate amount of energy: 4% of commutes in Yorkshire and the Humber are greater than 50 km, yet these account for almost 30% of energy costs.

¹³This assumes that D_c is a valid proxy for isolation. Whether or not the assumption holds is debatable, based on the method used to calculate D_c for each zone: D_c is defined here as the distance to the nearest employment centre in each transport to work (TTW) zone. D_c was calculated for the population centroid of each medium super output area (MSOA) using the command 'nncross' from the 'spatstat' package in the computer program R.

¹⁴Yorkshire and the Humber's transport infrastructure contains 380 km of motorways, 2,300 km of major roads and over 30,000 km of roads in total. By contrast there are 1,500 km of railways and less than 500 km of bicycle paths in the region.

TABLE 8.1: Proportion of trips (T), distance (D) and energy (E) used by the three most popular forms of transport in Yorkshire and the Humber.

Dis. (km)	Car*			Walk			Bus			All modes		
	T	D	E	T	D	E	T	D	E	T	D	E
0-2	1.2	0.1	0.2	3.5	0.4	0.0	0.2	0.0	0.0	16.8	0.6	0.2
2-5	12.8	3.8	4.9	5.9	1.4	0.1	4.8	1.5	0.5	28.3	8.1	5.6
5-10	15.5	10.4	13.4	0.4	0.3	0.0	3.8	2.5	0.9	23.4	15.7	14.6
10-20	14.0	17.3	22.2	0.7	0.8	0.0	0.9	1.1	0.4	17.7	21.7	23.0
20-50	7.9	21.1	27.0	0.0	0.0	0.0	0.3	0.8	0.3	10.0	26.5	27.7
50+	3.0	22.3	28.6	0.0	0.0	0.0	0.0	0.0	0.0	3.8	27.5	28.8
All	54.6	75.0	96.4	10.6	2.9	0.2	10.1	5.9	2.1	100	100	100

*Excludes car passengers

The spatial variability of the vulnerability indices is shown in Fig. 8.6. The metrics are closely related, as illustrated by the concentration of high vulnerability in isolated rural areas in all but one of the metrics. Spatially this correspondence can be seen as an arc of vulnerable areas defined in terms of V_{cfp} , V_e and V_h in Fig. 8.6. This area runs from East Leeds to Castleford Selby and north-east towards Hull and the Yorkshire Wolds. The correlation between the metrics, at the MSOA level, is shown in Fig. 8.7.

An unexpected result is that some employment centres are associated with high levels of commuter fuel poverty — measure a). This can be seen in the dark patches next to Harrogate, Malton and Whitby and a number of urban settlements — for example to the East of Sheffield. This result can be explained by distance of commute: each of the areas mentioned is associated with long commutes¹⁵ and low levels of deprivation scores in the surrounding areas.

In order to test the relationship between commuter oil vulnerability and broader social disadvantage, the vulnerability measures were compared with the Index of Multiple Deprivation (IMD). Because the IMD dataset is available at the lower super output area (LSOA), aggregation was used to find the mean IMD score in each MSOA. This allowed correlations to be calculated. Negative correlations were found between aggregated IMD and all four vulnerability metrics; Pearson's coefficient of correlation (r) ranged from -0.59 to -0.22 for the V_{ei} and V_{cfp} measures respectively. This result implies that areas at risk from high oil prices are not currently identified as being in urgent need of support. A comparison of the choropleth maps of IMD in Fig. 8.8 with the vulnerability metrics (Fig. 8.6) illustrates the reason for negative correlations: deprivation is primarily an

¹⁵The average Euclidean distances of commutes in the area are 18, 15 and 23 km for MSOA areas surrounding Harrogate, Malton and Whitby, respectively. The average for the region is 11 km.

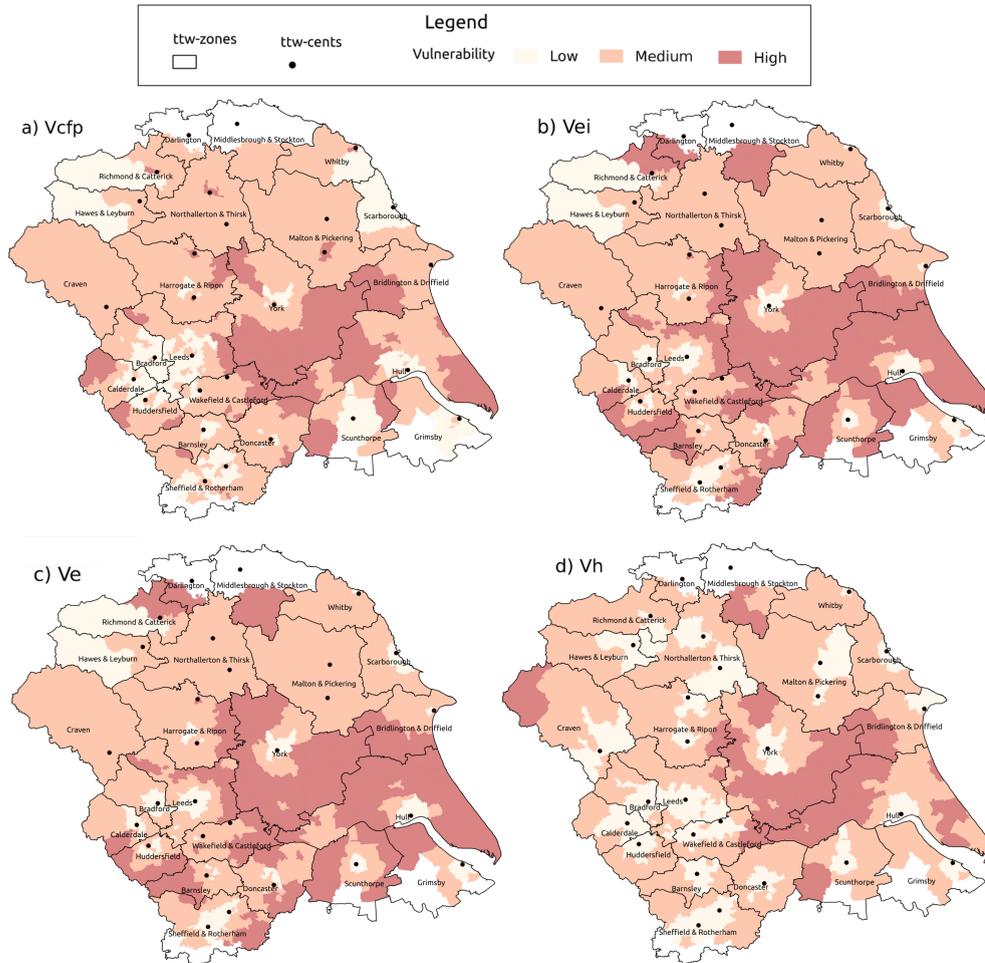


FIGURE 8.6: Vulnerability of commuter patterns in Yorkshire and the Humber according to four metrics: a) Commuter fuel poverty, b) individual energetic, c) zonal energetic, d) hybrid vulnerability. Bins were allocated by Jenks' classification of natural breaks.

urban phenomenon in Yorkshire and the Humber (the three most deprived MSOA areas are located near central Grimsby and Bridlington & Hull), whereas oil vulnerability tends to be rural.

To explore this link further, the average distance from employment centre¹⁶ was calculated, based on the population-weighted centroids of the MSOA areas and the economic centre of each transport to work area, based on 2001 data. The results (illustrated in Fig. 8.9) demonstrate the importance of taking account of population clustering in the analysis of zones: population-weighted centroids are often much closer to employment centres than centroids that are based on area alone. The similarities between the metrics plotted in Fig. 8.6 and the distance from employment centre illustrated in Fig. 8.9 suggest a strong link between distance from employment hub, energy use, and vulnerability.

¹⁶“Employment centre” here is defined as the towns and cities referred to in the names of the 2001 transport to work areas (TTW) (ONS, 2011).

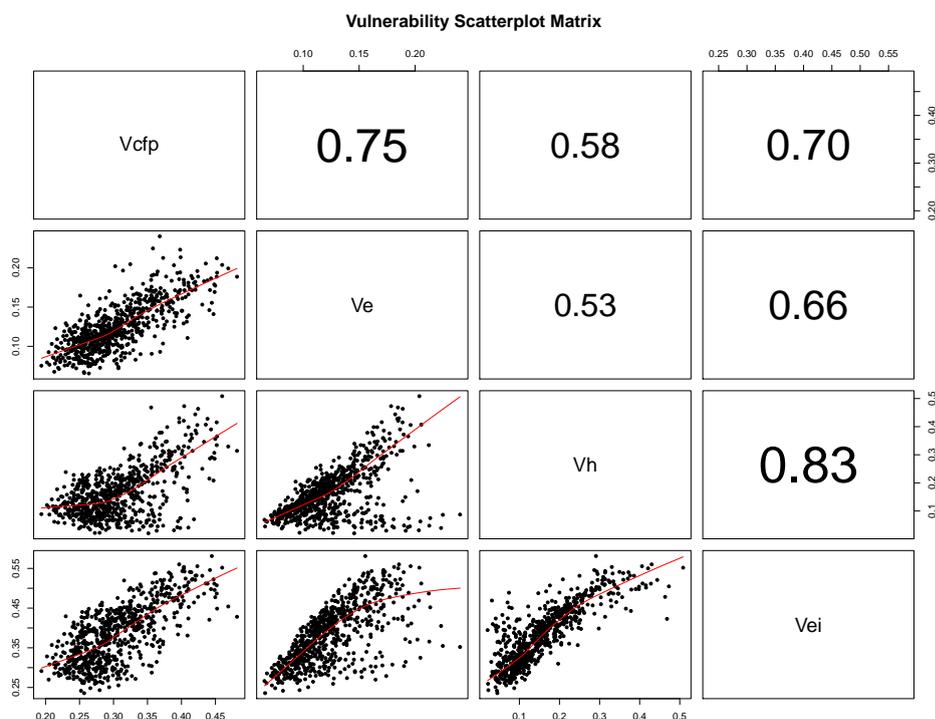


FIGURE 8.7: Scatterplot matrix illustrating the relationships between each of the 4 vulnerability metrics.

So far only geographically aggregated results have been presented. A key advantage of spatial microsimulation, however, is that individual level characteristics can be modelled.

8.4.3 Local and individual level results

The spatial variability described in the previous section provides insight into the types of places where commuters are expected to be most vulnerable to oil shocks. However, high oil prices affect people, not places and a wide range of commuter habits are present in every area. Geographically aggregated data therefore only tell part of the story and, if interpreted incorrectly, can mask intra-zone variability. In a worst-case scenario this could lead decision makers to overlook vulnerable groups. Indeed this situation has been described in Albuquerque, where a new bus network failed to aid those most in need (Tribby and Zandbergen, 2012).

Hypothetical commuters illustrate the point. We would expect a high-income manager, for example, to have a low commuter fuel poverty (V_{cfp}) score due to high income. Their individual level energy vulnerability (V_{ei}) score may be higher, however, especially if they live in an energy efficient home but drive a large car many miles to work and back every day, as is common for high earners (Green et al., 1999). If they live in a car-dominated area far from employment centres in a rural ‘commuter belt’, the area in which they live

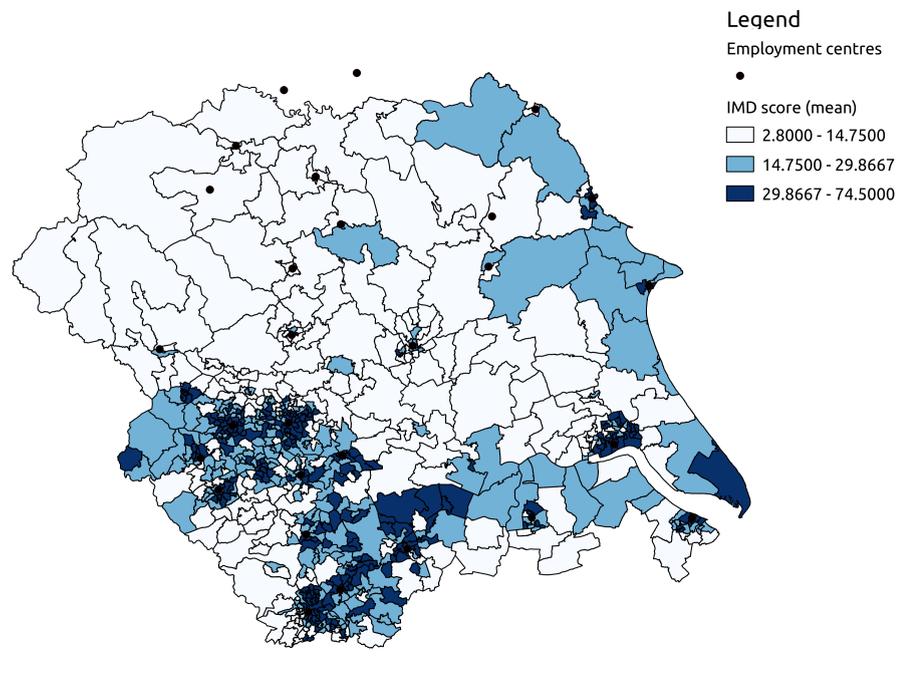


FIGURE 8.8: Choropleth map illustrating the spatial variability of the Index of Multiple Deprivation at the MSAO level. (Values are average IMD scores for LSOA centroids.)

may well have a high aggregate energy vulnerability V_e score. These are clearly not the characteristics of a deprived area. By contrast, an unskilled worker living in a deprived urban area (with a poorly insulated house) who travels a few kilometres to work may have a low V_{ei} but high a V_{cfp} score if they spend a portion of their low income on expensive bus tickets.

These suppositions may seem obvious but the relative numbers and spatial distribution of different groups are not. Spatial microsimulation, by estimating the characteristics of individuals, provides a means of gaining insight into the likely impacts of oil vulnerability on people beyond aggregated statistics associated with the areas in which they live. An example of three areas from the city of York (selected because it is the most unambiguous employment centre surrounded by countryside in the region) serves to illustrate the point: one is right in the city centre, the second is a low income suburb, and the third is on the rural outskirts of York (Fig. 8.10).

Table 8.2 illustrates summary vulnerability statistics for each of the three areas numbered in Fig. 8.10, and the average weekly income for household in each zone.¹⁷ It is interesting to note that the wealthiest zone, in the centre, is also the most oil vulnerable according to V_{ei} and the second most vulnerable in terms of V_e and V_{cfp} . This finding

¹⁷The income estimates are from the Office of National Statistics Neighbourhood Statistics service. The estimates presented in Table 8.2 are the central estimates for equivalised income from the table “Income: Model-Based Estimates at MSAO Level, 2007/08”.

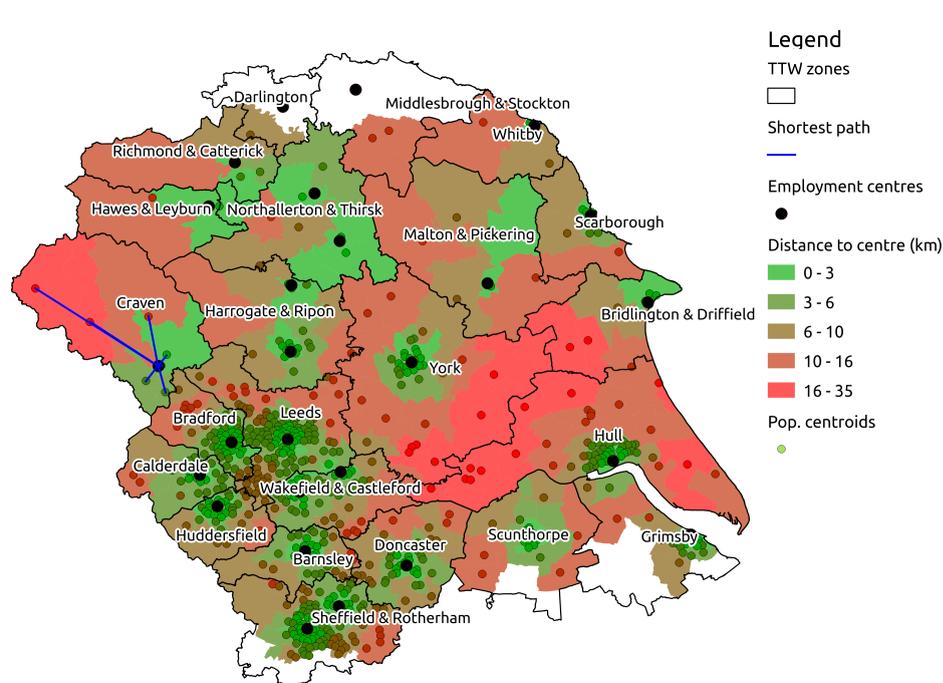


FIGURE 8.9: Distance to employment centre, calculated as the shortest distance between zone population centroids and TTW zone employment centres (see blue lines, which illustrate this calculation for zones in Craven TTW zone). Compare with Fig. 8.6.

can be explained by the high average distance travelled to work by commuters living in the city centre: wealthy people tend to commute further, leading to higher energy and monetary expenditure on travel to work. Commuters in the rural zone (three) commute, on average, the same distance yet they are deemed to be less vulnerable when vulnerability is measured as the proportion of people spending more than 10% of their energy budget on commuting. This can be explained by the higher baseline energy use in rural areas (Druckman and Jackson, 2008), meaning that although commuting energy use is high, it does not form a large proportion of total energy use for most. The rural zone is most vulnerable in terms of V_e , V_{cfp} and V_h , illustrating the importance of income, overall energy use and distance from employment centre for these metrics.

Because V_e and V_{cfp} are also calculated at the individual level, it is possible to estimate the characteristics of vulnerable individuals at the local level. These results (presented in Table 8.3) illustrate that different types of people are defined as ‘oil vulnerable’ in different areas. The average income of people living in commuter fuel poverty (for whom $V_{cfp} \geq 0.1$), for example is much higher in the city centre than in the outskirts. Table 8.3 illustrates that the characteristics of individuals defined as ‘oil vulnerable’ can also vary greatly within areas depending on how oil vulnerability is defined. People living in commuter fuel poverty, for example, tend to be older than those for whom $V_{cfp} \geq 0.1$. We could hypothesise whether this is due to a greater reliance on motorised modes amongst generally less active older citizens or perhaps also due to lower energy use amongst

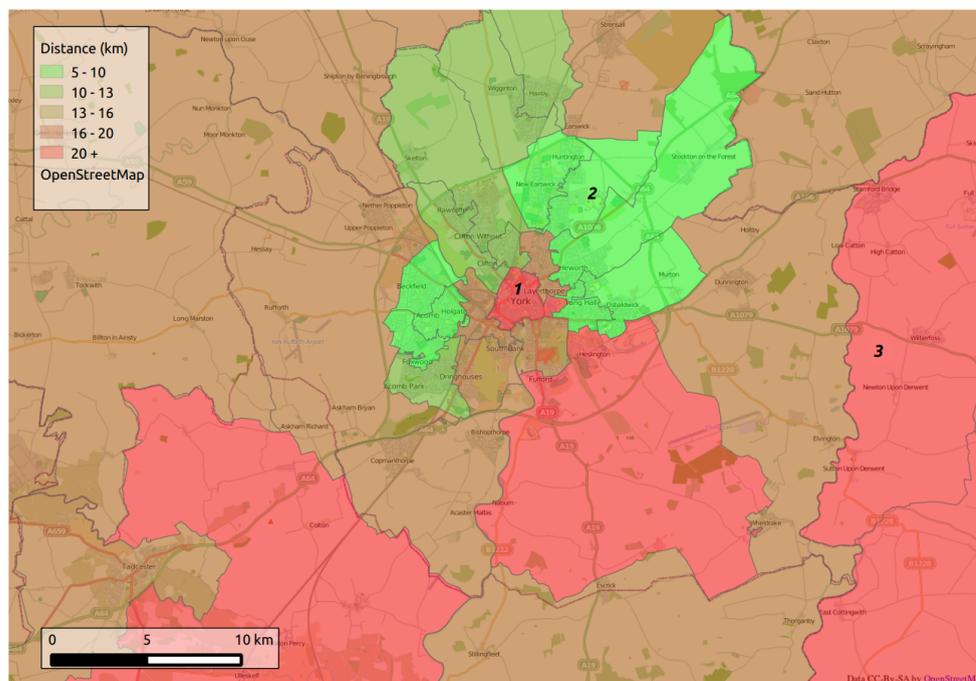


FIGURE 8.10: MSOA zones in York, coloured according to distance travelled to work. The zones 1, 2 and 3 are referred to below.

TABLE 8.2: Summary statistics of vulnerability metrics and income estimates for three areas in York. All results presented as percentages, unless otherwise stated.

Variable	Statistic	1: Central	2: Suburb	3: Outskirts
Income (£/wk)	Mean	440	400	390
Distance (km)	Mean	16.5	8.3	16.5
V_{cfp}	Mean	2.0	1.1	2.1
	SD	3.5	2.8	4.9
	$\geq 10\%$	3.3	1.7	5.9
V_e	Mean	14.9	9.1	8.4
	SD	13.9	11.5	12.3
	$\geq 10\%$	55.7	32.0	28.6
V_{ei}	-	17.0	10.0	18.0
V_h	-	3.0	9.0	33.0

young people. Estimates of the average number of children under the care of commuters were also generated by the model. These have no bearing on the vulnerability scores, but illustrate how additional socio-demographic variables could be included to provide additional information to the simple univariate oil vulnerability metrics. The distance and mode of school travel, for example, could have a major impact on the viability of working closer to home in cases where travel to work is combined with the school run (Hensher and Reyes, 2000). Based on the results from our metrics, it would seem that commuters living in commuter fuel poverty living in zone 2 and 3 are particularly

vulnerable, with high levels of car dependence yet low incomes.

TABLE 8.3: Individual level characteristics of ‘oil vulnerable’ commuters in living in the three zones of York depicted in Fig. 8.10, estimated by the spatial microsimulation model.

Subset	Statistic	1: Central	2: Suburb	3: Outskirts
V_{cfp} $\geq 10\%$	N	241	51	151
	Average age	39	41	44
	Average income	19100	15800	14300
	Income SD	9400	10100	8400
	N. children	0.51	0.88	0.67
	% drive to work	45	53	56
V_e $\geq 10\%$	N	1168	990	2466
	Average age	35	31	41
	Average income	18000	16600	19200
	Income SD	11900	8000	10300
	N. children	0.67	0.64	0.67
	% drive to work	43	40	61
All commuters	N	4085	3091	4424
	Average age	36	41	42
	Average income	19500	17900	19686
	Income SD	12600	10800	12000
	N. children	0.56	0.7	0.67
	% drive to work	25	49	61

By providing estimates for a range of individual level variables, spatial microsimulation can highlight the various types oil vulnerability. Returning to the two hypothetical commuters mentioned at the beginning of the section, one could further predict their relation to policy interventions. Policies encouraging telecommuting may be more effective if targeted towards the manager (with the potential co-benefit of freeing up oil for shorter commutes or public transport). The unskilled worker, by contrast, may be better served by pro-cycling policies or subsidised buses to increase the viability of cheaper and more active forms of travel. (Public transport is generally more active than driving, as people tend to walk to and from bus stops (Besser and Dannenberg, 2005).) Based on a dynamic spatial microsimulation models, the local impacts of these policies could be projected (Ballas et al., 2005c). As with aggregate measures, commuter oil vulnerability at the individual level clearly has multiple meanings and interpretations. The model results support this view and could, if combined with additional vulnerability metrics (e.g. those used in the IMD), be used as a multifaceted concept oil vulnerability overall.

8.5 Discussion: policy relevance and limitations

In this chapter the potential of the spatial microsimulation approach for the analysis of commuter patterns for informing policy has been tested. Three ‘what if’ scenarios of change leading to lower commuting energy costs have been developed and two of these have been quantified, yielding interesting and policy-relevant results. The first aim of this thesis, set out in section 1.5, was to not only investigate the variability of commuter energy costs, but also its policy implications. The previous two results chapters also have policy-relevant findings, but it is only here that scenarios of change in commuting patterns have been evaluated in energy terms. As set out in chapter 1, the motivation behind this research was to some degree political: the perceived need for policies to rapidly reduce the rate at which fossil fuels are burned, to avoid the worst impacts of climate change and fuel depletion. It is easy to say that such policies are needed in the transport sector (Chapman, 2007), but quite another to select precisely which policies are likely to be most effective at achieving this aim.¹⁸ The second aim was to “Formulate and analyse scenarios of change”. This has been achieved for case studies in South Yorkshire, based on the potential of commuters to shift mode to bicycles and reduce the frequency of their trips to work through telecommuting. Other plausible scenarios of change could have been developed, such as increases in car sharing, and shifts to other forms of transport. Both of these options have great potential to reduce energy costs of commuting in the short-term, but were not formalised as quantitative scenarios due to data and time constraints in the first case and the fact that widespread investment in public transport, high speed railways notwithstanding, currently seem a remote possibility in the latter.¹⁹ The spatial microsimulation method could be used for evaluating many other scenarios of policy intervention, and can estimate change in many other variables beyond energy use. The likely distributional impacts of proposed policy interventions is an area where the method has greatest potential for policy influence. Although there are many other unexplored scenarios that could usefully be evaluated

¹⁸Indeed, Berners-Lee and Clark (2013) show that many well-intentioned efforts to reduce emissions have a tendency to simply displace emissions to a different time or place (they liken trying to reduce emissions to ‘squeezing a balloon’ — it always bulges out somewhere else). To provide one example in the context of commuting, the shift to electric cars certainly reduces direct emissions at the point of use, but may increase emissions at the power plants that charge the batteries, and in the mines, factories and freight transport networks than are needed to produce electric cars.

¹⁹The potential of car sharing depends not only on the number of people driving similar distances to work, but also the direction of travel. This dataset is not used in the spatial microsimulation model presented thus far, although it is available at Output Area and Ward levels, as described in section 7.3. Car sharing, it is hypothesised, has great potential to reduce commuting energy costs, as it allows long distance trips to be tackled, forming an interesting future direction for this research. The replacement of car journeys with public transport also has great potential as buses, coach, trams and trains are far more efficient than cars. However, during this time of fiscal constraint, it seems unlikely that the large-scale roll-out of new public transport services that this scenario would require will happen any time within the next decade or so. In fact, some bus services are in jeopardy of being cut altogether due to financial pressure (Owen et al., 2012).

using spatial microsimulation, a strong argument can be made that the results generated in this chapter are interesting and relevant in themselves.

8.5.1 Policy relevance of findings

A substantial shift to bicycles in England (with bike trips reaching 10% of all trips to work) was modelled by the ‘go Dutch’ scenario. This would affect around 13% of the population (and 14% of car drivers) but only reduce commuter energy use by 3%, an unexpectedly low figure for such a dramatic shift. Perhaps this surprise comes primarily as a result of preconceptions of the bicycles as being a ‘green’ mode of transport: it is often assumed that promoting this mode of transport will lead to large and rapid reductions in energy use and associate emissions.²⁰ The results suggest that more than uptake of cycling is needed for substantial reductions in energy use in the current system. In addition, it was found that the greatest savings would accrue to individuals (who drive short distances to work) and areas (located near to employment centres) that have relatively low energy costs for commuting *already*.

In the ‘go Finnish’ telecommuting scenario, by contrast, altering the behaviour of a small proportion of the population was found to have a disproportionately large effect on total energy use in the case study region. Because a switch to telecommuting is more likely amongst long-distance commuters, and long-distance commuting is associated with higher incomes, it can be inferred that policies that promote telecommuting would be ‘energetically progressive’, affecting those who already use most energy the most. Pro-cycling measures, on the other hand, could be seen as ‘energetically regressive’ based on the results presented in this chapter: only people who already live relatively close to home are, in general, able to switch to cycling. None of this is to say that cycling promotion is ‘bad’ per se, simply that its energy and environmental benefits may not be as great as expected, and lower than policies which target the most energy intensive commuters. Differences between the individuals affected by the ‘go Dutch’ and ‘go Finnish’ scenarios are illustrated in table 8.4. This table shows that the distribution of climate/energy policies vary widely in the transport sector: those affected by the telecommuting policy have a substantially higher average income than those affected by the pro-bike scenario. One could argue that they would be better able to deal with the

²⁰Studies that have quantified the likely savings tend to have similarly pessimistic findings, however: that potential energy and emissions savings from bicycling uptake alone are small in the grand scheme of things. Lovelace et al. (2011) found maximum savings of only 90 MJ/person/yr (less than 0.1 kWh/p/-day, well around 0.1% of current per capita energy use in the UK) by 2020 even under the most optimistic cycling scenario in one city. Lindsay et al. (2011) found that “Shifting 5% of vehicle kilometres to cycling would reduce vehicle travel by approximately 223 million kilometres each year, save about 22 million litres of fuel and reduce transport-related greenhouse emissions by 0.4%”, a strikingly similar finding given that transport causes around 1/4 of emissions.

resulting effects. Most strikingly, the results show that those affected by the cycling scenario already use quite little energy for their daily commute, whereas those who take up telecommuting use on average more than 3 times more energy per trip to work than the county-wide average. In energy terms, the ‘go Dutch’ scenario is regressive, whereas the ‘go Finnish’ scenario is progressive. That’s not to say that the latter is ‘better’ — energy and emissions will be only one of several considerations taken into account. The analysis suggests that the two policies would complement each other well: The areas of greatest energy savings from a shift to bicycles tend to be close to city centres where many people commute a short distance by car. Telecommuting, by contrast will have most impact in commuter belts far from urban centres.

TABLE 8.4: Differences between commuters affected by the ‘Dutch’ and ‘Finnish’ scenarios, expressed as averages over all commuters in South Yorkshire

Variable	All commuters	‘Go Dutch’	‘Go Finnish’
% affected	100	8	2.8
Etrp (MJ/trip)	39	22	134
Income (£)	18090	17910	24357
Age	39	40	41
Distance (km)	11	5	33.5
Energy saving (%)	0	2.8	9.2

The final scenario was by far the most ambitious. ‘Eco-localisation’, it was decided, would occur long in the future. People would have different attributes, the distribution of jobs would be different and the entire structure and function of urban systems may have changed due to previously unforeseen processes and events (some driven by technology, others by unexpected ‘black swan’ incidents (Korowicz, 2011)). Based on these features of this final scenario, it is difficult to model. It was decided that the spatial microsimulation approach set-out in chapter 4 would not be appropriate to estimate the energy savings of this scenario, as it would simply be a function of the author’s (subjective) assumptions about what a more localised economy would look like in terms of commuting. As Vaclav Smil has pointed out on several occasions (e.g. 1993; 2010a), there are limits to quantification and modelling, and these are especially applicable in long-term forecasts on the basis of which decisions must be made. It is important to consider these limitations lest the results be misinterpreted, leading to ineffective policies. Many of the limitations of the approach expounded in this thesis are well-exemplified by the eco-localisation scenario, which would push any modelling approach to its limits.

8.5.2 Limitations of the approach

Firstly, it is vital to remember that we are dealing with *virtual* individuals, whose characteristics have been simulated based on a set of constraint variables. Even the total population represented by these individuals in each area is not completely objective: the total number varies in our dataset from one constraint to the next so one must be selected (in this case mode of travel) and the others set equal to this. Beyond this minor issue the constraint variables (and total counts within each constraint category) can be relied upon as accurate if the process of spatial microsimulation works properly and the IPF converges properly to a single result (see section 4.6.2): census data are highly reliable, and the correct number of individuals with certain characteristics will be selected.

A critical distinction must be made when using data generated by spatial microsimulation: between the aforementioned constraint variables and target variables that are unconstrained. Income is a good example of a target variable because it is clearly linked to age, sex, distance and mode of travel to work and especially to social class, but is not totally determined by these constraints. The high ($r \sim 0.8$) correlation between official average income estimates and those generated by the spatial microsimulation presented in figure 4.17 provide confidence that the model is working correctly but also raise the question: what accounts for the other 20% of variability in average income between wards? The answer is that the model, based on the current constraints, cannot tell us. Even if more constraints such as car ownership and tenure were added, still not all of income variability would be accounted for at the aggregate level, let alone the local level. Reality is complex, and it must be acknowledged that models cannot (and probably should not) attempt to encapsulate the totality of the interacting, sometimes unquantifiable factors that are at work. In this context, the energy use variable that has been calculated for individuals and regions is ‘semi-constrained’. By this is meant that the main mode and (crudely binned) euclidean distance band for individuals’ *usual* (not constant) trip to work is known. These two factors are the most important controls on energy use chapter 5 and are constrained by census data, so the estimates are likely to reflect the reality of commuter energy use to a large extent.

The second critical limitation of the approach with respect to future scenarios is that it is static. No dynamics are included in the model, so the only way future change can be represented is by updating the constraint variables and holding everything else constant, or by selecting individuals based on certain attributes who are deemed to be most likely to switch behaviour, as done here. This approach has the benefit of simplicity, clarity and transparency, yet lacks the sophistication of agent-based models.

Beyond these issues of interpretation and the need to develop carefully constructed assumptions for the model to be of use to policy-makers, spatial microsimulation, as implemented in this thesis, lacks the sophistication and detail of the recent breed of agent-based transport models. MATSim, for example, can include individual level characteristics, model trip demand *and* allocate this demand to the transport network in near-continuous time (Balmer et al., 2009). On the other hand, such detail and sophistication comes at a cost: MATSim may be harder to configure and interpret than the comparatively simple approach taken here. Also, coming from the transport perspective, transport models tend to be inherently less interested in distributional impacts than impacts on road traffic, although distributional impacts could still be built in provided appropriate input data (with socio-economic variables) is used. This raises the possibility of using the output of the spatial microsimulation approach advocated in this thesis as an input into more advanced model, something that is further considered in the conclusion.

The final limitation of the modelling approach that has already been alluded to, and that to some extent afflicts all models that are built on static assumptions about the world, is the potential of unexpected events to render them ineffective. An ‘oil shock’ is one example of this, that has already been tackled, in section 8.4. One near-certainty about the future, however, is that climate change will continue to produce weather that is extreme by historical standards (Koetse and Rietveld, 2009).

In summary of this chapter, it has been shown that scenarios about the future can be modelled by a spatial microsimulation model of commuters, with important policy implications. It is important to acknowledge the limitations of this approach, however, which include its use of simulated individuals who may differ from real people, and its treatment of an uncertain future. Overall great progress has been made towards meeting the aims of the thesis.

Chapter 9

Conclusions

This thesis has investigated the energy costs of commuting and how they vary between people and over space. Motivated by the major problems of climate change, peak oil and social inequality, the research set out to offer evidence, and tools, to policy makers tackling these issues in the realm of personal travel. To complete the task, the methodology had to provide insight into the spatial distribution of commuter energy use, inequalities in its social distribution and the likely social and spatial impacts of different intervention options. Based on reviews of previous transport studies (in chapter 2) and individual level methodologies (chapter 3), it was decided that a *spatial microsimulation approach* was most appropriate, due to the maturity of the techniques involved, flexibility of application and ease of use. A spatial microsimulation model was developed and tested, building on previous work and implemented in the free and open source programming language R (chapter 4). The model was used to combine geographically aggregated count data from the UK's 2001 National Census with individual level data from the national Understanding Society dataset, resulting in simulated *spatial microdata*: individual records which have been selectively sampled based on 'constraint variables' shared between the individual and aggregate level datasets.

Spatial microdata form the foundation of the spatial microsimulation approach. Yet it is during the subsequent *analysis* of this spatial microdata that value for decision makers is generated: the interrogation of spatial microdata enables calculation of energy costs at high geographical resolution (section 6.4), analysis of social and spatial inequalities in the distribution of this energy use (chapter 7) and the development of quantitative 'what if' scenarios to model the impacts of change (chapter 8). Thus the spatial microsimulation approach developed here includes not only the generation of spatial microdata but analysis, visualisation, testing and modelling as well.

This thesis provides, for the first time, estimates of the energy costs of commuting at a range of geographic scales in the UK, and an exploration of its social and spatial variability. Some of the methods used to achieve this result are already well established. What is new methodologically is the way that these methods, and datasets on which they depend, have been integrated with one another in novel ways to provide results that are reproducible and consistent regardless of the scale of analysis.

This chapter summarises what has been learned during the research project: methodological contribution (section 9.1), its policy relevance (section 9.2) and the central findings (section 9.3). The research opens many new pathways for further research which are discussed in section 9.4. Finally, the thesis is evaluated in terms of the original aims and objectives, in section 9.5. It is worth reflecting on the conclusions in the context of the two main aims of the thesis, introduced in section 1.5:

- A1 Investigate the energy cost of transport to work, its variability at individual and geographic levels, drivers, and policy implications.
- A2 Explore and evaluate the potential of spatial microsimulation models for the social and spatial analysis of the energy costs of commuting.

9.1 Methodological contribution

The main methodological contribution of this thesis is the application of spatial microsimulation to the social and spatial analysis of the energy costs of commuting. It is concluded that commuting research is an area that can benefit from this increasingly accessible technique. Individual level analysis is becoming the norm in transport modelling (chapter 3) but often these omit distributional impacts of new policies. From the geographical literature, the vast majority of analysis into the spatial variability of transport energy use and commuting patterns operates solely at aggregate levels. Spatial microsimulation has several practical advantages over these aggregate approaches, enabling outcomes that are otherwise inaccessible. More specifically, the four central methodological achievements of the work are as follows:

- The development and testing of algorithms to ‘integerise’ the weight matrices generated by iterative proportional fitting, allowing analysis to be conducted on whole individuals rather than fractions of individuals (section 4.7).
- The calculation of energy costs per commuter trip in zones for which distance/mode cross tabulated count data are unavailable (e.g. output area levels) from official sources.

- Insight into the intra-zone variability of commuting energy costs and the links between commuter energy use and other socio-demographic variables, based on analysis of spatial microdata.
- The manipulation of this dataset to achieve goals outside the reach of aggregate level studies, such as the targeting of specific groups in what-if scenarios of the future, and assessment of the distributional impacts of localised transport interventions.

Each of these points highlights the advantages of the spatial microsimulation to analysing the energy costs of commuting and modelling travel to work. Although spatial microsimulation has not been used to generate every energy cost estimate presented in this thesis (it has been demonstrated that per trip energy use can be estimated based on geographical data that provides mode/distance cross-tabulations), the approach has been critical to achieving the four outcomes listed above. These are arguably the most important outcomes from a policy and methods perspective, hence the title of this thesis as a *spatial microsimulation* approach. During some sections (the national level results presented in parts chapter 6 and chapter 8), a simpler ‘spatial approach’ has been used to assess energy costs. Yet, as illustrated in section 8.1, the two approaches are not incompatible. On the contrary, the scenario of modal shift shows that aggregate level analysis can be useful for a rapid assessment of the basic determinants of change (in this case mode and distance categories) and for generating national level results (which would be overly resource consuming using spatial microsimulation). The progression from aggregate to micro level undertaken in this scenario illustrates the benefits of using a micro level approach in tandem with preliminary aggregate level analysis. The individual level implementation of the scenario, based on spatial microsimulation, allowed greater sophistication: new variables (age and distance as a continuous variable in this case) were taken into account when estimating the extent of modal shift; the results were displayed at a higher resolution, and information about the socio-demographics of those affected was generated.

In the process of moving from an aggregate to a micro level model of modal shift many new possibilities were opened up, not all of which were implemented (section 8.1.3). The decision to commute, how far and by what mode, is ultimately determined by individuals (section 2.2), so a micro level approach makes sense in theory. Of course, transport infrastructure and other geographic factors also have a major influence, and the spatial microsimulation approach would enable the interaction between geographical and individual level factors to be included. The reason for choosing the topic were not only academic, but related to issues that require an urgent policy response. Policy-makers often lack the tools and skills needed to evaluate which policies would actually work to

reduce energy use and emissions, let alone at local levels and taking consideration of the social distribution of these changes (Banister, 2008; Tribby and Zandbergen, 2012).

In light of the evidence presented throughout the thesis, the kinds of question that the spatial microsimulation approach helps answer seem to be precisely those that policy makers should be asking before implementing new strategies to meet climate change targets in fair way. Will the policy work? Are there more effective alternatives? and which types of areas will be most affected, and is this fair? The thesis cannot answer these questions in general terms, but the results show that the methods can provide important evidence to aid the evaluation process, if the policy options are clearly defined. The policy relevance of this work is one of its major strengths.

9.2 Policy relevance and limitations

Climate change, resource depletion and standard of living provide the underlying motivation for this research. One of the broad conclusions is that methods of calculating energy costs of everyday activities are highly relevant to policy makers concerned with sustainability. The ‘sustainable mobility’ paradigm requires new tools of assessment as well as new concepts if it is to move out of pure academic discussions and into practice around the world (Banister, 2008). In this respect, the research presented in this thesis has much to offer. Too often, academic research into the energy and climate impacts of transportation operates solely at the level of entire nations or regions (section 2.3). Yet actual transport policies are often implemented locally.¹ The spatial microsimulation approach can help bridge such a ‘scale gap’ between academics and practitioners, by making individual and local level analysis of personal travel patterns accessible.

Not all local transport policy makers will have the time, skills or desire to apply the methods advocated in this thesis to their local areas and problems. However, some may be prepared to use techniques, with potential gains in their ability to evaluate different scenarios of change. Would increasing the cycling rate have greater impacts in location A or B? This kind of question can be answered using the simple what-if scenarios presented in chapter 8, and refined to provide insight into the distributional impacts using spatial microdata.

¹The recently announced £77 million funding to promote cycling in cities and national parks has been allocated to 7 specific urban areas and particular routes within 4 national parks (Prime Minister’s Office and Department for Transport, 2013). £20 million of this funding is allocated to Manchester alone, for 56 km of new cycle paths, amongst other facilities. The question of where to invest these funds for the greatest social and environmental benefit is of great policy importance.

The spatial microsimulation approach is not without limitations: it is complex,² requires specialist knowledge to implement and produces simulated results that may be prohibitively expensive to verify. For these reasons, it has been emphasised that spatial microsimulation results should build on, rather than replace, simpler aggregate level analyses for corroboration. There is a real danger that, without proper understanding of the assumptions on which spatial microsimulation is based, the approach could lead to incorrect interpretation of results or, in worst case scenarios, fudging of results for political purposes (Openshaw, 1978). For this reason the reproducibility of the method and results is of utmost importance if spatial microsimulation does become widespread for evaluating real (and not just hypothetical) interventions in transport systems. Following best practice guidelines (Peng et al., 2006), government or private analyses can be made both transparent and reproducible. Using free, open source and cross-platform programs such as R can give analyses on which transport decisions are made attributes vitally important in the democratic system: accessibility and transparency.

9.3 Summary of findings

Returning to energy in transport, a range of interesting results have been generated using the methods developed during the PhD project. No single, overriding factor that determines commuter energy has been found. In broad terms the findings presented in chapter 6 support the conclusions of past research that energy use in transport is complex, varies on a range of scales, and appears to be affected by many factors, especially urban form (Levinson and Kumay, 1997; Smith, 2011; Levinson, 2012). More specifically, it has been found that at the regional level London is the ‘greenest’ area in terms of commuter energy use, but that this is partly offset by the surrounding regions which have the nation’s most energy intensive average commute. This finding provides tentative support to the ‘compact city’ hypothesis (Breheny, 1995), but suggests that the energy use in surrounding areas may be pushed up beyond the average due to long-distance commuting to concentrated employment centres.

Nationally, it was calculated that commuting uses 4.1% of direct energy use in England. Commuting was found to account for almost 15% of transport energy use, representing an important and relatively inelastic contribution to the total. Individual level variability was also explored in the same chapter (section 6.4). It was found that in urban centres the 20% top energy consuming commuters can account for over 90% of commuter energy use, a very high level of inequality.

²Spatial microsimulation is complex relative to simplistic cost-benefit scenarios, but *not* compared with some transport models currently used in local government such as SATURN (SATURN Software, 2012).

At lower geographical levels, the variability in average commuting energy costs increases as would be expected, and a clear spatial pattern, in which urban centres and their direct surroundings have low energy costs compared with the rural surroundings. However, commuting energy costs still vary greatly between many areas that are similar ‘on paper’ at the level of statistical wards (section 6.2). At the local level, the pattern appears to be more complex still, with a tendency for large city centres to be associated with above commuter energy costs greater than their surroundings in South Yorkshire. Later, in section 7.5 this finding is replicated in terms of the relationship between areas’ distance to the nearest employment centre and average energy costs across Yorkshire and the Humber, adding further evidence to suggest that the compact city hypothesis, in its simplest form, is over simplistic.

In agreement with Boussauw et al. (2010), the average distance between home and work, which in itself depends on a range of social and geographical factors, seems to be the major driver of energy intensive commuting: when distances are large, the possibilities for modal shift are greatly reduced, and telecommuting can only be seen as a realistic solution for certain types of jobs, many of which are out of the reach of the most vulnerable (chapter 8). Further modelling work could contribute to the debate about the factors underlying transport energy use, providing statistical evidence about the range of factors at play. But the focus here has been policy, not theory. To summarise, the most important policy relevant findings are as follows:

- Energy use for commuting varies at all geographical levels and is distributed highly unevenly between individuals in most zones. Even between areas that appear to have similar levels of energy use at the aggregate level, there are great differences in how commuter energy use is divided up between their inhabitants (section 7.5).
- At the scale of cities, there is a tendency for highest energy costs to appear furthest from the city (around 60 km in the case of London), which tends to fall towards the city centre, but then rising again in the city centre (figure 7.13).
- At the international level, England appears to have lower per-trip energy costs than the Netherlands, despite Holland’s reputation for excellence in environmentally benign transport planning.
- In terms of modes of travel, cars were found to completely dominate the energy costs of commuting in most areas. This can be easily overlooked based on existing statistics that focus on modal split by number of trips and distance. In Yorkshire and the Humber over 95% of energy use for commuting was found to be due to cars (section 7.5), implying that environmentally aware policy makers there should

focus on reducing private car use as a priority rather than the current focus on modal shift.

- The energy impacts of an ambitious scenario of modal shift from cars to bicycles would be relatively modest, compared with telecommuting, which is rarely framed as a transport policy. Active travel policies need to be supplemented by policies encouraging car sharing, reducing demand for long-distance travel and, in the long-term, reducing average home-work distances.

Each of these findings has implications for transport planning strategies in the UK in broad terms. Exploring what these implications are on a case-by-case basis is outside the scope of this thesis, and further exploration of the most policy relevant overall findings provides a strong incentive for further work at the local level in different case study areas. Because of the applied nature of this research, it is suggested that much of it is conducted by policy makers. In terms of opportunities for building on the thesis in the academic context, there is also much scope for further work, as outlined below.

9.4 Further work

The work undertaken has provided new contributions to knowledge, both empirical and methodological. The latter contribution, used appropriately, could outlast the former: the spatial microsimulation approach has the potential to generate many more interesting results than are presented in the preceding chapters. The empirical results also raise important research questions, by challenging conventional wisdom about the energy costs of commuting and how these costs can be best be reduced.

It is therefore hoped that the thesis is not seen simply as an ‘end product’ or ‘final result’ but as a tool for stimulating and enabling further lines of study into energy and transportation. It is up to other researchers to judge how best to use the methods for their own purposes, so the concluding remarks in this section are intended to provide general guidance, rather than a prescriptive research agenda. It was decided that the following research areas, in rough descending order of priority, would benefit from further investigation, building on the methods and findings presented in this thesis:

- The use of spatial microdata as an input into agent-based transport models: the recent advances in microsimulation in urban and transport models outlined in

section 3.4 make modelling techniques simultaneously more accessible to transport planners and much more powerful.³ Starting from the other side of the spatial microsimulation versus transport planning/modelling divide, the addition of agent-based models with inbuilt capability to load and interpret the road network (e.g. from Open Street Map data), has the potential to vastly improve the ease with which infrastructure interventions can be assessed by academics already acquainted with spatial microsimulation. This approach could be far more advanced (and potentially user friendly) than the crude methods presented in section 7.3.

- Extend the spatial microsimulation methods presented in chapter 4 so that they are capable of classifying individuals into family units (Pritchard and Miller, 2012, see section 3.3.2) and allocating their home and work locations to precise geographical coordinates (as described in section 7.3).
- Development of more realistic and localised ‘what if’ scenarios: the modal shift scenario presented in section 8.1 is useful to gauge the potential magnitude and spatial distribution of cycling uptake in the UK, but is unlikely to be realistic as the same proportion of short-distance car drivers are expected to shift in every area. In reality, most transport interventions are localised. The recent allocation of £77 million to cycling cities schemes (BBC News, 2013), for example, will inevitably be spent locally. Localised scenarios of different expenditure options could help planners maximise the benefits resulting from this expenditure.
- Prediction of energy use: variation in energy use variable has been explained intuitively as the result of a few key factors: wealth, distance to employment centre and the nature of the surrounding transport network all seem to have an influence (chapter 6). The next logical step forward would be the creation of a predictive model to estimate energy use based on underlying geographical drivers. This could include flow data (Simini et al., 2012) as well as more conventional explanatory variables such as topology, wealth and connectivity measures. Such a predictive model would be useful academically, enhancing understanding of the geographical drivers of energy use (Steemers, 2003) and practically, as a basis to project the energy impacts of future change.
- The application of the method to more countries at more time periods, to investigate the generality of the findings and provide further guidance to policy makers based on the international evidence.

³In this regard MATSim in particular seems to hold great promise for ‘open sourcing’ transport modelling for the evaluation of specific schemes, due to its uptake by US planning authorities. Yet environmental/energy and distributional impacts are still under-reported in scheme evaluation. Combining the socio-demographic variables contained within simulated spatial microdata with models such as MATSim therefore has great potential to further enhance the use of models for practitioners.

This is a diverse set of recommendations that can be explored using a variety of methods. It is therefore suggested that resulting research does not need to fit into the ‘spatial microsimulation approach’ advocated in this thesis to build on its findings. However, approach may offer certain advantages as a way of framing the research methodologically. Returning to the central policy issue of energy use in transport it is recommended, if an overriding agenda or paradigm is deemed beneficial at all (it may not be), that future research in this area uses the sustainable mobility paradigm Banister (2008).

9.5 Thesis evaluation and summary

To evaluate the thesis by its own standards, we return to the aims and objectives introduced at the end of the opening chapter (section 1.5), and discuss to what extent they have been accomplished. The first aim (A1) was to “Investigate the energy cost of transport to work, its variability at individual and geographic levels, drivers, and policy implications.” This aim was mostly accomplished in chapter 6, in which national commuter energy costs were estimated in terms of both energy use per trip and energy use per year per commuter. In the same chapter commuter energy use was also found to vary at all geographical scales, with the range of average values unsurprisingly increasing at lower geographies and the spatial pattern becoming more complex at the local level. In terms of individual level variability, it was shown in section 6.4 and throughout chapter 7 that the distribution of energy use across the population varies greatly from place to place and that socio-economic factors play an important role in determining an individual’s use of energy to travel to work that is likely to be missed in analyses that operate only at the aggregate level.

Sub aims 1.1, 1.2 and 1.3 relate to the variability of commuting energy costs; the factors most closely associated with high and low energy use; and how the spatial microsimulation approach can be used to inform policies using scenarios of change, respectively. The following bullet points summarise progress in achieving these aims:

- The quantification of the variability of commuter energy costs at various levels has been a major output of the research, as detailed above. However, the variability over time has received less attention due to data constraints.⁴ Aim 1.1 was also

⁴The observation that energy costs have increased tenfold over the past century (section 5.5, figure 5.22) was based on a small sample and crude assumptions about average distances travelled by, and efficiencies of, different modes of transport. Still, this is an interesting result. Also, the changing distribution of car dominance for the trip to work, illustrated in figure 5.24, is an interesting finding that likely relates to changes in the spatial distribution of energy intensive commuting over time.

to investigate household level variability. This has not been achieved in the thesis, although pointers of how to do this have been suggested.⁵

- The explanation of this variability set out in aim 1.2 was largely achieved. At the aggregate level, distance from employment centre was found to account for much of the variability in average commuter energy use, although this was not formalised as a predictive model or linked to additional geographical factors such as the road network. At the individual level it has been shown that average commuting behaviour also varies depending on age, number of cars in household and, more importantly for policy makers, by socio-economic class and income (section 7.5).
- Regarding the formulation of models for change (Aim 1.3), a number of ‘what if’ scenarios were considered in chapter 8. Only 2 of these (high cycling and telecommuting scenarios, based on evidence from Holland and Finland) were quantified, but the results were interesting, policy relevant and surprising. As stated in the previous section, there is great potential for further research in this area.

The second main aim was methodological, to test the potential of spatial microsimulation for the “social and spatial analysis of the energy costs of commuting.” It is concluded that the thesis has succeeded in meeting this aim: spatial microsimulation has for the first time been applied to the investigation of this issue and the methodology has been developed in a way that should be reproducible by others based on code and documentation that has been made available to others.⁶ It is also concluded that the benefits of using the spatial microsimulation approach outweigh the additional complexity, computing and time costs of the individual level methodologies compared with more common aggregate level approaches. The ability to target specific groups in scenarios of change, to explore the interaction of individual and geographical factors in influencing travel behaviours and to investigate the distributional impacts of change suggests the approach has great potential as a tool for policy makers and academics. Overall the thesis has achieved most aspects of all of its original aims, although further work is needed to include household level impacts and better explain the variability of energy use based on a wider range of variables than those used here.

In summary, this thesis has contributed methods and findings to the emerging area of energy use in transport. The research was motivated by the seemingly intractable socio-environmental problems of climate change and resource depletion, leading to a focus on pragmatic policy relevance rather than theory. The methodological innovations of

⁵See the second bullet point in the list of further research in the previous section.

⁶In the ‘[thesis-reproducible](#)’ repository and other personal repositories hosted on the social coding site [github.com](#)

integration and allocation of home-work locations in the context of spatial microsimulation are relatively minor achievements academically, yet their application to real-world transport planning decisions could yield major benefits for policy makers.

Some of the findings were unexpected and challenge conventional wisdom about what constitutes 'good' transport policy environmentally. The current emphasis on bicycles, for example, is at odds with its relatively minor potential for large emissions cuts (although health and social considerations should also play their part in transport policy, areas in which the bicycle has much more to offer). The key message for policy-makers wanting to reduce fossil fuel dependence is that policies that can reduce the consumption of the most energy intensive areas and individuals (such as telecommuting) should take priority over policies that will further reduce energy use in places that are already quite energy efficient in terms of travel to work. This finding was reinforced by the comparison between commuter energy use in England and the Netherlands, where the Dutch were unexpectedly found to use *more* energy for commuting.

These findings not only challenge wishful thinking in the area of energy and transport, they lay the foundations for further work from which additional results can be generated. The findings are also important in their own right: they provide insight into the interventions that would be needed if reducing energy use in personal transport becomes a political priority. The impacts of this research may thus depend more on the extent to which the approach is adopted by practitioners, than its direct influence in academia. In terms of social and environmental impact, a single well-designed intervention in the transport system resulting from this research could be worth several thousand words.

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