Essays on the health and welfare impacts of road transport in low- and middle-income countries

Oliver Kaonga

PhD

University of York
Economics

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Abstract

This thesis consists of four essays at the intersection of transport and health with the underlying theme of exploring the effects of road infrastructure and road transport externalities on household health and welfare in low- and middle-income countries.

Chapter 2 is a literature review of the pathways through which road transport affects health and methods that are used to estimate these effects. The results reveal extensive inconsistencies regarding aspects of that are health evaluated, methods used, and the values attached to health impacts in both government documents and published literature. Chapter 3 estimates the impact of road traffic injuries on household welfare. The chapter applies a mix of genetic matching and multilevel modelling techniques to isolate effects of Road Traffic Injuries (RTIs) on household health expenditure, non-health consumption expenditure, asset ownership, household indebtedness and labour force participation. Results suggest that RTI affected households incurred significantly higher health expenditure, reduced expenditure on competing basic needs and faced a higher likelihood to borrow at positive interest rates to purchase health services.

The fourth chapter analyses the effects of upgrading earthen roads to a paved status on the cost of travel to seek health services, level of health services utilization, incidence of Respiratory Illness (RI), and level of household consumption expenditure. Results suggest that households nearer to a road development project reported higher consumption but were more prone to RIs. The effects on transportation costs and level of health care utilisation were negligible.

Chapter 5 is an economic evaluation of a road decongestion infrastructure project. The objective is first to assess how inclusion of health impact frequently omitted in transport cost benefit analysis (CBA) influences the decision to invest. Secondly, to determine, in a Cost-Effectiveness Analysis (CEA) framework, whether transport projects such as this one, would represent value for money if solely considered for their potential as interventions to prevent health loss. The analyses demonstrate that decisions to invest may be largely influenced by cross-sector impacts that the evaluator chooses or is able to include in the decision model. The chapter also highlights the significance of consistency in choice of approaches used to value aspects of intervention impacts, especially where the projects are being compared and ranked.

Table of Contents

List of Figures

List of Tables

Declaration

I declare that this thesis is a presentation of original work, and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

Parts of this work have been presented and discussed at conferences. Earlier versions of Chapter 3 were presented at the 2021 Health Economists' Study Group (HESG) Summer Meeting (University of Cambridge), the 2022 Africa Health Economics policy Association (AfHEA) conference in Kigali, Rwanda, and the 2020 Health Economics and Data Group (HEDG) seminar series at the University of York. Earlier versions of chapter 4 were presented at the 2022 Academic Unit of Health Economics seminar series, University of Leeds, and at the 2022 Thanzi La Onse Dissemination Extraordinary Think Tank Conference, Health Economics policy unity, Malawi College of Medicine. Chapter 5 has been presented at the University of York student seminar series in the Department of Economics and related studies.

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Chapter 1

Introduction

This thesis comprises four papers on the effects of transport infrastructure and associated externalities on household welfare in Sub-saharan Africa (SSA), with a special focus on impacts on health. The health and transport nexus is a phenomenon that has a large audience in Transport and Health economics beginning with studies of road traffic injuries and later Jerry Morris' seminal work on the scientific link between active transport and health (Morris et al. 1953). Most early work on the health impacts of transport focussed on two major externalities: injuries and air pollution. Starting in the 1990's, research in the areas of Health economics, Transport economics, and Public Health turned to a new array of transport externalities on health. As the World Health Organisation (WHO) noted, the world could no longer ignore the possibility that transport and planning policies were having major effects on health, through, noise and ever-diminishing physical activity (World Health Organisation, 1999 as cited in (Sitlington 1999)). Notwithstanding the growing interest in the examination of positive and negative health impacts associated with transportation, lack of quality data has limited the ability to develop effective, evidence-based solutions. In particular, the paucity of evidence on transport externalities on health in low-income countries remains a public health concern. Thus, the study of the extent of these impacts and methods for quantifying them have continued to raise considerable interest, especially since they form the basis for designing interventions, cross-sectoral planning and resource allocation decisions.

Recognising the importance of road transport as a social determinant of health, this thesis focuses on road transport and road infrastructure as both an enabler and inhibitors of public health. The thesis begins with a review of previous work on transport impacts on health presented in Chapter 2. While road transport plays a critical role in promoting health including in accessing health services, a central issue is establishing the extent of externalities that are imposed on the public in the process and the potential means to mitigate them. Chapters 3 and 4 explore the impact of road transport and road infrastructure on household health and welfare. Part of the work focuses on the effects of road injuries on household welfare and highlights the various ways that a road transport externality can adversely affect a household. This work is timely from a policy perspective with the United Nations integrating road safety into two of the 17 sustainable development goals (SDGs), SDG 3 and SDG 11, proclaiming the Decade of Action for Road Safety 2021-2030, and setting an ambitious target of preventing at least 50% of the global road traffic deaths and injuries by 2030 from an estimated 1.3 million deaths and 50 million injuries in 2021(World Health Organization 2022). Chapter 5 assesses how the inclusion of health impact, frequently omitted in transport economic evaluations, influences recommendations on a given intervention's viability. The chapter further investigates whether a transport project would be valuable if solely considered as an intervention for preventing future health loss and reducing costs on the health system.

Despite the significance of health and related impacts associated with transportation in LMICs, the contribution to the overall health burden is often underestimated and overlooked. Consequently, the Health in All Policies concept was introduced in health policy discussions to compel decision-makers in all sectors to consider health effects as they formulate policies and interventions. However, significant challenges remain in disentangling the actual causal pathways of transport impacts on health, estimation of effects and incorporation in transport sector decision models. At the core of these challenges is the conflicting primary goals between sectors and an inadequate understanding of the full extent of transport impacts on health, particularly for countries in SSA. Understanding the health impacts of road transport and the extent to which these are considered in transport sector evaluations is important for at least two reasons: Firstly, the information is potentially useful to inform a comprehensive valuation of costs and outcomes associated with externalities such as road traffic incidents and the burden imposed on households. This is critical in lobbying for investments in interventions to mitigate negative transport externalities. Secondly, the analysis shows how the inclusion of cross-sectoral impacts may alter intervention ranking and prioritisation, stressing the point that considerations of project viability may be hugely influenced by which impacts are included in the evaluation. An analysis such as this one may also provide a basis for cost allocation discussions in settings where intervention co-financing between departments, ministries, or sector budgets is possible. The paragraphs that follow outline the motivation and contribution of each chapter.

Chapter 2 is a review of literature on the pathways through which road transport impacts on health, and a review of economic evaluation methods in the transport sector. The aim in this chapter is twofold: First is to explore the various ways in which transportation affect public health. The pioneering work that linked several health outcomes to transport can be traced to the Health on the Move report of 1991 (Hannah et al. 1991). Two decades later, the Health on the move framework was expanded to cover other health-transport pathways such as, climate change and health, various types of pollution, physical activity, stress, land and livelihood loss, and separation of communities (Mindell 2014). Since then, various conceptual models have sought to explain the transport health nexus; For example, Dannenberg & Sener (2015) examined the relationship through five pathways, that included road safety, air quality, physical activity, equitable access, and noise. More recently, Frank et al. (2019) developed a model that categorized the transport-health pathways into two categories: behaviours and exposures. Behaviour pathways refers to the influence of transportation in terms of promoting or discouraging specific health-related practices, such as nutritional consumption, physical exercise, and social engagements. On the other hand, Exposures pathways refers to human exposures to harmful substances and stressors and this category includes pathways such as air pollution, traffic safety and crime, and noise (Frank et al. 2019). The chapter does not attempt to expand on the established transport-health linkages, rather the contribution of this chapter is to consider the extent to which these models have been used to assess transport health impacts in Africa. These models also provide the theoretical underpinning for the empirical analysis that is conducted in chapters 3 and 4.

The second objective of the chapter is to determine which health impacts have been included in previous transport economic evaluations and methods that have been used to capture and measure these impacts. The health impacts of transport are diverse and include both mortality and morbidity effects. The wide range of health effects means the task to aggregate and incorporate them in transport evaluations and decisions is challenging. In the Health Economics literature, a widely applied approach that enables the aggregation of different health effects is the use of health metrics such as Disability-Adjusted Life Years (DALYs) or Quality Adjusted Life Years (QALYs) (Anand and Hanson 1997). However, this approach to quantification of health effects, does not readily allow integration into broader non health specific economic assessments without imposing a monetary value on these effects. Where done, expressing loss of life or burden of disease in a common monetary unit has been applied using a variety of approaches. Thus, the motivation of this preliminary chapter is that assessment of the various transport public health pathways and the methods used to value these effects would facilitate further understanding of the transportation-health nexus in a more holistic approach to promote decision-making that considers and prioritizes health. Additionally, the chapter highlights gaps in current practices, and makes recommendations for consideration in future evaluations.

Chapter 3 explores household level effects of road traffic injuries on health and welfare in 10 sub-Sahara African countries. The aim is to estimate the effects of injuries and understand the extent of its impact on both health and non-health indicators of household welfare. The rationale for focussing on road traffic injuries in this chapter, from among the various road transport externalities explored in chapter 2, is because road traffic injuries imposes the largest burden on health, ranking among the top 10 causes of death in SSA region (World Health Organization 2019). The literature on the effects of RTIs in the region can be categorised into two main strands. The larger stream of studies focusses on analysing the impact of RTIs on the costs of health service providers (e.g Parkinson et al. (2014), Urua et al. (2017), Matiwane & Mahomed (2018), Prakash et al. (2019)). The interest in these studies is determination of the amount and apportionment health expenditures on treating RTI to direct, human resource, and overhead costs at health facility level. The other strand of literature attempts to investigate a broader impact of RTIs beyond the costs of health care providers to include aspects of household level direct and indirect costs. Few published studies fall in this category. Juillard et al. (2010) explored the economic consequences associated with RTIs focusing on household expenditures on medical treatment, the effect on ability to work and changes in earnings of persons who had suffered RTIs. A related study estimates the economic burden of road crashes based on a sample of RTI victims admitted to a hospital. While the main focus is on estimating medical costs, the study also reports the number of days that care givers dedicated to caring for the RTI victim during the period they were admitted to hospital (Ipingbemi 2008). Mowafi et al. (2021) considered multiple outcomes that included lost wages or schooling days and assets sold to ease the financial hardship. However, the methods applied in the study are limited to a qualitative description of household costs associated with RTIs . Chapter 3 falls in this second category of literature with the main contribution being, firstly the application of robust econometric methods to examine the effects of RTIs and secondly the inclusion of a wider range of impacts at the household level.

The study uses data from the Word Health Organisation's Multi-Country World Health Surveys (WHS). The chapter uses a diverse set of household welfare indicators with the motivation that understanding the extent that RTI affects aspects of household welfare contributes towards efforts aimed at improving household health and economic outcomes. The chapter analyses households out of pocket health expenditures incurred in times of injury, in addition to wider impacts that includes non-health consumption expenditure as well as non-expenditure indicators such as labour force participation, and household borrowing. Estimating differences in household economic welfare based on exposure to RTI, in an observational study setting, presents two methodological challenges; selection bias and confounding which may lead to under or overestimation of RTI effects. To address these challenges, a mix of matching and regression methods is employed. The rationale for selection of these estimation methods is on the understanding that household and individual attributes affect the probability of involvement in road traffic incident. For example, being male and residing in urban areas may increase the likelihood of being involved in a road traffic incident. It is possible, therefore, that households that experienced RTIs are systematically different from those that did not. Further, there is a possibility a set of variables exists such that they influence both the likelihood of exposure to RTI and atleast one of the outcomes. This creates the risk of committing type I error where estimated effects are incorrectly attributed to exposure to RTI when it could also be due to effects of a confounding variable. This chapter attempt to minimise these estimation challenges by firstly attaining similarity between control and treated households through genetic matching [1] based on their pre-treatment characteristics. Using the matched dataset, a multilevel Generalised Linear regression Model (GLM) is estimated. Results highlight that households are worse off in several ways following an RTI; incur significantly higher health expenditure, reduce expenditure on competing basic needs and face a higher likelihood to borrow at positive interest rates to purchase health services.

Chapter 3 demonstrated the extent that a road transport externality, i.e. an RTI, can adversely affect households. However, besides the negative effects, households that are located closer to road transport facilities might experience improvements in welfare in various ways. Chapter 4 explores the impact of road infrastructure development on cost of travel to seek health services, level of health service utilization, incidence of Respiratory Illness (RI), and level of household consumption expenditure. In theory, the effects of road development on households are well established. However, estimation of causal effects of such an intervention using econometric approaches has presented challenges that includes the endogeneity problem and the difficulty of defining the scope of effects. Defining exposed households for new roads, rehabilitation, or upgrading of existing ones is often blurred, as benefits and costs often spill beyond the communities where the infrastructure are located. One way that studies examining the impacts of road development projects have attempted to define the target group is based on distance from the project. Further, varied econometric techniques to address the endogeneity problem that includes Instrumental Variables (IV), Regression Discontinuity (RD), Difference in Difference (DiD) and panel data regressions have been applied. The limitations of each of these approaches are highlighted in the chapter.

This chapter combines various data matching techniques with the Difference in Difference estimation to analyse the effects of road development projects that were completed between 2016 and 2018 and covered thirteen different districts in Malawi. The intervention involved the upgrading of earthen roads to a paved status. The data extracted from the road development records is linked with a panel household survey dataset. The resulting combined dataset which contains information on transport infrastructure, households' health and socioeconomic characteristics, forms one of the contributions of the chapter. Results suggest that households nearer to a road

[1] Genetic matching automates the process of finding a good match by attaching a set of weights for each covariate such that optimal balance is attained in the matched dataset (see Diamond 2012)

development project reported higher consumption but were more prone to RIs. The effects on transportation costs and level of health care utilisation were negligible. The findings in this chapter are discussed in light of related literature on the subject, recognising firstly, that transport costs incurred through payment of fares on public transportation tend to be sticky downwards thus limiting the trickledown effect to end users. Secondly, improved access following road development may prompt patients who otherwise would seek health care at the nearest health facility to opt visiting health facilities located further away in search of more advanced or better-quality health care.

Chapter 5 shifts the focus from estimating the effects of road transport on health and welfare to evaluation of road transport infrastructure developments as interventions for preventing health loss. The objective is first to assess how inclusion of health impacts, which are frequently omitted in transport cost benefit analysis, influences the decision to invest in an interevention. Secondly, to determine, in a CEA framework, whether transport projects, would represent value for money if solely considered for their potential as interventions to prevent future health loss. The models developed in this chapter are based on a road decongestion infrastructure project in Kampala, Uganda and draws parameters from multiple sources including the impacts of RTIs estimated in chapter 3. Ideally, economic evaluations of transport sector interventions should assume a multi-sector approach encompassing important impacts regardless of the sector the impacts are falling on. In practice this is too ambitious (Mackie et al. 2005), the scope of evaluations seems to be determined by two main factors; Firstly, the decision maker may decide the scope based on their sector of primary interest. Secondly, availability of good quality and complete data on the expected impacts of the project (Dutra et al. 2014). Chapter 5 can serve as an illustration of how to proceed with project evaluations in instances where, despite limited data, it is known that the intervention has impacts that goes beyond the project's primary sector. The analyses in this chapter demonstrate how decisions to invest are largely influenced by the selection of cross-sector impacts that the evaluator values or is able to include in their decision model. The chapter also highlights the significance of ensuring consistency in the choice of approaches applied in the main valuation of aspects of intervention impacts, especially where the projects are compared and ranked in order of priority for investment.

Finally, Chapter 6 wraps up the thesis with a discussion of key contributions of the work given the findings. The chapter also outlines the significance and implications of findings for policy and concludes by briefly highlighting potential directions for future research.

Chapter 2

Road transport impacts on health: Review of pathways and economic evaluation methods

2.1 Introduction

The transport sector plays a key role in economic and social development of every economy. In Sub-Saharan Africa (SSA), the communications and transport sector contributes an average 3% to economic growth per annum (Calderón & Servén 2008). The centrality of transportation to the functioning of an economy and the diverse effects of transport on social aspects of life has led to an interest in transport operations beyond the transport sector. In the health sector, it is understood that population health is not only a function of health care but a product of various societal factors that affect individuals and the interaction of individuals, such as transportation. For example, opening new rural roads in difficult-to-reach areas provides an effective way to reduce perinatal and pregnancy-related mortalities. Notwithstanding the positive effects, transportation also tends to impose detrimental effects on health outcomes.

The complex linkages between transport and health represent one of the challenges faced by policymakers in attempts to incorporate health effects into transport sector planning and decision making. The sparse evidence that demonstrates how the transport sector impacts population health in SSA points to the possibility that these effects are overlooked in decision making. Early work linking transport to health considered positive health effects through health promotion and improved access while detrimental health effects were limited to injuries and pollution effects on health (Hannah et al. 1991). Later, various pathways by which transport affects health including effects on physical activity and vehicle emissions have been evaluated. A recent paper by Khreis et al. (2019) extended the Transport-health effects framework to include the stress-related effects as well as the health effects related to mobility independence. However, these aspects of health effects of transport are largely still ignored in both research and policy formulation in developing countries. In SSA, the focus of most studies conducted on the transport health nexus to date have been limited to evaluating health impacts arising from road incidents.

Besides the limited evidence that quantifies the extent of health impacts through various pathways, considerations of health effects in transport planning may be influenced by two factors: Firstly, the structural set up where each line ministry largely works independently raises the possibility of conflict in priorities. To illustrate, a primary objective in transport planning is the reduction in travel times where lower travel times, are considered a core indicator of an effective and efficient transport system (Sampaio et al. 2008). Thus, transport sector planning would primarily focus on prioritising interventions with a high potential to contribute towards the attainment of this objective and less about the resulting cross-sector externalities including health impacts. Consequently, decision-making models used in the transport sector might overlook health effects. For example, to address road traffic incidents, a popular recommendation is to regulate the driving speed of vehicles through the enforcement of speed limits among others. This recommendation, however, directly leads to an increase in travel time. Conflicting goals such as these present a real hindrance to incorporating health effects in transport planning and project implementation.

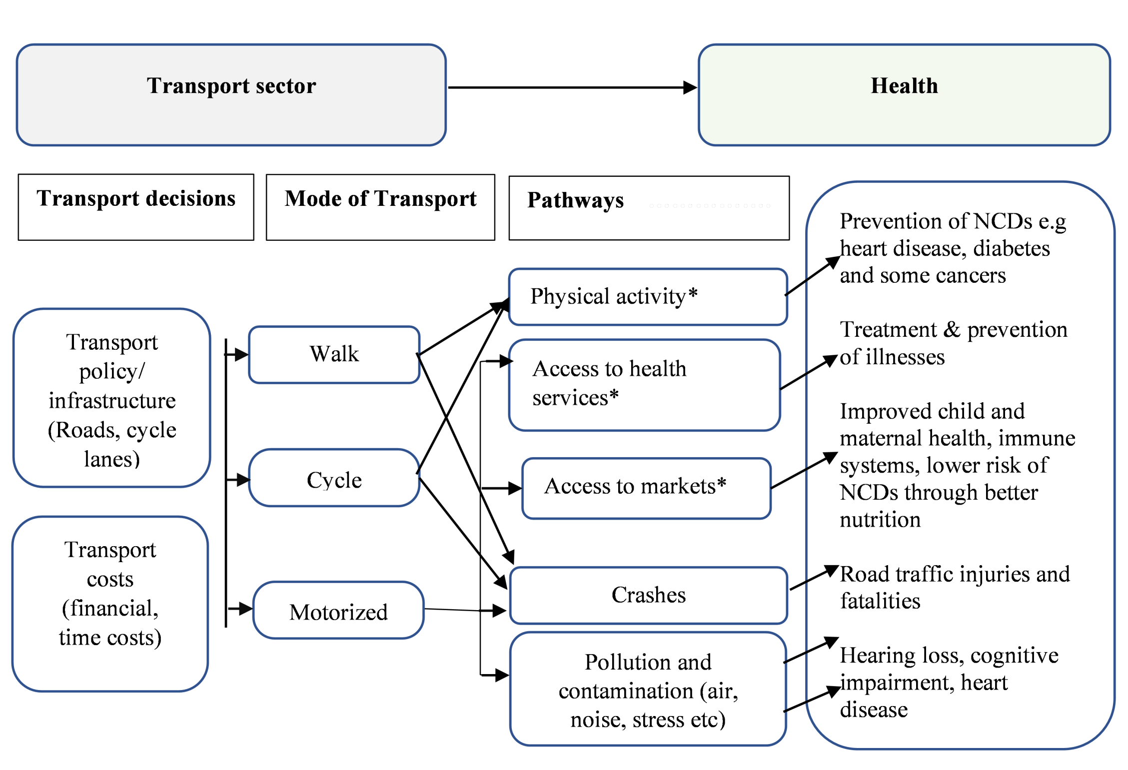
The second factor is the difference in primary decision-making tools between transport and health. While Cost Benefit Analysis (CBA) is the more commonly applied economic evaluation method in the transportation sector, evaluations in the health sector have mainly relied on Cost-effectiveness methods. Evaluations based on CBA models are characterised by the conversion of costs and benefits to monetarized values while CEA apply non-monetary outcome measures such as DALYs and QALYs. This variance may present a barrier to the inclusion of aspects of projects' costs and benefits that impact health but cannot be quantified in monetary terms with reasonable accuracy and/or consensus.

In this chapter, the aim is to contribute towards understanding transport effects on health through a review of existing studies to provide evidence on the extent of transport effects on health, and how such effects have been accounted for in transport sector evaluations. The objective of this chapter is therefore to first assess the different ways in which transport and transportation policy affects health and the degree to which these effects constitute a health challenge in the SSA region. Under this objective, I do not attempt to expand on the established models on transport-health linkages, rather the goal is to analyse the extent to which pathways identified in these models have been examined in Africa. The second objective of the chapter is to determine which health impacts have been included in previous transport economic evaluations and methods that have been used to quantify these impacts. Although the analysis focuses on SSA region, most practices and challenges faced will be similar in many developing country settings. This chapter is structured as follows: Section 2.2 presents the transport-health pathways framework that I use to assess what is known about transport-health impacts in SSA. In section 2.3, I describe the approach used to obtain the papers that are reviewed, and this is followed by section 2.4 which reports the results of the review. The results section is presented according to the two objectives of the chapter. Section 2.5 offers conclusions, recommendations, and directions for future research.

2.2 Transport -Health pathways: the framework

Figure 2.1 presents the main transport-health pathways based on the most comprehensive and recently developed transportation-health framework. In total, they identify 14 pathways linking transportation to various health outcomes are identified and includes physical activity, vehicle crashes, pollution and contamination, and access. Others are green space, social exclusion and community severance, mobility independence, greenhouse gas emissions, and aesthetics, urban heat islands, and electromagnetic fields. The starting of the model is that factors such as transportation policy, availability, lack of, or construction of transport infrastructure, and transportation costs, shape individuals' decision to travel using a given mode of transport. The act of travelling or construction of road transport infrastructure is what then leads to identified impacts on health through environmental exposures, lifestyle and crashes etc, collectively referred to as the transport pathways to health.

Figure 2.1: Transport-Health pathways: the framework



Source: Adapted from Khreis et al, 2019

The first three pathways in figure 2.1 (marked with an asterisk) are associated with beneficial health impacts, while the others are associated with detrimental health impacts. Various levels of literature and evidence support each pathway and its associated health outcomes in the African context and subsequent sections explore this evidence.

2.3 Methods

Studies that have sought to examine the channels and extent of transport activities impact on health in SSA were identified through a literature search. We aimed to include studies from published articles as well as non-peer-reviewed government and non-governmental institutional reports and policy documents. The search was performed based on a search plan that specified search terms, and databases to be considered. Though this review is not systematic, a search plan is developed to ensure the inclusion of relevant grey literature which tends to be more varied in both content and structure (Adams et al. 2017). The search was conducted over an extended period of six months between 1st December 2019 and 30th June 2020 to ensure as many records as possible were captured for review.

The data sources that the search focused on included: 1) electronic literature databases, (2) customized Google search (3) targeted website searches for road transport agencies, ministries of transport, and related research institutions, and (4) consultations with authors of reports and articles not publicly accessible. These were complimented with articles identified from the references list of the articles obtained in the first round of the search. Databases searched include Science Direct, Web of Science, Econ papers, and Google scholar. The key search terms included: "traffic", "transport", "car", "public transport", "walking", "cycling" , "motor vehicle crashes", "air pollution", "noise", "temperature", "physical activity", "carbon", "emissions", "surface contamination", injury/morbidity", or "mortality/death", "Trauma" "respiratory disease", "cardiovascular illness/disease", "maternal health", "chronic illness", " "travel time" "distance" and "access" and their variants in combination withlocation and context specifiers such "Africa" or "developing countries". To ensure the comprehensiveness of the search, the search terms used included individual names of all countries in SSA.

2.3.1 Inclusion/Exclusion Criteria

The retrieved papers were further processed based on the inclusion and exclusion criteria shown in Table 2.1.

Table 2.1: Inclusion and exclusion criteria

Inclusion	**Exclusion**
Published peer-reviewed articles and non-peer-reviewed government documents	Study settings outside of Africa
The study must involve original analysis and establish a relationship based on data	Incomplete documents with only sections such as abstracts being publicly available
The direction of the relationship must be from transport to health	Studies which reported health effects of related to deaths due to other means of transportation including water, air
The paper must report outcomes that are health-related	Unavailable in English
Must present evidence drawn from within Africa	
Most recent versions of research articles with more than one version available.	
Published in English	

Retrieved articles were initially reviewed based on titles and abstracts of references to ensure they described a relationship detailing how transport sector policy and activities impacted health outcomes and also to ensure that all other inclusion criteria was met. The search aimed to retrieve articles that provided an original analysis or established a relationship, based on data, between transport and health outcomes with direction of the relationship from transport to health. To be eligible for inclusion, articles had to demonstrate a clearly defined pathway of the impact from transport to health (e.g the health losses experienced through road traffic injuries rather than injuries in general, and exposure to traffic-related air pollution and not air pollution in general). This also included studies that reported on multiple pathways provided they were clearly identified. Further, only studies conducted within the African continent were considered to ensure relevance of the identified pathways to the study setting. Studies that described the health impacts of transportation modes other than road transport, were excluded. For example, studies that investigated the effects that airplane engine emissions have on air quality in areas around the airports and the subsequent impact of exposure to these emissions on the health outcomes of airport workers, frequent travelers, and residents living in proximity, were not part of the study.

The documents that informed the second objective which explores how health impacts are treated in transport economic evaluations, included published articles and project feasibility reports. Feasibility studies are grey literature obtained from Government transport departments, the African development bank, and the world bank, institutions that have provided grants and loans targeted at infrastructure development in the region. The search strategy included a combination of the search terms: road, economic evaluation, cost-benefit, cost-effectiveness, cost-utility, cost minimisation, road traffic incidents, air pollution, vehicle emissions, and physical activity. Economic evaluations which did not report health effects are not included, also studies reporting only the costs are excluded. Further, only appraisals conducted in the last 10 years were included to capture relatively recent practices in evaluations.

2.4 Results

2.4.1 Transport-Health pathways

The search yielded 69 titles and abstracts from electronic databases, a further 14 documents were retrieved from websites and reference searches of published articles. Preliminary screening based on record titles and abstracts narrowed the number to 51 papers that were potentially eligible. A thorough reading of the 51 papers and reports led to the exclusion of a further 35 papers. The total number included in the review is 16 papers. More details of the stages followed in the selection process are included in Appendix A1. The papers that form the core of the analysis, and the key messages therein, presented according to the pathways, are summarised in Table 2.2.

The findings in Table 2.2 show that research linking transport to health in the SSA region has focused on four categories of pathways: physical activity, road traffic incidents, pollution and contamination, and the role of transport on access to health services. The below section expands on these findings and provides supporting evidence and country-specific examples to document the extent of health effects through each identified pathway.

Physical Activity

Health benefits linked to physical activity through transportation are a result of walking and cycling as a means of transporting oneself or goods. Physical activity has been recognised by the World Health Organisation as a critical factor that should be considered in the planning and formulation of policies and programs to prevent chronic conditions and non-communicable diseases (NCDs). As a preventive measure against risk for NCDs, 50 min per week of moderate-intensity activity, and 10 min weight-bearing activity twice a week is recommended (World Health Organization 2009). In SSA, it is estimated that 46% of overall physical activity comes from transport-related activities (World Health Organization 2009). Despite the high contribution of active transport to overall physical activity, the contribution towards health promotion is insignificant in African countries due to the short trip duration and/or low-intensity trips that fail to meet recommendations(Guthold et al. 2011). Estimates on the extent to which increased active travel impacts specific health indicators such as Body Mass Index (BMI), blood pressure, or other cardiovascular risk factors in the SSA region, did not exist at the time of review.

While active physical activity through walking and cycling yields health benefits, there is some evidence that links to an increased risk of exposure to air pollution as well as exposure to and severity road traffic injuries. The incidence and severity of RTIs is reported to be worse among pedestrians and cyclists compared to motor vehicle occupants. For example, in Malawi, about 60% of the road traffic incidents involve a pedestrian or cyclist being hit by a vehicle and about 44% of this type

Table 2.2: Transport effects on health

Pathway	Potential channel of impact on health outcomes	Extent of effects	Source
Physical activity	Active transport (Walking and cycling) encourages physical activity among population. In African countries, WHO estimates that 46% of overall physical activity comes from transport related activities.	Physical inactivity is linked to approximately 21–25% of breast and colon cancers, 27% of diabetes cases and around 30% of ischemic heart disease cases.	(Guthold, Louazani et al. 2011, Ding, Lawson et al. 2016, Oyeyemi, Kasoma et al. 2016)
Pollution	About 98% of cities in low- and middle-income countries with more than 100 000 inhabitants do not meet WHO air quality guidelines. Vehicle emissions account for about 90 % of urban air pollution in developing countries including in SSA. More than 70% of the sub-Saharan Africa Road network is unpaved. Particulate matter and dust from transportation sources poses direct health risks.	People from low- and middle-income countries are disproportionately affected by the global burden of adverse health effects caused by ambient air pollution (AAP). However, estimates on extent in Sub-Saharan Africa (SSA) do not exist.	(Awuah 2018, Katoto, Byamungu et al. 2019)
Traffic crashes	Road incidents impacts health through premature mortality, injuries, traumas and post- traumatic stress	(1) About 27 people out of every 100,000 are killed in road incidents annually in SSA (2) The estimated pooled rate for road traffic injury was 65.2 per 100,000 population (3) Prevalence of Post-Traumatic stress disorder among road incident survivors is between 22% to 50%	(Iteke, Bakare et al. 2011, Adeloye, Thompson et al. 2016, WHO 2018, Yohannes, Gebeyehu et al. 2018, Fekadu, Mekonen et al. 2019)
Access to services	Transport serves as link between health facilities and home. Unaffordable transport services can deter those in need from seeking health care. Lack of transportation infrastructure (lack of vehicles for travel and poorly designed road infrastructure) is reported in the majority of the studies on delays in seeking maternal health.	In developing country contexts, an estimated 35% of all maternal mortality can be directly attributed to lack of transport and 75% of the women who die in the course of childbirth as a result of inadequate emergency transport	(Babinard and Roberts 2006, Transaid 2013, Nwameme, Phillips et al. 2014, Austin, Gulema et al. 2015, Niyitegeka, Nshimirimana et al. 2017, Varela, Young et al. 2019)

of traffic collisions are fatal (Schlottmann et al. 2017). This raises the question of whether active transport yield a positive or negative overall health benefits. Although studies that estimate the net health benefit are not readily available in the current study setting, evidence from the rest of the world suggests that, overall, the benefits from active travel generally outweigh health risks from air pollution and road traffic incidents and therefore should be further encouraged (Panis et al. 2010, Tainio et al. 2016, Cepeda et al. 2017). However,while promoting cycling and walking is justified in the vast majority of settings, there exists a possibility for a small number of cities that have the highest PM2.5 concentration in the world that cycling and walking for transportation could lead to increase in health risks that outweigh the benefits (Mueller et al. 2015, Tainio et al. 2016).

Road traffic incidents

Road traffic incidents are a major externality arising from transportation. Approximately 27 people out of every 100,000 are killed in road incidents annually in Africa while a further 8 million incur non-fatal injuries per year in SSA alone (World Health Organization 2019). RTIs remain a leading cause of injury-related loss of DALYs and pose a significant economic and societal burden (which may further impact health). Although the focus of most studies on this externality is on health impacts on the RTI victim, the potential for intra-household health externalities exists. Two potential channels through which RTI effects spill over to other members of the household include the risk that the involvement of one household member in a fatal RTI might cause mental health effects on other family members. For example, Ridha Ashkanani (2009) reports that household members of an RTI victim who either died or was severely injured suffered high levels of trauma similar to the victim. Secondly, the financial burden resulting from expenditures associated with an RTI indirectly affects household members. The out-of-pocket medical and rehabilitation costs incurred to treat injuries may compel households to reduce both medical and non-medical consumption. Further, there are associated indirect costs through production losses borne by households when caring for RTI victims during recovery or when permanently disabled. Overall, RTI shocks have the potential to negatively impact household welfare, plunge households into poverty, and increase the chances of poor health. There is minimal evidence of studies that sought to systematically investigate the impacts of RTIs on household members who are not directly involved in the traffic incident in SSA, this is the subject of Chapter three of the thesis.

Access to health services

Access to health services is a crucial pathway that transport impacts health (Peters et al. 2008) identifies four dimensions of barriers to access to health care; geographical barriers, availability, affordability, and acceptability. The state of the transportation system can be linked to the first three dimensions. Geographical access considers the distance travelled and time taken for a patient to and from a health facility. Patients residing further away from health facilities are less likely to utilize health services on account of distance. For example, the 2016 Demographic Health surveys of Malawi and Uganda show that 56% and 37% respectively of women who needed health care could not access it due to long distances to a health facility (National Statistical Office of Malawi and ICF Macro 2011, 2017). One way to overcome geographical barriers to accessing health services is the construction of additional public clinics and hospitals closer to the people. However, geographical inaccessibility is not only a function of physical distance but also the state of the road and the availability and affordability of transportation. Thus, interventions that lower the time spent on travelling such as road upgrading from gravel to bitumen standards hold the potential to promote access to health care in a timelier manner.

The affordability dimension refers to the level of financial costs associated with transportation needed to access health care. Transportation costs have been cited as a huge barrier to accessing health services in SSA. For example, in Uganda, about 48% of women do not manage to access health services when needed because they could not afford the cost of transportation (Allen et al. 2017). Similarly, Varela et al. (2019) reports that in Malawi, lack of suitable transport, finances, and prolonged travel time, all pose serious barriers to timely access to health care. Investments in transport projects with the potential to lower transportation costs may improve access. Chapter four of the thesis investigates how investments in upgrading roads might influence the cost of transportation to health facilities and the level of health service utilisation in more detail.

Pollution

Traffic-related pollution includes exhaust emissions from tailpipes in form of carbon monoxide, carbon dioxide, nitrogen oxides, and particulate matter, as well as non-exhaust emissions from tires' tear and wear, and dust. The effects on health outcomes are wide-ranging and may include non-allergic respiratory morbidity, and symptoms (such as asthma), cardiovascular morbidity, cancer, pregnancy, and birth outcomes (Katoto et al. 2019). Although motor vehicle emissions account for about 90% of urban air pollution in developing countries, studies that have sought to quantify the effects of transport-related air pollution on health in SSA are nonexistent. One of the challenges often encountered is the identification and isolation of health effects due to transport-related air pollution from the effects of other forms of air pollution such as emissions from industrial and manufacturing processes.

Compounding Traffic-related air pollution (TRAP) is noise pollution. This form of pollution has been linked to health problems including hearing loss, heart disease, learning difficulties in children, annoyance, and sleep disturbance (Babinard & Roberts 2006, Dzhambov & Dimitrova 2017). In Western Europe, for instance, an estimated 1,685,000 DALYs are lost per annum due to ischemic heart disease, cognitive impairment of children, sleep disturbance, and annoyance linked to noise pollution. A significant contributor is traffic-generated noise, with close to half of the population exposed to road traffic noise (World Health Organization 2011). Besides air and noise pollution, motor vehicle transport can affect health through surface contamination arising from oils, tear and wear of tires among other particulate matter. In places with heavy motor vehicle traffic, roadway surfaces are often found covered with such chemical substances which could end up slipping into water sources and soils and could potentially end up in what humans consume (Adamiec et al. 2016). Prolonged exposure to contaminated surfaces has been linked to a host of illnesses including Abdominal pain, Arthritis, Depression, Fatigue, Headache, Hypertension, Kidney failure, and Liver failure among others (Nieuwenhuijsen & Khreis 2020). Estimation of impacts of noise pollution and water and surface contamination on health in SSA remains unresearched.

Transport health pathways: a summary

This review has shown that while there are research efforts to understand how transport impacts health in SSA, the focus has been limited to four channels: road crashes, air pollution, physical activity, and access to health care. The remaining transport health pathways have not received much attention. A possibility for the low research interest in these pathways could be that their impact on health may still be low. For example, the impact of electric transportation systems through electromagnetic field effects may not constitute a health problem in SSA which mainly relies on non-electric transportation systems. Similarly, with a significant population residing in rural areas with low vehicle densities, noise pollution may not yet pose a serious health problem in parts of Sub-Saharan Africa. However, as the region industrialises and coupled with a growing vehicle population, residents, particularly those in urban areas, could more likely be affected through a wider range of pathways.

2.4.2 Health impacts in economic evaluation of transport sector interventions

The results in section 2.4.1 revealed that four transport health pathways have been the focus of research in SSA. This section considers how these health impacts are estimated and incorporated into economic evaluations of transport interventions. Eight studies are found to have had an economic evaluation component of a transport sector-based intervention that included health effects among the outcomes considered. The papers reviewed are listed in Table A1 and grouped by health effects categories they evaluated as well as the main evaluation method used. Two methods for economic evaluation were employed, cost-benefit analysis and cost-effectiveness. The cost-effectiveness analysis is applied to interventions aimed to reduce traffic incidents such as the installation of speed humps and enforcement of speed limits. The CEA approach compares costs to outcomes measured in non-monetary units, which in the field of health is often DALYS or QALYS. Under the CBA, a more common approach in transport, estimated effects are converted into monetary terms. On the cost side, the economic cost is interpreted to mean the financial cost of implementing the intervention adjusted for taxes, duties, and subsidies. The benefits are based on the reduction in road user costs estimated as the difference between the "with the project" and "without the project" scenarios. For example, for a road construction project, road user costs assessed would include vehicle operating costs, travel time for passengers and cargo, road maintenance costs, effects of vehicle emissions, and road incidents. While some of the expected effects are already or readily convertible to money terms, this is not the case with health impacts, varying approaches have been employed for estimation and monetisation.

Non-Market Valuation Methods

While some costs and benefits which go into Economic evaluations can be determined based on market prices, it cannot be assumed that all impacts of policies and programs are measurable using market prices. For some goods and services, the appropriate market is absent. This is particularly the case for interventions with health, social or environmental impacts. The main approaches used in non-market valuation include the stated preferences and revealed preferences methods. Preferences in this case refer to the order that an economic agent gives to alternatives based on their relative utility. Therefore, revealed preferences are preferences revealed by studying actual decisions people make (measured by their actions) to determine the value of non-market goods and services (Klose 1999). For example, in the case of road traffic injuries, this means determining the amount of money that people are prepared to pay for a reduction in crash risk on the basis of actual behaviour, for example purchasing behaviour regarding vehicle safety provisions. In this method, the value of market goods or services serves as a proxy for understanding the value of non-market goods or services. On the other hand, stated preferences are survey-based approaches to valuation; individuals are presented with hypothetical situations about a good or service and are asked about their willingness-to-pay or willingness-to-accept under different scenarios (León et al. 2023). For example: How much would consumers be willing to pay to reduce the risk of being involved in a road traffic incident? Using the stated preferences, we can understand the value that consumers place on an intervention that reduces RTIs via their stated preference within a hypothetical scenario.

Valuation of road traffic incidents

Previous studies have costed road incidents using two main methodologies; the gross output or human capital approach, and the willingness to pay (WTP) approach. The Human capital (HC) approach estimates the cost of a fatal casualty based on the loss of future output approximated by average wages lost while the WTP method involves an assessment of risk and the willingness of individuals to pay for a small reduction in the risk of suffering a road traffic incident (Johannesson 1996, Turner et al. 2021). Of the two, Human capital is commonly used, and all but one of the reviewed studies obtained estimates using the human capital approach. Under the Human capital approach, prior to valuation, road traffic incidents are categorized as either fatal, severe, minor, or damage only. Fatal RTIs are classified as those involving at least one death of the victim within 30 days as a result of injuries sustained in the traffic incident; severe injuries involve cases where the casualties require hospital treatment and have lasting injuries, but do not die within a 30 day period as is the case for fatalities; Minor injury includes those not requiring hospital treatment or, if they do, the effects of the injuries quickly subside. The days of productivity lost to RTIs are then converted to a monetary measure based on the average daily wage. In some cases, the HC also captures human costs besides production losses. Human costs in this context refer to pain, grief, and emotional suffering as a result of being involved in a traffic incident. Because of the reliance on wages, the estimated value of RTIs varies widely within the SSA region. As an example, Table 2.3 shows the values attached to RTIs of varying severity in selected countries. A fatal RTI in south Africa was valued at several times higher than a fatality in Uganda. Accounting for the two-year time difference is unlikely to close this gap. These differences suggest that the application of the Human capital approach can further be refined to make it more holistic. The current practice considers only the forgone wages of the victim while potential wage and leisure losses of RTI victim household members and caregivers are omitted. Thus, variations in time allocation to both economic and non-economic activities of household members following a serious injury or death of one of the members remain largely ignored.

Table 2.3: Variations in estimated cost of an RTI in US$

Country (Year)	Fatal	Severe	Slight	Source(Author, year)
Malawi (2012)	29,704	1,108	277	(Ministry of Transport, 2017)
Uganda (2018)	33,685	700	41	(Wanume, Nduhura et al., 2019)
Namibia (2011)	141,193	21,979	4,864	(Namibia Roads Authority, 2014)
SouthAfrica (2016)	436,214	51,503	9,141	(Labuschagne, 2016)

Pollution effects valuation

Estimating the value of reducing air pollution involves first modelling the expected impacts, and then monetising them. In practice, the impacts of air pollution reduction interventions are estimated using dose-response functions. The estimated impact is then converted to money values using either revealed or stated preferences. In this review, two studies are found to have attempted to evaluate health effects linked to motor vehicle pollution in SSA. Both papers fail to establish unit social costs of vehicle emissions and the benefits of emission reductions in their local contexts, rather they base their overall estimates on an economic valuation framework developed to evaluate the social cost of emissions elsewhere. A major limitation in this way of evaluating health impacts is the failure to account for conditions specific to the local contexts, such as the location of emissions, proximity to population, population age distribution, projected population growth, urbanization, and baseline disease rates. Further research efforts could improve the characterization of social costs of vehicle emissions by explicitly accounting for these factors.

Valuing physical activity

Only one study was found to have estimated effects on levels of physical activity. This is a cost-benefit analysis of improved and segregated cycle lanes in South Africa (Sean Cooke 2017). To estimate the health benefits of the project, a difference between the new level of physical activity and the previous level is taken. An Economic Assessment Tool (HEAT), created by the World Health Organisation (WHO), is then used to monetise the health benefit. The process involves several steps, firstly, the HEAT estimates changing relative risk of mortality of a new user due to the change in physical activity. Then, to estimate health benefits, the mortality risk of regular cyclists and pedestrians is compared to that of an average individual. Based on this comparison, relationships are built drawing from extensive studies that translate the level of physical activity into a factor that represents the relative risk of mortality for the new Non-Motorised Transport (NMT) users. The all-cause mortality rate is used to estimate the number of new NMT users that would be expected to die in any given year had they remained at their pre-intervention level of physical activity. The relative risk factor is then applied to estimate how many lives are likely to be saved due to increased physical activity. Finally, the average value of a statistical life is then used to calculate the monetary value of the lives saved due to the increased levels of physical activity.

The value of travel time

The value of travel time denotes the benefits associated with a reduction in time spent on moving from one point to another. Reduction of travel time leads to time-saving which constitutes the most significant aspect considered in transport cost-benefit analyses of road projects. For economic evaluation purposes, time saved is converted to monetary values as a product of time spent travelling multiplied by unit costs associated with travel if known. Ideally, the estimation of unit travel costs ought to vary depending on the type of trip, travel conditions, traveller preferences, and type of transportation mode. In practice, simplifying assumptions are applied when valuing passengers' travel time for inclusion in cost-benefit analysis. It is assumed that people use their time saved for two purposes: work or leisure. Therefore, the opportunity cost of time spent travelling is either the wage that could have been earned from work or leisure forgone. Accordingly, the value of work time saved is valued based on the average hourly wage rate. Leisure is considered less valuable and is approximated as a fraction of the wage rate.

Accounting for health impacts in valuing travel time remains largely unanswered. This is despite the realisation that some health conditions tend to be very time sensitive. It has been shown that access to timely emergency health care services is critical for time-sensitive conditions such trauma, stroke, and heart conditions among others. Because of the significance of travel time on health outcomes, the Roads Economic Decision (RED) tool includes a provision for incorporating various health effects. The challenge is that these effects, first, must be estimated and monetized from outside the tool. As there exists no established approach to monetizing travel time from the health perspective, the steps that could be followed are suggested. The first step is to recognise the two channels through which travel time impacts health; the first is through influence on an individual's decision whether to travel to seek health services and the second is the impact of travelling time on health outcomes of time-sensitive health conditions. This can then be followed by an estimation of the potential reduction in the health burden (mortality and/or morbidity) due to travel time reduction. Once the health losses avoided are estimated, these could then be converted to a monetary measure in the case of CBA using valuation techniques; forgone earnings, medical costs, the value of statistical life estimates or stated preference approaches.

2.5 Conclusion

This chapter has shown that while transport activities and transport interventions affect public health in various ways, research on the extent of impacts has been limited to a few pathways; traffic incidents, physical activity, access to health care, and aspects of pollution. The larger share of evidence on transport impact on health in the region focuses on two pathways: road traffic incidents and through improvements in access to health services. The focus on research on road traffic incidents could be attributed to the size of the impact imposed on health relative to other pathways. For example, this review has shown that in 2019, about one life out of every five thousand lives is lost through road incidents per year in Africa with another eight million suffering non-fatal injuries per year in SSA alone (World Health Organization 2019). The second strand of literature investigates the impact of road infrastructure on access to health services. The bulk of the evidence aims to answer the question of how the lack of appropriate and affordable transportation affects the decision to access health services when needed.

There is a lack of evidence on the health impact of TRAP and active transport. A possible reason for this is that relative to road traffic incidents, the determination of loss of health attributable to externalities such as loss of health related to TRAP and physical inactivity is more difficult and requires stronger assumptions in the estimations process. Similarly, we do not find studies that report on health impacts through the indirect link from transportation to health through improvements in access to markets and improved nutritional outcomes. The pathways shown in Figure 2.1 constitute transport externalities on health that are frequently highlighted among the social determinants of health. A possible reason for the low research interest in the other possible pathways could be that their impact on health is still considered low. For example, at present, the impact of electric transportation systems through electromagnetic field effects may not constitute a health problem in SSA, which predominantly relies on non-electric transportation systems, compared to the health threat posed by road traffic injuries(e.g the use of electric vehicles (EVs) is still low with South Africa, which has the most advanced e-mobility market in Africa, having about 500 electric vehicles (EVs) in 2019 out of a total fleet of 12 million automobiles (Collett et al. 2021))

Economic evaluation studies have followed a similar pattern, with a few studies evaluating the effectiveness, benefits, and costs associated with interventions aimed at reducing traffic incidents. Evaluations of some aspects of health effects are still hugely underdeveloped as evidenced by the non-existent literature. We found six papers evaluating the impact of road RTAs, two studies evaluating traffic-related pollution and a single paper on active transport. The chapter has also shown wide variances in the evaluation studies. For example, a wide range of values is placed on the monetary value of averting an RTI. These differences are, firstly, due to variations in adopted methodologies which are attributed to a lack of guidelines in the region to guide what components to include and how to value them. Secondly, the differences in the estimated values are due to the differences in key inputs parameters used in different contexts. For example, when estimating the cost of RTIs using the human cost capital, a larger component in this approach is the forgone output which is usually estimated based on the average wage. The variations in average wages among the countries mean different values attached to similar types of RTIs.

Overall, the results of this review point to an apparent lack of good quality evidence needed to reliably estimate the health impacts of most road transport externalities. Countries in the SSA region need to invest in the capacity to collect, store, manage and analyse transport and health data which is critical to assessing the magnitude of transport health impacts and essential in assisting decision-making. Further, to ensure uniformity and comparability of data at country and regional levels, countries must adopt international standards or develop similar guidance, which could allow the production of comparable datasets.

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Chapter 3

Impact of road traffic injuries on household health and economic welfare

3.1 Introduction

Road traffic injuries (RTIs) remain a major contributor to health loss leading to the death of approximately 1.35 million people globally, with a further 20 to 50 million suffering effects of non-fatal injuries in 2018 (World Health Organization 2018). Low-and middle-income countries (LMICs) account for a larger share of the road traffic injury burden and with more than double, the fatality rate compared to high-income countries. For example, between 2013 and 2018, the risk of dying as a result of a road traffic injury was highest in the SSA region with a fatality rate ranging between 24.1 and 27.5 deaths per 100,000 while that of high-income countries averaged 8.3 deaths per 100,000 people (World Health Organization 2018, 2013). Road traffic injuries are also the leading cause of death for young people aged between 15 and 29 years in the region and remain among the top 10 causes of death for all ages (World Health Organization 2015). At the regional level, countries in SSA suffer an estimated annual economic loss of about 0.15% of aggregate output on average due to severe RTIs and fatalities (Chen et al. 2019).

At the household level, the abrupt nature of RTIs coupled with costs associated with caring for injured persons and the possibility of permanent disability impose financial pressures on families, threatening sustainable livelihoods in multiple ways;

Firstly, there are direct out-of-pocket medical and rehabilitation costs incurred to provide RTI patients with health services. For households in LMICs, out-of-pocket expenditure on health has the potential to pose economic distress, especially in countries with low health insurance coverage (Otieno & Asiki 2020). Secondly, reduced earnings due to RTI and/or a shift in household resource allocation to accommodate medical consumption compel households to forgo non-health consumption. Thirdly, the households' risk of being drawn into indebtedness increases due to RTI-related financial challenges. In addition, household asset and wealth accumulation may also be affected; it is not uncommon for households to sell assets to cover expenditures which also reduces their ability to invest in additional assets. Finally, labour force participation of RTI victims or their caregivers could be affected; for example, when the RTI victim is unable to engage in paid work because an RTI led to permanent disability. Similarly, informal caregivers within households, who are often women and girls (Gururaj et al. 2004), may be deprived of the opportunity to fully participate in the labour force. Despite the numerous potential economic costs associated with RTIs, there is little published research that has sought to examine the impact that RTIs have at the household level in the SSA region. The focus of most work in this area is around the impact of RTIs on the costs of health service providers (e.g Parkinson et al. (2014), Urua et al. (2017), Matiwane & Mahomed (2018), Prakash et al. (2019)). These studies are mostly single site and aim to determine the level and distribution of hospital costs using micro-costing approaches. Few studies have considered some aspects of economic burden from the household perspective; Juillard et al. (2010) explored the economic consequences and disabilities associated with RTIs focusing on expenditure for medical treatment of persons who had suffered an RTI. Ipingbemi (2008) estimates the economic burden of road crashes in Nigeria based on a sample of RTI victims admitted to a hospital. While the main focus of their study is on estimating medical costs, they also report household-level effects in terms of the number of days that the RTI victim had at least one person from their family present with them during the period of admission. Mowafi et al. (2021) compares the household economic impact of RTI versus other emergencies treated at a hospital in Uganda. They considered several aspects of household economic welfare including lost wages or schooling, household costs incurred due to their injury or illness, and assets sold. However, the study only takes a descriptive approach to exploring costs associated with RTIs.

This paper contributes to the literature on the economic costs of road traffic incidents by utilising advanced econometric methods to estimate the impact of RTIs on households' economic welfare based on a multi-country household dataset from ten countries in sub-Saharan Africa. Specifically, we examine how RTIs affect the likelihood to spend and the level of household health expenditures; whether households with RTIs spend less on non-health items; the association between RTI and household's asset index; the effect of RTIs on the likelihood of households falling into debt, and the association between RTIs and labour force participation within households. Understanding the extent to which RTI affects households is potentially useful in estimating the costs of road traffic incidents that result in injuries.

3.2 Linking RTIs, Consumption, investments, and labour supply

The relationships between RTI, household consumption, investments, and labour supply can be expressed in form of a modified version of the household consumption and investment decisions model. In a household setting, an RTI will influence resource generation and allocation; we assume a household, i, whose members earn a wage,w, from supplying labour and total household earnings wN_i depends on the number of hours worked N_i. The number of hours worked is a function of total disposable time DT_i in a household, where DT_i is the amount of time available in any given period to a household to allocate between supplying labourN_i , and leisure, L_i. Further assume that households derive utility from non-medical consumption, NMC_i , stock of health, H_i and leisure, L_i . In a given period, t, a household allocates both time and financial resources to maximise the utility function.

$$Maximise\ U_{it} = f(NMC_{it}, H_{it}, L_{it}) \tag{3.1}$$

$$subject\ to$$

$$DT_{it} = N_{it} + L_{it} \tag{3.2}$$

$$and$$

$$N_{it}w_t = NMC_{it} + MC_{it} + I_{it} \tag{3.3}$$

Where MC_{it} is expenditure on medical consumption and I_{it} is allocation to investments including purchase of household assets. In this set up, RTI occurrence influences household resource allocation in two ways; first it affects the total amount of disposable time as some of the time is take up to seek care and also provide informal health care. This reduces leisure time and time allocated to both formal and informal labour supply by household members. Secondly, RTI requires investment in health stock through expenditure on medical products in order to restore health stock to the pre-injury level. Assuming RTI results in reduction of disposal time equal to a proportion λ and affects MC_{it} by a factor σ, then a household with RTI maximises utility subject to a new constraint:

$$(N_{it}w_t)^{rti} = ((1-\theta)(DT_{it} - L_i)w_t = NMC_{it} + (1+\sigma)MC_{it} + I_{it})^{rti} \tag{3.4}$$

In equation 3.4, RTI leads to a reduction in earnings equal to $\lambda(DT_{it} - L_i)w_t$ while increasing expenditure on medical consumption by σMC_{it}. Households are compelled to reallocate resources to accommodate the changes. In this constrained optimization, households could shift part of the resources for NMC_{it} to cover part of σMC_{it} or convert a proportion of investments in assets into cash. If the reallocations within a given period do not release adequate resources to cover σMC_{it}, a household can borrow against future earnings in period $t+1$. Utility maximization in the next period would then be subject to the constraint that takes into account the repayment of borrowed funds.

$$N_{it+1}(w_{t+1}) + (1+r)I_{it} = NMC_{it+1} + MC_{it+1} + I_{it+1} + (1+r)B_{it} \tag{3.5}$$

Where r is the interest rate and B_{it} is the amount borrowed. We estimate the mean magnitude of the component σMC_{it} and the subsequent effects on the size of NMC_{it} and I_{it}, following an injury, along with the impact on the likelihood to supply labour and incur debt.

3.3 Data

We estimate the effects of RTIs based on household survey data collected by the World Health Organization as part of the 2003 multi-country World Health Surveys (WHS). Comparable household and individual questionnaires were used which enables the aggregation of country-level data into one regional dataset. The sample was probabilistically selected and representative at the country level. Sampling weights were generated and adjusted for the population distribution with final post-stratification correcting for non-response (Üstün et al. 2003). The analysis in this paper is limited to households drawn from 10 LMICs in the SSA region. Table 3.1 lists the countries selected and the proportion of households with at least one RTI incident.

Table 3.1: Number of sampled households and proportion with RTIs by country

Country	Households	RTI incidence,%
Burkina Faso	4,783	2.43
Ethiopia	4,908	0.14
Eswatini	1,980	1.82
Ghana	3,903	3.00
Kenya	4,385	2.58
Malawi	5,279	2.78
Namibia	3,884	2.47
South Africa	2,273	3.70
Zambia	3,797	1.26
Zimbabwe	3,964	1.82
Total	39,156	2.11

The WHS data identified households that had any members suffering road traffic-related injuries which are classified based on when the injury happened: in the last 6 months and those happening between 6 and 12 months. The dataset also records whether the injuries were treated at a health facility and how the soon medical treatment was received from the time of the traffic incident but there was no indication of the severity and the number of injuries experienced in any given household

3.3.1 Variable definitions

Variables used in the analysis are defined in Table 3.2. The effect of RTI on health expenditure is examined through association with the likelihood to spend, the magnitude of expenditure and the incidence of catastrophic health expenditure. We adopt the proportion of total household expenditure on health exceeding 10% to define catastrophic health expenditure. A similar measure has previously been used (Pal 2012, Rashad et al. 2015, Mchenga et al. 2017). All expenditures are estimated as monthly amounts converted to United States dollars based on average purchasing power parity exchange rates. The asset index was constructed using the Multiple Correspondence Analysis (MCA) approach and normalised using a min-max technique.

3.3.2 Choice of explanatory variables

We identified demographic, socioeconomic and health attributes at household and individual level that could potentially impact household economic welfare and which we need to control for in our analyses. These include age and sex of household head, and household size, all of which are linked to economic opportunities and income earned. For example, female-headed households often have access to a lower level of resources compared to male-headed households for reasons that include gender-income inequality (Tibesigwa & Visser 2016). Household size is likely to influence the magnitude of household expenditures.

We also controlled for rural/urban residence as urban households tend to have and spend more money compared to those in rural areas where part of what is consumed is grown by the households (Biyase & Zwane 2018, De Magalhães et al. 2016). Region of residence also affects the coping mechanism, urban households are more likely to resort to borrowing money while rural households would probably sell assets often due to limited borrowing opportunities (Ranson et al. 2012). We further explore the interaction of RTI and region of residence. To account for socioeconomic differences the highest level of education attained by the household head is used as an indicator of the socioeconomic status of the household (Patrinos & Psacharopoulos 2020, Psacharopoulos & Patrinos 2018). Effects of existing health conditions are controlled for using self-reported health status and experience of illness involving a household member. We include alcohol consumption which could influence both health and non-health expenditure (World Health Organization 2019). We also controlled for health insurance coverage because of its influence on out-of-pocket health expenditure and coping means.

Country-level variables are included to reflect differences in economic activity and health systems. We group countries based on whether some health care services were accessible for free which could affect the amount spent on health. Countries that had implemented free primary health policy at the time of the survey in 2003 include South Africa, which introduced free primary health care in 1996, Malawi which always has had free primary care and Eswatini (Mngadi et al. 2008, Goudge

Table 3.2: Definition of variables

Variable name	**Definition**
Outcome variables	
Household health expenditure	Amount spend on health care costs, drugs, health products, and travel in 4 weeks period converted to US$ based on purchasing power parity exchange rates.
Catastrophic health expenditure	Health expenditure as a proportion of total monthly consumption expenditure exceeding 10%
Non-health consumption expenditure	Amount spent on food, education services, housing, and housing amenities
Asset stock index	Asset stock index as an indicator of household wealth constructed based on household's ownership of selected assets, such as televisions and bicycles
Household indebtedness	whether households had to borrow funds to cover health expenditure in the past 12 months
Labour force participation	whether the head of the household was in the labour force at time of survey
Other variables	
Age of household head	Number of years the household head had lived at the time of survey
Sex of household head	1=female; 0=male
Marital status	0=Married or cohabiting, 1. Otherwise
Number of children	Number children born from the same mother
Region of residence	The setting of household settlement, 0=rural, 1=urban
Country	Country where survey respondent was resident
Level of Education	Highest level of education completed by head of household, 1 =No formal schooling, 2=primary, 3=Secondary, 4=Tertiary level
Healthcare charges	Whether a country had provided some health care services without charging the beneficiaries
Percapita GDP	Percapita Country GDP, PPP (expressed in constant PPP 2017 international USD)
Road traffic injury	household had at least one member involved in road traffic incident as motorist, cyclist, or pedestrian
Health insurance	Household paid a positive amount on health insurance premium
Illness	At least one household memberhad any other illness not related to road traffic incident in last twelve months
Health status	Self-reported health status of household head: 1. Good or better, 2. Moderate, 3. Bad or very bad
Alcohol consumption	Number of alcoholic drinks consumed in a week

et al. 2009, Watson et al. 2016). The rest of the countries had some form of user fees at the time of the survey (Masiye et al. 2010, Van Rooy et al. 2012, Obare et al. 2018, Bicaba et al. 2020).

3.4 Methods

The treated group includes all households that had at least one member injured in a road traffic incident. Estimating variations in household economic welfare based on exposure to RTI presents methodological challenges of selection bias and confounding. This is because while the occurrence of road traffic incidents and injury could be thought of as a random event, there are household and individual attributes that affect the probability of suffering an RTI. For example, being male and residing in urban areas may increase the likelihood of being involved in a road traffic incident implying that individuals suffering RTIs may be systematically different from those that did not. Similarly, confounding could occur if there exist variables that influence the likelihood of exposure to treatment (i.e. RTI) and also affects the outcome variables. For example, alcohol consumption affects both the exposures to RTI, health expenditure and labour force participation rate (Jørgensen et al. 2019, World Health Organization 2019). Selection bias and confounding are largely addressed through the use of multivariate regression; however, the validity of estimates depends on several assumptions. One key assumption is the correct model specification. We, therefore, employ a mix of matching and regression methods to deal with issues of possible model misspecification, selection bias, and confounding. We first pre-process data using matching so that the treated households are as similar as possible to those in control before estimating a multilevel regression. With matched observations, the treatment variable is more independent of covariates which implies that subsequent parametric estimations become less reliant on model specification (Ho et al. 2007). Different matching approaches were considered, each approach varies based on the choice of the function of covariates, also referred to as balancing scores, that are used to minimize differences in the distribution of covariates between control and treatment groups. Exact and coarsened exact matching methods resulted in the loss of a high number of unmatched households from the treatment group. After a comparison of output from the different matching approaches, we opted to match households using a combination of propensity and Genetic matching approaches. Genetic matching matches on generalized Mahalanobis distance (MD), an alternative to matching on a propensity score, defined as a distance between the treated and control.

$$MD = (X_T - X_C)'\Sigma^{-1}(X_T - X_C) \tag{3.6}$$

X_T is the vector of treatment covariates, X_C is a vector of control covariates and is the variance-covariance matrix of X in the pooled treatment and control groups. The main input into Genetic matching is a matrix of matching variables but we also include the estimated propensity score as an additional matching variable to improve the match result (Sekhon 2008). The matching was done independently for each country so that households drawn from the same country were matched with each other. Households are matched based on all the independent variables defined in Table 3.2.

3.4.1 Regression model choice

We estimate a two-level mixed model with households (first level) nested within countries (second level). The model choice is based on the understanding that households drawn from the same country would be more similar to each other compared to households from other countries. Individuals in a given country seek medical treatment in the same health system and face similar economic conditions which subsequently affect the level of health expenditure and coping mechanisms following a road traffic incident. Further, the results of the five null models for random effects, which assessed heterogeneity between country clusters and dependence of individual households on countries using the Likelihood Ratio (LR) test (Table 3.3), suggest that country-level clustering effects on the chosen dependent variables are present in our data. Additionally, we opt for a multi-level mixed model because it allows for the possibility to estimate both fixed effects, which are parameters associated with an entire population, and random effects, which are associated with individual units drawn at random from a population (Raudenbush & Bryk 2002).

Table 3.3: Country level clustering effects

Dependent variable	σ_u^2	σ_u^2 **CI**	**ICC**	**LR test, p-value**
Health expenditure	21.7951	[9.0335 52.585]	0.0506	0.0000
Non-health expenditure	2346.324	[968.819 5682.419]	0.0344	0.0000
Labourforce participation	0.0236	[0.0098 0.0569]	0.0942	0.0000
Borrowed funds	0.0007	[0.0003 0.0017]	0.0085	0.0000
Asset index	0.0068	[0.0028 0.0165]	0.2740	0.0000

3.4.2 Two-level regression model specification

To establish an association between RTIs and household economic welfare, we estimate a random intercept-random slope Generalised Linear Regression model (GLM). GLM is recommended to model data in which the variance is not constant for all observations (Deb & Norton 2018). In addition, GLMs offer the flexibility to fit different types of functional forms and the opportunity to select one which provides a better match of the relationship between the expected value of the dependent variable and the linear index of covariates (McCullagh & Nelder 2019). The general model that we estimate is specified as:

$$y_{ij} = \gamma_{0j} + \gamma_{1j}x_{ij} + e_{ij} \tag{3.7}$$

$$\gamma_{0j} = \beta_{00} + \upsilon_{0j} \tag{3.8}$$

$$\gamma_{1j} = \beta_{10} + \upsilon_{1j} \tag{3.9}$$

where y_{ij} is the observed response for household in country j , γ_{0j} is the country dependent intercept, γ_{1j} is the slope and e_{ij} is the error term. The intercept γ_{0j} consists of the overall mean intercept β_{00} and a country-specific random intercept υ_{0j}. The slope γ_{1j} consists of the overall mean slope β_{10} and a country-specific random slope υ_{1j}. The random effects and residual errors are assumed to be independent of one another and also normally distributed with zero means and constant variances. For continuous variables, a version of equation 3.7 is specified in equation 3.10 and a corresponding model is estimated for binary outcomes (equation 3.11).

$$y_{ij} = (\beta_{00} + \upsilon_{0j}) + (\beta_{10} + \upsilon_{1j})RTI_{ij} + (\beta_{10} + \upsilon_{1j})x_{2j} + e_{ij} \tag{3.10}$$

$$\log\left(\frac{\Pi_{ij}}{1-\Pi_{ij}}\right) = (\beta_{00} + \upsilon_{0j}) + (\beta_{10} + \upsilon_{1j})RTI_{ij} + (\beta_{10} + \upsilon_{1j})x_{2j} + e_{ij} \tag{3.11}$$

In both equations, the fixed part specifies the overall mean relationship between the response and the predictor variables; that is, the relationship that applies across countries. The random part of the model specifies how country-specific relationships differ from this overall mean relationship. The fixed part includes level 1 or household predictor variables and level 2 or country-level predictor variables. The household-level matrix of predictors includes the same set of covariates used to match treatment and control observations, country-level predictor includes the type of health system and per capita GDP. For continuous response variables, the generalized linear model with Gaussian family and log link estimated a better fit. For binary outcome variables we estimate using a Bernoulli family and logistic link. To test the robustness of the main results, we check the sensitivity of the estimated coefficients to a different definition of the treatment variable by using a different cut-off for the injury period window. Models are re-estimated after redefining the criteria used to categorise a household into the treatment group based on whether the RTI was suffered within six or more than six months to the time of the survey.

3.5 Results

3.5.1 Matching output

Table 3.4 shows the balance between treated and untreated households before and after matching. There is an improvement in the balance across all outcome variables in the matched sample; the gap in the proportion of households that incurred expenditure to acquire health services shrinks from about 14% to 6% after matching with 62% treated households reporting a positive amount compared to 56% among comparable non-RTI households. The variance in mean health expenditure also reduces from US$ 8 to US$ 5 with RTI-affected households spending more on health-related products and services. Among households, an average of 15% of households had indicated borrowing money to meet health care needs. The proportion rises to 17% among RTI households compared to 14% among similar households with no RTIs. In terms of non-health expenditure, matching reduces the variation between groups from more than US$ 20 to about US$ 4, in both cases, RTI-affected households spent less.

Table 3.4: Matching results

	Statistic			Differences (Treatment-Control)	
Household characteristic	**All**	**RTI-yes**	**RTI-no**	**Raw**	**Matched**
Positive health expenditure (%)	48.34	61.99	48.04	13.95	6.17
Mean health expenditure	16.89(21.1)	23.72(24.4)	15.79(21.0)	7.93	5.36
Mean non health expenditure	81.6(74.8)	81.0(171.2)	107.4(76.6)	-26.38	-4.89
Mean asset index	0.89(0.15)	0.83(0.2)	0.89(0.1)	-0.06	-0.023
Labour force participation (%)	54.13	63.4	53.92	9.48	4.62
Borrowed for health (%)	12.18	17.18	9.10	8.08	3.79
Region of residence is urban (%)	33.09	46.00	32.81	13.19	0.37
Head of household is female (%)	56.25	34.5	56.73	-22.23	-0.04
Mean age	37.3(15.1)	34.6(1.5)	37.4(15.9)	-3.02	-0.21
Marital status is married (%)	24.84	34.26	24.63	9.63	0.50
Av. number of children	5.9(2.7)	6.1(2.7)	5.9(2.7)	0.15	0.61
Level of education (%)					
No education	52.82	39.85	53.11	-13.26	-0.20
Primary	25.73	31.11	25.61	5.5	-0.10
Secondary	17.77	22.84	17.66	5.18	0.10
Tertiary	3.68	6.20	3.62	2.58	0.40
Health status (%)					
good	68.75	66.75	68.79	-2.04	-0.75
Average	22.76	24.15	22.73	1.42	-0.73
bad	8.49	9.1	8.48	0.62	1.48
Has health insurance (%)	4.25	6.9	4.19	2.71	0.12
Charged patient fees (%)	67.14	62.83	67.23	-4.4	0.60
Higher percapita gdp (%)	19.49	25.18	19.37	5.81	-0.43
Has chronic health condition (%)	47.77	56.05	47.59	8.46	-0.12
Av. alcohol consumption	2.08(7.82)	3.44(11.63)	2.05(7.71)	1.39	0.64
Number of observations	38161	826	37335	38161	2469

standard deviations in parentheses

3.5.2 Generalised linear model estimations

Table 3.5 presents the results of the two-level generalised linear model estimated on the full sample as well as subsamples splitting the treatment group into two groups; those with RTIs that occurred within six months and more than six months from the date of the survey. Full sample estimates show that households that experienced RTI had a higher likelihood of incurring any amount of health expenditure compared to households without RTI (OR=1.48). Further, RTI-affected households were more likely to spend more than 10 % of their total expenditure on health services (OR=1.314). In terms of the magnitude of health expenditure, households with RTIs spent 39% more compared to those in the control group.

Table 3.5: Generalised Linear Model estimates

Outcome variable	**Full sample** (all RTIs)	**Sub sample** (RTI six months or less)	**Sub sample** (RTI more than six months)
Positive health expenditure	1.480***	1.536**	1.255**
	(0.10)	(0.03)	(0.09)
Catastrophic health expenditure	1.314**	1.350**	1.110**
	(0.149)	(0.138)	(0.027)
Magnitude of health expenditure†	1.393***	1.432**	1.303**
	(0.100)	(0. 171)	(0.116)
Household non health expenditure†	0.773***	0.789***	0.745***
	(0.052)	(0.123)	(0.191)
Asset index†	1.063*	1.087*	1.06
	(0.078)	(0.259)	(0.092)
Borrowed funds	1.251**	1.458***	1.431**
	(0.196)	(1.331)	(0.279)
Labour force participation	0.977	1.136*	0.835
	(0.133)	(0.491)	(0.137)

† indicates continuous dependent variables, the rest are binary outcomes; all coefficients are exponentiated;

Standard errors in parentheses ; p* $< 0.05, p{*}{*} < 0.01, p{*}{*}{*} < 0.001$

We hypothesized a negative effect of RTI on non-health consumption inclusive of food, education expenditure, housing, and amenities; the estimate shows that RTI-affected households spent about 25% less on this category of consumption. It is noteworthy that this estimate captures the average impact and could change based on the ratio of fatal to non-fatal and by the severity of injury among the non-fatal. Estimates of RTI effects on the borrowing finances to meet the financial demands of accessing health care show that RTI-affected households were more likely to borrow funds for health. We find weak evidence of the impact of RTI on the stock of assets owned. While the effect is there, the magnitude is small and of weak significance. Labour force participation does not appear to have a significant association with the occurrence of RTI; this is not supportive of the hypothesis that households that experienced road traffic injuries are unlikely to participate in the labour force.

Predicted country-level margins in Table 3.6 show how switching a household from a state of non-RTI to an RTI-affected, impacted household health and economic welfare indicators. The trend in terms of the direction and magnitude of effects appears consistent across countries; the magnitude of marginal effects appears to vary but within a narrow range. In marginal terms, the effect of a household having a member with RTI increases expenditure average of about US$ 5.00 per month. Monthly non-health expenditure for households that experienced RTIs was less by close to US$ 30.00. The results also show that increases in health expenditure versus the decrease in non-health expenditure are not a one-to-one proportion, the decrease

Table 3.6: Country level GLM margins estimates

Country		Continuous outcomes HE	NHE	Categorical outcomes 10% of THE	Borrow
Burkinafaso	no	11.38	44.96	0.25	0.14
	yes	16.01	23.08	0.32	0.16
Ethiopia	no	13.3	55.07	0.28	0.10
	yes	18.18	27.83	0.37	0.12
Ghana	no	10.26	54.9	0.24	0.13
	yes	15.61	25.71	0.31	0.15
Kenya	no	11.5	65.9	0.25	0.14
	yes	17.43	30.01	0.32	0.16
Malawi	no	4.63	42.23	0.2	0.11
	yes	8.58	17.12	0.25	0.13
Namibia	no	8.89	158.59	0.16	0.20
	yes	13.59	74.93	0.20	0.23
South africa	no	6.58	150.17	0.14	0.16
	yes	9.88	74.05	0.17	0.19
Zambia	no	6.73	64.08	0.21	0.10
	yes	10.36	30.91	0.26	0.12
Zimbabwe	no	5.85	90.41	0.18	0.23
	yes	10.25	36.57	0.22	0.26
Eswatin	no	11.88	67.73	0.25	0.13
	yes	18.02	32.53	0.32	0.15
Overall	no	8.54	82.34	0.21	0 .14
	yes	13.87	51.14	0.27	0.17
Observations		1,435	2,469	2,469	2469

HE=Health Expenditure; NHE=Non Health Expenditure; THE=Total Household Expenditure

in non-health expenditure is higher, a result suggestive of reduced earnings though we do not find evidence of this effect.

As part of sensitivity checks, estimated models based on two subsamples, that include only injuries that happened in the 6 months window to the time of the survey and then those which happened six or more months ago (results column 2 and 3 respectively in Table 3.5). The direction of the effect of road traffic injuries on the dependent variables remains the same. However, the magnitude of effects on health and non-health expenditure is amplified for households that had recent injuries.

Sub-group analyses

To explore how the RTI affected various groups of households and obtain more insights beyond the observed impact on the overall sample, we divided the households in the study sample into several subgroups based on area residence and social economic status. We compare the health and economic outcomes of road traffic injuries for urban households with rural households and also based on whether the household could be classified as richer or poor. We use the level of household consumption expenditure as a proxy of socioeconomic status (SES). Due to sample size limitation, we divide the sample into only two groups, those above the average and those below average expenditure. We re-estimate the models for each of the subgroups. Tables 3.7 and 3.8 report findings from our sub-group analyses for the region of residence and socio-economic status respectively.

Table 3.7: Generalised Linear Model estimates by region of residence

Outcome variable	**Full sample** all households	**Rural** households	**Urban** households
Positive health expenditure	1.480***	1.458**	1.139*
	(0.10)	(0.196)	(0.124)
Catastrophic health expenditure	1.314**	1.47**	1.210*
	(0.149)	(0.991)	(0.052)
Magnitude of health expenditure†	1.393***	1.522*	1.106**
	(0.100)	(0. 193)	(0.081)
Household non health expenditure†	0.773***	1.033	0.699**
	(0.052)	(0.072)	(0.023)
Asset index†	1.063*	0.992**	1.001
	(0.078)	(0.001)	(0.013)
Borrowed funds	1.251**	1.242*	1.182
	(0.196)	(0.195)	(0.217)
Labour force participation	0.977	1.084*	0.989
	(0.133)	(0.138)	(0.176)

† indicates continuous dependent variables, the rest are binary outcomes; all coefficients are exponentiated;

Standard errors in parentheses ; p* $< 0.05, p{*}{*} < 0.01, p{*}{*}{*} < 0.001$

Table 3.8: Generalised Linear Model estimates by socioeconomic status

Outcome variable	**Full sample,** All households	**Rich** households	**Poor** households
Positive health expenditure	1.480***	1.200	1.575**
	(0.10)	(0.11)	(0.17)
Catastrophic health expenditure	1.314**	1.191**	1.560**
	(0.149)	(0.101)	(0.033)
Magnitude of health expenditure†	1.393***	1.022*	1.492**
	(0.100)	(0. 021)	(0.094)
Household non health expenditure†	0.773***	0.714**	1.046***
	(0.052)	(0.0650)	(0.034)
Asset index†	1.063*	0.970*	1.107
	(0.078)	(0.013)	(0.006)
Borrowed funds	1.251**	1.115*	1.347
	(0.196)	(0.190)	(0.229)
Labour force participation	0.977	1.323*	0.858
	(0.133)	(0.187)	(0.126)

† indicates continuous dependent variables, the rest are binary outcomes; all coefficients are exponentiated;

Standard errors in parentheses ; p* $< 0.05, p{*}{*} < 0.01, p{*}{*}{*} < 0.001$

We find that the impact of RTI on the likelihood of incurring OOP spending on healthcare was higher for the poorer households' subgroup relative to the effect on the richer subgroup. The estimated odds ratios for this outcome are higher for the poor sub-sample when compared with the estimate for the rich sub-sample (OR=1.575 vs OR=1.200). Similarly, the likelihood of facing catastrophic health expenditure is higher in the rural compared to the urban sub-sample (OR=1.470 vs OR=1.210). However, the reduction in non-health expenditure is more evident in the richer sub-sample. A comparison of the impact between rural and urban sub-samples shows that rural residents were more burdened with out-of-OOP. This is true across all three measures of health expenditure burden (Positive health expenditure, magnitude of health expenditure and catastrophic health expenditure). The impact of RTIs on assets, which is not detectable in the overall sample estimates, shows a small but significant negative effect on rural households.

3.6 Discussion

This chapter examined the impact of RTIs on households' economic well-being and sought to demonstrate various channels that the effects of RTIs go beyond the injured person in a household setting. Overall, we find that road traffic injuries place a significant burden on households in terms of health expenditures. In particular, we find RTI's incremental effect on health expenditure could be more than a third higher. The increase represents an amount that could push health expenditures to a catastrophic level for some households. This finding is consistent with findings in general literature on illness and injury impact on health expenditure at the household level (Xu et al. 2003, Mchenga et al. 2017, Kumar et al. 2012). The paper has also shown that road traffic injuries caused a reduction in the amount spent on education, housing, and food items. Possible explanations for this negative relationship include a substitution effect where households shift resources from the purchase of non-health goods in order to consume more health services necessitated by RTI. It could also be that households reduced consumption of both health and non-health goods due to reduced ability to generate earnings within the households following RTI. The relation between non-health consumption in households and illness or injury has been investigated in other settings with mixed results; a reduction in consumption levels (Gururaj et al. 2004) and no significant effect on non-health consumption (Alam & Mahal 2016). The variance in results could be attributed to the varying scope of non-health consumption expenditure analysed; a broader definition that includes transport-related expenditure would likely increase following an RTI.

The result that RTI do not show the anticipated negative effect on labour force participation could be due to the possibility that RTIs did not compel affected individuals to entirely leave the labour force but rather reduce the number of hours of labour supply. The result could also be driven by a competing effect that individuals who are likely to be involved in a road incident are those in the labour force as they are more exposed when going to work or looking for work. Further, our inability to control for injury severity means some RTIs were minor to warrant staying away from the labour force for both the RTI victim and informal caregivers. A counter explanation of the seemingly positive effect on some subgroups (injury less than six months and richer households) could be that households chose to supply more labour to raise additional resources for RTI treatment

This study finds no evidence to support the hypothesis that households that had RTI were more likely to have a lower stock of assets. The results still hold after excluding from analysis vehicles, motorcycles, and bicycles, assets considered as road incident risk factors. However, the hypothesized effect does show in the rural households subgroup. The result in the overall sample may posbility be diluted by households in urban areas where the phenomenon or selling assests to fund health needs may be less prevalent. The chapter also show a significant positive association between borrowing money for health purposes and households reporting an RTI. The phenomenon of borrowing in order to meet health expenditure following an illness is commonly reported in developing countries (Leive & Xu 2008, Kruk et al. 2009, World Health Organization 2019). For RTI households, borrowing for health is more prevalent probably due to the unexpected nature of road incidents which leaves households with no time to earn or reallocate resources. Our Subgroup analysis based on the region of residence and socio-economic status shows that the health and economic outcomes of poorer households and rural households are more affected by RTIs compared to richer and urban households. The findings based on the subgroups are subject to small sample estimation problems due to the small number of RTI-affected households in the sample.

Findings from this chapter are potentially useful to inform the valuation of the costs of road traffic incidents, particularly regarding the choice of evaluation perspective. Between the two perspectives often used when costing road traffic incidents; the individual perspective considers only costs suffered by the incident victim while the societal perspective essentially considers costs for the country or region as a whole. Costing road incident injuries from an individual perspective is considered too narrow and leaves out costs indirectly linked to the injury victim. Society's perspective on the other hand while considering wider costs presents the risk that the opportunity cost is allocated to sections of society further away from the event that there is no real impact. For example, without assuming full employment, society-level productivity loss attributed to severe RTI may be overstated. This is because for developing countries, with high unemployment, the injured individual now unable to work creates an opportunity for another member potentially thus leaving society-level output unaffected. Costing road traffic injuries from the household perspective may present a worthy compromise. The further practical advantage of this approach is that compared to society's perspective, data demands are lower and may improve the accuracy of estimates.

The findings are subject to some limitations; Firstly, it must be acknowledged that the structure of the problem analysed in this chapter could be set up to further exploit a possible natural nesting of data at more than two levels. For example, at third level would be countries, the second level be rural/urban residences and households as first level. However, we only estimate a two-level model estimated to an insufficient number of treated households. Secondly, the impact of injuries on household welfare is likely to span over more one period (year), especially for injuries that are fatal. Therefore, an intertemporal choice model becomes useful to describe how current decisions affect what options become available in the future. However, we do not estimate a two-period model due to the cross-section nature of the data. While we investigate the relationship between suffering an RTI leads and borrowing funds, we do not estimate the impact of this decision on household welfare in period two. Thirdly, our data on RTIs did not classify injury type in terms of severity and number of injuries suffered in a household which has potential to affect the outcomes. In addition, we make no distinction in terms of the position of injured person within the household setup; a household would face potentially higher economic impact if the RTI victim is the breadwinner. We are also only able to differentiate between being in the labour force or not but is not able to capture reductions in the number of hours worked. Lastly, are concerns about recall bias, especially for RTI incidences whose reference period was 12 months.

3.7 Conclusion

Road traffic injuries impose a significant economic burden on households in SSA countries. This paper examined the effect of RTIs on household expenditure on health and non-health commodities, household debt, labour force participation, and households' assets. Estimates show a mixed effect; we find evidence to suggest households are worse off facing significantly higher health expenditure, reduced expenditure on competing basic needs, and a higher likelihood to borrow at positive interest rates in order to purchase health services. We do not find adverse effects on some aspects of household welfare that include household assets and labour force participation. The estimates provide evidence of the effects that RTIs have at the household level beyond the RTI victim. The findings are potentially useful to inform the valuation of costs associated with road traffic incidents.

Chapter 4

Impact of road infrastructure development on household health and welfare in Malawi

4.1 Introduction

Developing countries spend a significant amount of resources on the construction and maintenance of transportation infrastructure. In Africa, the total resource commitment to transport infrastructure development has averaged 1.6% of the Gross Domestic Product (GDP) per annum since 2010, and the larger share of this investment has been towards building roads (African Development Bank 2018, Sinate et al. 2018). The investments are justified based on the expected impacts of transport infrastructure on social and economic outcomes. For road projects, these impacts can include both positive and negative externalities on health, especially for households located in project areas. However, the selection of road projects is primarily based on the economic internal rates of return which prioritise economic roads with higher potential returns in terms of trade facilitation and job creation ahead of the more difficult-to-quantify outcomes such as impacts on health (Curry & Whitlam 1997, Asian Development Bank 2013, African Development Bank 2014). Notwithstanding estimation challenges, road infrastructure development could affect health in several ways; through reduced transportation costs which are predicted to positively affect access to and utilization of health care services. Further, lower travel costs not only increase the affordability of travel to food and agricultural markets but also allows households to allocate more towards health and food consumption. If road development leads to overall economic growth, this also indirectly impacts health positively. Investments in road infrastructure could also negatively impact health; for instance, bringing major roads closer to residential places may pose negative consequences for respiratory health through increased exposure to traffic-related air pollution, and a higher risk of road traffic incidents.

While the effects of road infrastructure development on health are apparent in theory, estimating causal effects on health using econometric approaches has presented challenges. The endogeneity problem is a critical estimation issue that threatens the reliability of estimates and the source of wrong causal inferences. In practice, the government's decision regarding road infrastructure placement is guided by factors such as expected traffic volume, population growth, expected local production levels, cost of the project, and expected political benefits. These factors could also be directly or indirectly linked to household health and welfare, leading to a potential confounding problem. Secondly, defining the jurisdiction regarding the effects of constructing new roads, rehabilitation, or upgrading existing ones is often blurred, as benefits and costs often spill beyond the communities where the infrastructure is located.

Studies examining the impacts of road development projects have used varied econometric techniques to address endogeneity that includes Instrumental variables (IV), regression discontinuity, difference in difference, and panel data regressions. The instrumental variables estimation assumes the existence of a measurable exogenous variable that has an influence on road infrastructure development and has no effect on the outcome variable of interest except through the road development channel. In practice, it is often difficult to find a valid IV for road development, an example of this approach is Gibson & Rozelle (2003) who examined the effect that the construction of roads had on consumption. They use the year that a district was linked to the national highway system as an instrument and argues that while the linkage led to feeder roads being built, it was not expected to affect consumption independent of its effect on feeder roads. With regression discontinuity, a discontinuity is expected in outcome variables at the point the treatment, i.e road development, is administered. Casaburi et al. (2013) uses this design to study the impacts of improvements in rural road infrastructure on crop prices in rural markets. They take advantage of a feeder roads rehabilitation program to draw comparisons between roads “just above” and roads “just below” the rehabilitation cutoff.

Another alternative to address endogeneity involves the use of panel datasets to explore regional or household fixed effects. Fixed effects allow for control of time-invariant unobserved individual characteristics that can be correlated with both changes in household outcomes and changes in road development. However, it is noteworthy that in instances where the panel covers a longer period, the unobserved heterogeneity may cease to be constant over time. This means controlling for the initial area and household characteristics in a panel fixed-effects model may not be sufficient to account for time-varying factors that affect households’ response to road development. In this case, the difference in differences (DiD) technique could be used to estimate the effects. This study applies DiD impact evaluation technique to analyze the effects that road development projects, that were completed between 2016 and 2018 and covered thirteen different districts, had in Malawi. The road development mostly involved upgrading earthen roads to paved status. Paved roads tend to be less sensitive to weather changes and remain in usable condition across various seasons of the year. We use this road development information together with a panel household survey dataset to investigate the impact of road quality and access on household health and welfare. Specifically, we examine the effect of road infrastructure development on the cost of travel to seek medical care and further on the utilisation rate of health services increased. We also consider whether road upgrading influenced the incidence of respiratory illness symptoms. With reference to respiratory health, paving earthen roads can be expected to make the surrounding environment less dusty. At the same time, road improvement could stimulate traffic volume and a rise in the emission of pollutants from vehicles. This chapter will determine the predominant effect of the two health outcomes. Further, we seek to estimate the impact of road transport development on household-level consumption.

4.2 Literature review on RD and Health

The impacts of road development on health can be grouped into immediate and long-term effects. In principle, when a new road is built, new traffic will divert onto it thus increasing traffic levels (Litman 2017). The induced traffic if it is in residential areas would in the short-term lead to an increase in both injury risk and air pollution. These would likely persist in the long term unless corrective measures are put in place. However, new roads are typically designed to a higher standard and may be targeted at removing traffic from traffic incident blackspots, which may reduce injury risk. The impact of road development on transportation costs and access in the short-term accrues for owners of private vehicles and for households in previously hard-to-reach areas. In the long term, the users of public transport might benefit if RD enhances competition and leads to reduction in transport fares. The actual effect observed also depends on changes in the transport mode mix. The timelines of the impact on the growth of the local economy are uncertain; there are temporal benefits linked to locals' casual job opportunities in the construction sector. A more sustained change in the local economy might take time, where they exist, economic improvement linked to road projects may take as long as 4 years (Sloman et al. 2017).

Few studies have directly estimated the impact of road development on health in African country settings. The effects of road development on transportation cost to health facilities and consequently on health care utilization have mostly been studied indirectly in studies that have estimated correlations between distance to the nearest health facility and utilization of health services (Escamilla et al. 2018, McLaren et al. 2014, Schoeps et al. 2011). Most of the studies base their analysis on cross-sectional datasets to establish associations (dos Anjos Luis & Cabral 2016, Kyei-Nimakoh et al. 2015). While these studies are useful, they all share a common limitation; self-selection of people of a given socio-economic class into a residential place based on nearness and quality of health providers, among other factors (Tegegne et al. 2018).

Studies that have attempted to directly estimate the causal effects of road development on transportation costs have mostly taken advantage of opportunities in road placement programs that resemble a quasi-experimental setting. For example Aggarwal (2021) explores the road program in India to examine the impact of improved road accessibility on the adoption of maternal and child health services. Using data collected 8 years after the commencement of the program, their findings indicate that road construction led to more institutional antenatal visits and deliveries, higher vaccination coverage, and better access to medical care. In other settings, road development projects were found to positively influence health utilization one year after project completion Airey (1992) by attracting a higher proportion of patients from further afield, this is despite finding no change in financial transport costs, a result suggestive of lower travel time.

A secondary RD impact on health follows the transmission mechanism that reductions in the cost of transportation positively contribute to overall economic performance through easier access to labor and commodity markets and this in turn leads to improved health outcomes. Pursuit of this line of effects involves first establishing a link between road development impact on intermediate outcomes, for example, consumption expenditure or poverty more generally, and further between consumption expenditure and health outcomes. This channel of RD effects on health is supported by arguments that health, at the individual level, is influenced by socioeconomic status through health-related behaviors, ability to acquire non-medical purchased inputs, and purchased medical inputs (Rosenzweig & Schultz 1983, Mwabu 2007, Humphreys et al. 2014, Grossman 2017). Indeed, studies have established the existence of the first link; Khandker et al. (2009) considered how households in Bangladesh had profited from road improvement projects. Their key prediction is that villages located next to an improved road experienced a relatively higher reduction in poverty rates. Additionally, the impact on household expenditure is found to be higher for lower expenditure quintiles suggesting that road investments are pro-poor. A similar study in rural Ethiopia concludes that upgrading the nearest road to an all-weather road status led to a significant reduction in poverty, and that remoteness from towns and poor roads was consistently a significant contributor to chronic poverty (Dercon et al. 2009). If RD does reduce poverty, we could expect indirect positive change in health outcomes. Examples from the literature on household poverty and child health suggest that children born into poverty are more likely to suffer from chronic diseases such as asthma Wickham et al. (2016), as well as diet-related problems such as tooth decay, malnutrition, obesity, and diabetes (Griggs & Walker 2008).

However, some studies have found RD to have no such effect on reducing poverty, Asher & Novosad (2020) conclude that while Roads did cause a substantial increase in the availability of transportation services, there was no evidence for increases in assets or income. It can further be argued that infrastructural development rather has adverse effects on poor people's economic well-being and health; the presence of improved infrastructure quality and services increases the cost of living, thereby pushing poor households out of the area. To this effect, studies have established the existence of geographic concentration of poverty, i.e. poor households tend to live in areas where most of the people are poor (Mahmud Khan et al. 2006, Liu, Xu, Li & Li 2019). Further, high-poverty concentration areas are also likely to be located further away from facilities offering primary health care than low-poverty concentration areas and facilities closest to these areas often have fewer doctors, medical equipment, drugs, and generally a poor health service (Mahmud Khan et al. 2006).

This chapter also adds to the thread of literature that links road transport to health through air pollution channels. Studies investigating this health problem have used mixed and varied approaches to measure exposure to Traffic-Related Air Pollution (TRAP). This includes personal monitoring data, ambient air quality monitoring system data, modeled estimates of pollutant levels, and proximity to roadways(Miranda et al. 2013). The findings are largely consistent regardless of the approach used. Bowatte et al. (2017) base their analysis on residents living within 200 meters of a major road and find that exposure to Nitrogen Oxide, NO2, had an association with a higher prevalence rate for asthma. Using a similar measure, Garshick et al. (2003) concludes that exposure to vehicular emissions among individuals living close to high-traffic intensity roadways increased the likelihood of experiencing symptoms of chronic respiratory diseases in adults. Other authors have investigated the effects of long-term exposure to TRAP on lower lung function and airway acidification (Schultz et al. 2017). A different strand of literature considers the long-term exposure to TRAP on life expectancy through the cardiopulmonary mortality channel was associated with living near a main road (Hoek et al. 2002) while other studies look at effects on mental health (Clark et al. 2012, Dzhambov & Dimitrova 2017, Klompmaker et al. 2020). In this study, the analysis is limited to indirect effects of TRAP on general respiratory health symptoms based on the distance to the road and expected changes in traffic and dust levels following road upgrading.

4.3 Theoretical model

Road infrastructure development could have both positive and negative effects on health, in this section, a theoretical model to reflect these relationships is developed based on the Grossman model of health production. In this model, it is assumed that an individual's utility, U, is expressed as a function of consumption goods (C), and stock of health (H). The utility function for a person, i, can thus be specified as equation 1.

$$U = U(C_i, H_i) \tag{4.1}$$

and

$$\frac{\partial U}{\partial H_i} \geq 0; \frac{\partial U}{\partial C_i} \geq 0 \tag{4.2}$$

Utility maximization in equation 4.1 is subject to the stock of health that each individual produces and the amount of consumption available to them. In this basic model, health production is a function of two factors; goods purchased in the market that contribute to gross investment in health and non-health commodities that may have a positive or negative effect on health production. The health production function is modified by the inclusion of transport-related risk factors.

$$H = H(M_i, E_i, X_i) \tag{4.3}$$

$$\frac{\partial H}{\partial M_i} \geq 0; \frac{\partial H}{\partial E_i} \gtreqless 0; \frac{\partial H}{\partial X_i} \gtreqless 0 \tag{4.4}$$

where M denotes medical care, E denotes exposure to traffic air pollution or injury, and X denotes a set of other exogenous variables. To maintain a certain level of health, investments in health stock must equal depreciation. In our specification, (Equation 4.2) Medical health consumption and consumption of some items in X represents investments while exposure to transport risk factors and consumption of commodities such as smoking that may adversely affect health contributes to the depreciation of health. The utility function is maximized given the health production function and subject to the budget constraint:

$$Total\ ExpenditureTE) = M_i P_M + wT_N + C_i P_i \tag{4.5}$$

The total expenditure consists of the cost of obtaining medical care services $M_i P_M$, where M_i is the quantity of health care consumed and P_M is the unit cost of health care and includes expenditure on medical products and related costs including transport costs; wT_N is the indirect cost associated with transport-related time loss approximated by loss of production where T_N represents net time loss as a result of the change in levels road injury and TRAP related illness and w is the average wage rate. In this formulation, w is a parameter but might change in the long term if RD leads to a change in economic growth. The component, C_iP_C is the cost related to the consumption of non-health goods and services. Time loss , T_N, is related to the health production function through the level of exposure to risk factors such that $\frac{\partial T_N}{\partial E}$ <0. Substitution of equations 4.2 and 4.3 into equation 4.1 reduces to a utility maximization Lagrangian of the form:

$$L = U(C_i, f(M_iE_iX_i)) - \lambda(TE - M_iP_M - wT_N - C_iP_C) \tag{4.6}$$

So that

$$\frac{\partial L}{\partial E_i} = \frac{\partial U}{\partial H_i} * -\frac{\partial f}{\partial E_i} - \lambda w = 0 \tag{4.7}$$

$$\frac{\partial L}{\partial M_i} = \frac{\partial U}{\partial H_i} * \frac{\partial f}{\partial M_i} + \lambda P_M = 0 \tag{4.8}$$

$$\frac{\partial L}{\partial C_i} = \frac{\partial U}{\partial C_i} + \lambda P_C = 0 \tag{4.9}$$

In these first-order conditions, we examine the impact of road development on individuals' health production estimating the effect of exposure to traffic-related air pollution that is associated with road infrastructure development. A partial indirect effect of RD on T_N can be estimated from survey data by assessing whether RD resulted in an increase in respiratory illnesses and road injuries using distance to the road as a proxy of exposure to risk while controlling for exogenous factors, X, such as physical and socioeconomic characteristics of individuals including age, sex, income, and education. Further, aspects of the effects of a road development project are captured through their impact on the constraint (equation 4.2) through three channels; (i) the reduction of transportation cost so that the unit cost of accessing medical products, P_M is lowered (ii) road infrastructure development increases/decreases exposure to pollutants and consequently on time lost to illness T_L (iii) road development could further relax the total cost constraint through the general reduction unit costs and increase in overall non-medical consumption C_iP_C, though a possibility of RD having an opposite effect exists as noted in our literature review.

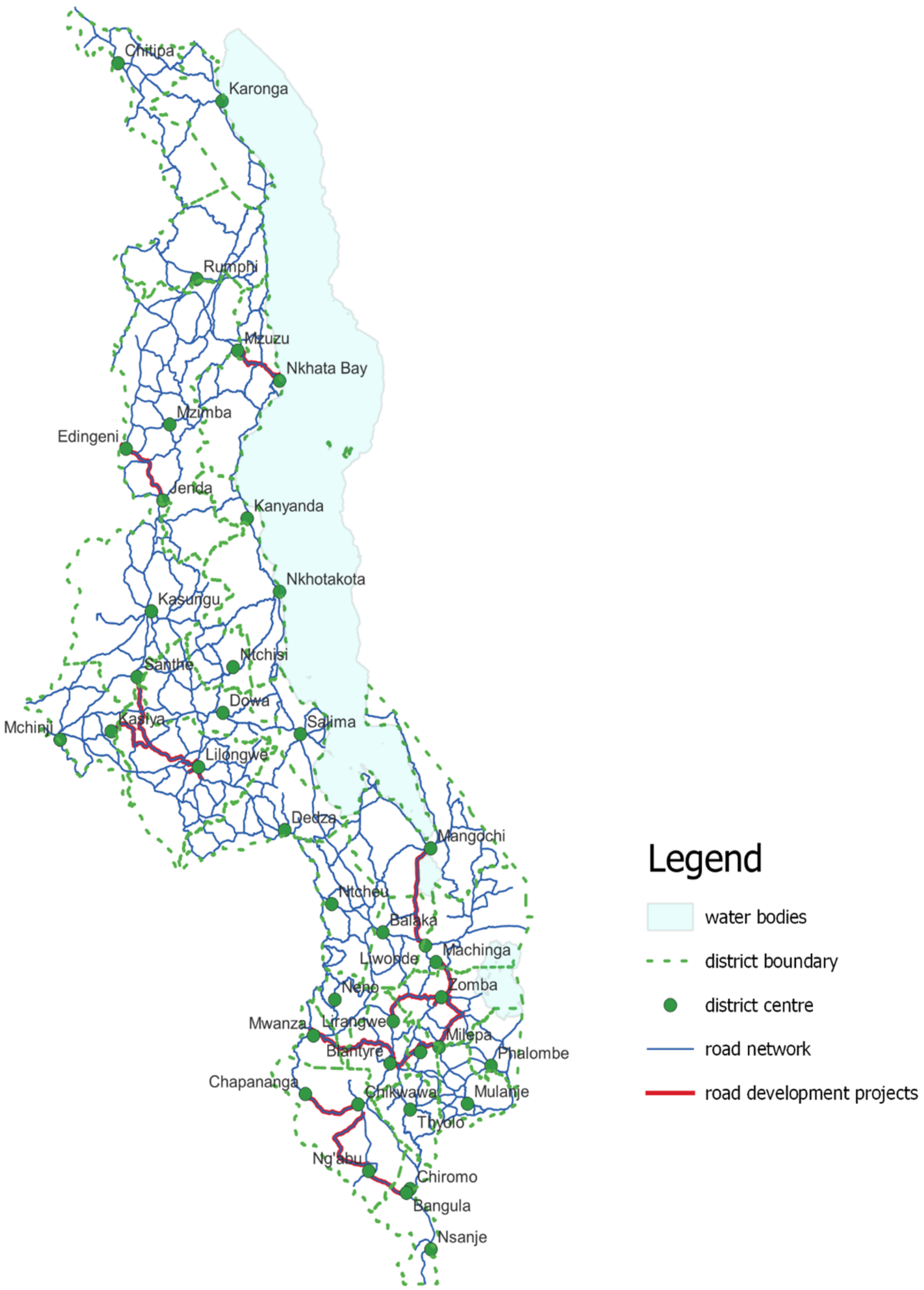
4.4 Setting

With a population of roughly 18.6 million people in 2019, Malawi is one of the most densely populated countries in Africa. The majority of Malawians are poor with the most recent estimate of the poverty incidence classifying roughly 51% of the population as poor, that is, they earn less than the international poverty level of US$1.90/day (World Bank 2021). A large proportion of the population lives in rural areas and relies on the sale of crops for cash income. The agriculture sector is a major source of livelihood for the majority of people, roughly more than three-quarters of the population survives on subsistence agriculture (Stevens & Madani 2016), and transport plays a critical role in accessing markets for their produce.

Malawi performs poorly on a number of health indicators; the maternal mortality rate stood at 439 per 100,000 live births (2014), infant mortality of about 21 per 1,000 live births, and about one in every six children suffer from respiratory illness symptoms (Rylance et al. 2019, United States Agency for International Development 2021). Transportation cost is among the key factors that have been shown to influence access to health care in the country (Lungu et al. 2000). Animal-drawn carts prevailed as the most common mode of transport from home to the primary health facility while travel to secondary and tertiary level health facilities is mostly by public transport (Varela et al. 2019). Median travel time from home to a health center takes about 1 hour and the average transportation costs to a health facility can go up to US$ 7 per trip(Varela et al. 2019).

The road network comprises about 15,000 kilometers of classified roads categorized into main, secondary, tertiary, urban, and district roads. About 28% of the road network is paved and the rest (72%) are unpaved and mostly earth standard. In addition, the country has close to 9000 kilometers of undesignated road network that serve rural communities. This places the country third highest in terms of primary road density (where road density is defined as the ratio of the length of the country's total primary road network to the country's land area) in Sub-Saharan Africa and second highest in secondary road density (Malawi roads authority 2021). While the extent of the road network is considered sufficient the capacity of some links, particularly in rural areas, is inadequate. For example, most roads are too narrow to accommodate motor vehicles alongside cyclists and pedestrians. Further culverts and bridges are also inadequate at numerous locations in districts across the country (Ministry of Transport and Public Works 2019) and sections of unpaved roads are impassable in rainy periods of the years. It is estimated that more than two-thirds of Malawi's rural population live more than 2km from an all-weather road (Malawi road fund administration 2021). In the last decade, the Government of Malawi commissioned replaceda multiple ofseveral road rehabilitation and upgrading works to improve the road network. This included rehabilitation and upgrading projects, with most completed between 2016 and 2018, specifically, a total number of seven road projects were completed in this period covering 13 different districts shown in Table C1. Figure 4.1 is a map showing locations and coverage of intervention roads.

Figure 4.1: Location of road projects



4.5 Data

We use data from two sources; information on road rehabilitation/upgrading projects is obtained from the records of the Malawi roads authority, and information on households is obtained from a panel dataset spanning a 9-year period.

4.5.1 Roads Development Data

The roads authority in Malawi collects and records information on projects that have been completed and those still ongoing together with maps showing the exact locations where these projects are being undertaken. The records indicate the type of infrastructure that was done as either new road construction, rehabilitation, or upgrading of an existing road, the length in kilometers of the road project, and the start and completion dates. Our interest is limited to road projects that involved rehabilitation and upgrading already existing roads and were commenced and completed between 2010-2018.

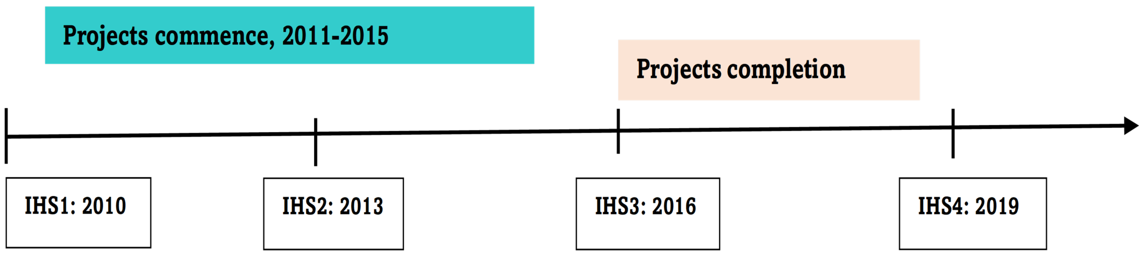
4.5.2 Household survey data

Data on households is drawn from the Malawi Living Standards Measurement Study-Integrated Household Surveys (LSMS-IHS), a panel dataset collected by the Government of Malawi through the National Statistical Office. Starting with the IHS round of 2010, subsequent rounds of data collection have been done every 3 years in 2013, 2016, and 2019. The surveys were designed to be representative at the national level. In 2010, the number of households surveyed was 1,619 and the sample size has increased over time to 1,990 in 2013, 2503 in 2016, and 3,175 households in the 2019 round. For this study, we focus on the 2010 and 2019 surveys drawing information from the health module in the household questionnaire. The health module includes information on individual illness types, health care utilization following illness, and expenditure on transportation to a health facility. The dataset also has geo-locations of households which enables us to determine the distance between households' locations and the nearest road development project. In Table C2, we define all the variables that we use in this study.

4.6 Methods

The road projects that we focus on were started between 2011 and 2015 with completion dates falling between 2016 and 2018. For the projects under consideration, the latest completion date was in August 2018 which is 9 months before the data collection for the fourth round began in April 2019. Figure 4.2 shows the timeline of the road rehabilitation program against the timing of the four rounds of the IHS. The time between project completion and data collection is sufficient to detect the effects on outcome variables which are estimated over a four-week window (consumption expenditure, respiratory health, health utilization rates) and transport costs (estimated over the past 12 months)

Figure 4.2: Road projects and survey timelines



To assess the effects of investing in road infrastructure, one would ideally like to compare the impact on households that are affected to similar non-affected households, but such a comparison is problematic for several reasons. First, roads in most cases are public goods that are available to all. This means a criterion to determine who is likely to be impacted by the intervention has to be defined. In this study, we rely on the distance of household location to a road project. Secondly, road projects are not randomly distributed across regions or households due to endogenous program placement where projects generally target areas where the return on investment is highest. Third, there is a self-selection problem, that is, whether a household decision-maker decides to reside closer to a road is determined by herself, not by chance. Further, in areas where the road projects are located, individuals sharing similar socio-economic backgrounds, for example, sex education, age, or assets owned (which we control for) might have different latent characteristics (for example, the ability may affect earnings and consumption levels, body immunity may determine proneness to illness) leading to different probabilities of being affected by the program. Hence, it is essential to account for the endogeneity and self-selection problems in assessing the impact of road infrastructure upgrading. We employ a difference in difference (DiD) estimation with matching to address these challenges.

The DiD estimation approach is essentially a combination of cross-sectional treatment-control comparisons and before-after studies. In the DiD setup, the dataset is structured such that there are two groups; the treated and control, and two time periods; before and after the intervention. In the main estimation, we define the treatment to include all households that were located within 20 kilometers of a road development project. The choice of 20 km is replaced motivatedinformed by two factors; First is the consideration that the cut-off is higher than the average distance that households travel to access health care. If the average distance travelled to access a service goes beyond the project area, the effects of the road project on utilisation and transport costs may be diluted. Second is the consideration of how far traffic-related pollutants spread; particulate matter from TRAP can travel more than 30 miles (48 km) from the source(Pénard-Morand and Annesi-Maesano 2004). However, the concentrations of the pollutants are higher closer to the pollutant source, the road, that we use a buffer distance /threshold of 20km assures us to capture not only the effects on households closest to the road projects but also on those remotely affected by TRAP. Studies that have used a lower threshold from the pollutant source have reported doubling incidence of respiratory illness (Mustapha, Blangiardo et al. 2011, Hu, Zhao et al. 2016). While the choice of how far to set the threshold is influenced by these considerations, the actual choice of 20 km is still largely an arbitrary cut-off. We thus augment the results by re-estimating the models after redefining the treatment to within 10 km. Considering the uncertainties in defining a binary treatment in this setup, we also explore predictive linear probability models with distance from a road project in its continuous form. These models are estimated on the unmatched dataset and prone to selection bias if unobservable attributes of individuals residing in project areas are different from those outside project areas. We thus do not interpret these estimates as causal effects but rather as an association and use them as an additional check of the expected treatment effects.

Another challenge we face when defining the treatment regards the imprecision introduced in the data generation of the household's geolocation coordinates. To fulfill the need to preserve the confidentiality of sampled households and communities, the published GPS (Geographical Positioning System) coordinates in the dataset are modified. The coordinates modification strategy applies a random offset to average coordinates over a cluster consisting of between 10 and 15 households. The offset factor is within a specified range of between 0 and 5 km. These adjustments mean that the number of unique coordinates used to generate the distance variable is reduced to equal the number of clusters in the dataset. In such a case, Zonal statistics (average or range of values within an area corresponding to the known range) could help minimize the effect of offsets when analysing the data (World Bank 2019). We thus opt to define treatment as binary for the main model specification by grouping households into two zones.

For purposes of the DiD estimation, baseline households were categorization into treatment and control based on distance from roads that were earmarked and eventually were either upgraded or rehabilitated. In this two-group-two period design, the DiD estimate of road development impact can be written as follows:

$$DiD = (\bar{y}_{c=treated,t=2019} - \bar{y}_{c=treated,t=2010}) - (\bar{y}_{c=control,t=2019} - \bar{y}_{c=control,t=2010}) \quad (4.10)$$

Where y represents the outcome variable, the bar signifies that the average value over all households in treated and control clusters calculated for each round. C indicates the treatment status of households in a cluster, and t is time, 2010 baseline, and 2019 the end line. With treatment and control defined before and after the intervention, the dataset is thus categorized into four groups and the double difference in equation 4.10 is calculated as the DiD estimate. While Equation 4.10 does yield a DiD estimate, calculating it this way does not provide for the significance level of estimates, hence a regression framework is used to obtain the estimates that we specify as:

$$Y_{ict} = \alpha_0 + \theta_c + \delta_t + \beta I_{ct} + \epsilon_{ict}$$

In this OLS framework, the DiD estimate is obtained as the β coefficient, the vector θ_c are treatment and control group fixed effects, δ_t are the before and after fixed effect, I_{ct} is a dummy equaling 1 for treatment observations in the after period (otherwise it is zero), also defined as an interaction between treatment and time variables, α_0 is the intercept of regression and ϵ_{ict} , the error term. Since we observe some household characteristics relevant to the estimation, the regression equation can be modified to include household level control variables, X_{ict}, so that the estimates OLS equation is

$$Y_{ict} = \alpha_0 + \theta_c + \phi X_{ict} + \delta_t + \beta I_{ct} + \epsilon_{ict} \tag{4.11}$$

The inclusion of covariates in the DiD regression estimation is recommended to control for compositional changes as some characteristics such as age tend to vary over time. Even in cases where the intervention is independent of observed covariates, adding those covariates may improve the precision of the DiD (Wooldridge 2010). We present estimates both with and without controls.

4.6.1 The parallel trends assumption

The identification assumption of the DiD approach is that in the absence of the intervention, the group-specific (treatment and control) trends in the outcome of interest would be similar. In terms our case this means that if the road development projects had not been implemented, then we could not observe systematic differences in the trends of consumption expenditure, transport expenditure, incidence of respiratory illness symptoms, and rate of health service utilization over time between individuals in the project areas and those living further from the intervention(road projects). The assumption that the treated group would have experienced a counterfactual change identical to the observed change in the control group is demonstrated through the satisfaction of the parallel trend assumption. This assumption is a necessary condition to ensure that the DiD method produces unbiased estimates. An assessment of the plausibility of the future parallel trends assumption is done by testing for “pre-trends,” i.e. differences in trends between the treatment and control group prior to the date of treatment assignment (Rambachan & Roth 2019). A common approach that is used to test is the graphical approach which requires at least two pretreatment data points.

In this study, we could not test the parallel trends assumption due to the inadequate outcomes data points prior to the intervention. Alternatively, we estimate the DiD model on the study sample after attaining covariate balance using various matching and weighting techniques to minimize bias. Matching on propensity scores before a difference in differences estimation is a potent approach to get around potentially different parallel trends in the pretreatment period and has previously been used in papers (e.g.(Ichino et al. 2017, Becker & Hvide 2013)).

Notwithstanding the importance of satisfying the parallel trends assumption, it is worth noting that in reality, the common-trend assumption cannot be easily satisfied, and two problems arise. Firstly, failing to reject that the outcomes in periods prior to treatment exhibit parallel trends is generally taken to mean that parallel trends exist though that does not necessarily confirm a future parallel trend. Secondly, even in event that the parallel trend is shown to hold, the factors explaining why the original levels in outcomes of the experimental and control groups are different should be discussed and addressed, otherwise, there is reason to think that this same mechanism would impact trends (Kahn-Lang & Lang 2020).

4.6.2 PSM + DiD

As one of the strategies to deal with bias and attain balance at baseline, propensity score matching is used to ensure that observations that get treated, and comparison groups are as similar as possible on a set of baseline characteristics. The propensity scores are generated as the probability of receiving the intervention as a function of a relevant set of covariates. These probabilities are commonly estimated using logistic regression.

In the case of road development, although the control group could be generally defined to include all households outside of what we classify as treated households based on distance, some characteristics of the control households may vary widely from those of the treatment group, for example, a household located outside road project area but is closer to a major road may drive similar benefits to treated ones and therefore not a good comparator. We thus seek to construct an appropriate control group by using nearest neighbour propensity score matching, and genetic matching. We also explore the use of propensity score weights to attain covariate balance. Ideally, households from the same districts or districts with similar characteristics should be matched together. Due to sample size limitation, we could not implement matching for these subgroups but rather include district-level road density and district-level multidimensional poverty index in the variables that we use for PSM.

4.6.3 Nearest neighbour propensity score matching (NNPM)

NNPM matches treatment and control units based on the distance between propensity scores. For each treated observation a given number, m, untreated units are selected, whose propensity scores are closest to the treated observation in question (Austin 2011). The choice of m determines the number of observations in the comparison group relative to treated cases. Choosing a lower m ensures the smallest propensity-score distance between the treatment and comparison units while a larger m increases the size of the control group, which may increase the precision of the estimates, but at the cost of increased bias (Baser 2006). Another decision was whether to match with or without replacement. Matching with replacement implies that once a control unit has been matched it can be reused and matched to multiple treated units while matching without replacement, each case can be used as a match only once. An advantage of matching with replacement is that each treated case gets matched to the closest possible untreated case and therefore the reduction in the level of bias is more compared to without replacement (Benedetto et al. 2018). Further, based on sample size, matching with replacement performs better when the number of available matches is small (Rosenbaum 1989). We match with replacement.

Regarding the choice between matching without and within a caliper, it has been noted that matching without any restrictions matching can lead to some poor matches if, for instance, there are no control units with propensity scores not close enough to a given treated unit, matching without caliper still retains these in the sample (Stuart 2010). A strategy to avoid poor matches is to impose a caliper and only select a match if it is within the caliper. A caliper, which is defined as maximum difference in covariates allowed between matches, has been shown to significantly improve nearest neighbor matching performance (Leite 2016). For matching purposes, a caliper is specified as a fraction of the standard deviation of the logit of the propensity score (Benedetto et al. 2018). To remove at least 90% of bias, a caliper of 0.25 standard deviations is recommended (Rosenbaum & Rubin 1985*a*), we adopt this parameter in our matching. It is noteworthy that using a caliper not only improves the quality of matching but also enforces common support and treated cases without any untreated cases within its caliper are discarded. This reduction in the sample can lead to difficulties in interpreting effects if many treated individuals do not receive a match. Additionally, this approach could lead to discarding many observations and thus would apparently lead to reduced power. Further details on the pros and cons of using a caliper are discussed in literature (Rosenbaum & Rubin 1985*b*, Stuart 2010).

4.6.4 Genetic matching

A notable drawback regarding NNPM is that while it enables the choice of the best available match among the untreated for each treated observation, it does so without accounting for the quality of the match of the entire treated sample (Handouyahia et al. 2013). This may lead to closely matched pairs but globally distant treated and control groups. We thus also obtain a second matched sample using an alternative Genetic matching, a procedure which also attempts to optimize global match quality (Diamond & Sekhon 2013). Genetic matching based on covariates can provide adequate covariate balance but could produce better balance if combined with propensity score matching (Sekhon & Grieve 2012, Diamond & Sekhon 2013). The distance measure minimized by the genetic matching algorithm and further advantages of genetic matching for selecting comparison group of households is discussed in the third chapter. In this chapter, we use Genetic matching with replacement and include both the propensity scores, and a reduced number of core covariates for a better match. We aim for a standardized difference in means of within 0.1. (Zhang et al. 2019)

4.6.5 Inverse Probability of Treatment Weighting (IPW)

The two approaches we apply so far to reduce selection bias, Genetic matching, and NNPM, both depend on how many observations are matched and discard the remaining. Rather than excluding unmatched households from the comparison group which effectively reduces the sample size, the Inverse probability of treatment weights can be used to estimate the counterfactual. IPW uses the propensity score to balance baseline characteristics of observations in the exposed and in unexposed groups. Each observation is weighed by the inverse probability of receiving actual treatment. To begin, the propensity scores, p_i, are estimated for observations in both groups given the covariates.

$$p_i = E(RD_i = \frac{1}{X_i}) \tag{4.12}$$

The weights for each observation in the treatment group is estimated as: $w_i = \frac{1}{p_i}$ While those in comparison groups is estimated as: $w_i = \frac{1}{(1-p_i)}$. This means that households in the comparison group that had a higher probability of exposure receive larger weights and therefore their relative influence on the comparison is increased while treated households with high propensity scores contribute minimally to the comparison(Chesnaye et al. 2022). Inclusion of the weights in the subsequent analysis renders 'assignment' to either the exposed or unexposed group independent of the variables included in the propensity score model (Chesnaye et al. 2022).

After calculation of the weights, we incorporated them in the difference in difference model as follows:

$$\begin{aligned} DiD = \{\frac{1}{p_i}E(Y_{ict=1}|RD_{it=1} = 1) - \frac{1}{1-p_i}E(Y_{ict=1}|RD_{it=1} = 0)\} \\ - \{\frac{1}{p_i}E(Y_{ict=0}|RD_{it=0} = 1) - \{\frac{1}{1-p_i}E(Y_{ict=0}|RD_{it=0} = 0)\} \end{aligned} \tag{4.13}$$

One concern of using weighting-based approaches is that the weighting creates a pseudo population that contains 'replications' of observations resulting in not only an artificially inflated sample size but also correlated observations. A suggested remedial measure to deal with this dependence is to estimate the model with the bootstrap option (Raad et al. 2020). After weighting the sample, it is important to ensure that the balancing property of each observed covariate and the overall balance between the treatment and control groups in the baseline is tested to verify whether a reduction in sampling bias has been achieved (Raad et al. 2020). One way of checking is checking the balance of means of covariates by comparing raw and weighted differences between the control group and the treatment group in the baseline dataset. A sufficient level of matching is attained if the weighted difference is not statistically significant from zero. Using the matched and weighted datasets, a DiD equation is then estimated for each of the outcome variables. For continuous outcomes, the following equation of DID model is estimated:

$$Y_{ict} = \alpha_0 + \theta_c RD + \delta_t period + \phi X_{ict} + \beta + \beta(RD * period)_{ct} + \epsilon_{ict} \tag{4.14}$$

Where Y_{ict} represents expenditure variables on consumption or transport for household i in cluster c at time t. The treatment variable RD is a binary indicator; it represents the group dummy variable in the estimation equation. RD = 1 represents the treatment group that a household is drawn from a cluster that is located within 20km of a road development project. RD = 0 represents the control group of households located further than 20km from a road development project. The variable, period, represents the time dummy variable, period = 0 means the time before the implementation of road projects (the year 2010), and period = 1 means the time after the road development works were completed (the year 2019); the variable $RD * period$ denotes the interaction between groups and time; X_{ict} represents a set of covariates of household i at the time t; ϵ_{ict} is a random error term that represents other unobservable characteristics.

For the binary outcome variables, health care utilisation and incidence of respiratory illness symptoms, the equation of DID model transforms into a Linear probability model (LPM). The basic form of the LPM is estimated by linearly regressing the binary outcome variable, D, on independent variables X, using ordinary least squares and assumes that the regressors are all exogenous. In this case, the LPM approach can be specified as:

$$E[D|X] = 0 * [1 - F(X, \beta)] + 1 * [F(X, \beta)] = F(X, \beta) \tag{4.15}$$

Thus, the linear probability model estimates;

$$F(X, \beta) = X^{'}\beta + \epsilon \tag{4.16}$$

$$= \alpha_0 + \theta_c RD + \delta_t period + \phi x_{ict} + \beta(RD * period)_{ct} + \epsilon_{ict} \tag{4.17}$$

and

$$E(RD, \epsilon) = E(X, \epsilon) = 0 \tag{4.18}$$

and β is then interpreted as the change in the probability that $D_i = 1$, holding other regressors constant. Although the LPM could lead to predicted probabilities outside of the range between zero and one, the easy of interpretation of coefficients in LPM is one of the attractive features of this model. LPM models the probability of the outcome as a linear function of covariates and therefore consistently recovers the conditional expectation of the outcome (Greene 2003). The estimates for the impact on health care utilization are based on the subset of households that reported an illness at both baseline and endline.

To determine the effect of the treatment on the financial cost of transport to a health facility, we estimate a two-part model within the difference in difference framework. Because the majority of households reported that they had not spent any money on transportation during the past 12 months, the excess zeros are clearly also an issue in our data. In this case, OLS regression would produce biased estimates. Based on guidance from the literature, if the distribution of OOP expenditure shows a high density at zero and a right-skewed continuous distribution of positive amounts, fitting a two-part estimation procedure might be more appropriate (Deb & Norton 2018). In the first part of the model, we use a logistic regression to estimate the probability of an individual incurring a positive transport cost. The second part of the model predicts the magnitude of transportation cost for the subset of households that reported a positive amount. Based on the Akaike information criterion and the deviance statistics, the best-fitting model was the Generalised Linear Model (GLM) with a gamma family and a log link function. As the two-part model is nonlinear, the estimated coefficient of the interaction term between period and treatment does not represent the treatment effect and requires predicting a combined marginal effect. The marginal effect captures in this context, captures the treatment effect on the treated and is defined as "the expected value of the dependent variable for the treatment group in the post period with treatment compared with the hypothetical expected value of the dependent variable for the treatment group in the post period if they had not received treatment" (Deb & Norton 2018).

4.6.6 Check for attrition

Between the 2010 and 2019 rounds of the Household Integrated Surveys (HIS), some households were lost to follow-up. Using the Parent ID to track the droppers, we find that up to 15% of baseline households could not be linked to endline data either as original households or split households. This indicates the presence of attrition in the data which could lead to biased estimates if the households which dropped are significantly different from the ones that remained. The differences in characteristics between those who prematurely dropped out and those who remained in the sample can be assessed by conducting a regression analysis (Wooldridge 2010). This approach involves a comparison of baseline characteristics of the two groups, a dichotomous independent variable is created with 1 representing those tracked and 0 representing lost households. The idea is to see whether the variable capturing attrition influences the treatment and outcome variables. If the estimated effect of attrition turns out with a statistically significant coefficient for any of the variables, the implication is that there is a difference between the two groups and confirms the existence of attrition bias. Table 4.1 shows the results of the attrition regression estimates.

Table 4.1: Attrition regression estimates

	Dependent variables				
Independent var.	(1) Treated [Yes=1, No=0]	(2) Consumption expenditure [Continuous]	(3) Respiratory illness [Yes=1, No=0]	(4) Health care utilisation [Yes=1, No=0]	(5) Transport expenditure [Continuous]
Attrition	-0.119	-188.2	-0.274	-0.333	0.00762
	(0.150)	(225.7)	(0.210)	(0.217)	(0.0243)
Constant	0.235***	854.0***	-1.507***	1.065***	0.0337***
	(0.0568)	(85.04)	(0.0732)	(0.0833)	(0.00880)
Observations	1,465	1,465	1,465	871	871

Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

Regressing the attrition variable on the treatment shows no significant relationship between the two. Similarly, the regression of attrition on the four outcome variables shows that attrition does not have a significant effect on them. Based on this, it can be concluded that the group of households lost to follow-up was not significantly different from the ones which remained in terms of the outcome variables and therefore do not require correcting for attrition bias.

4.7 Results

We begin with a description of the sample at baseline and show how the characteristics of treated households compared to those in control before analyzing the factors associated with receiving an intervention. We then show the results of the sample matching and weighting processes demonstrating the changes in the level of bias. In the main results, we first investigate the effects of the treatment on the level of consumption expenditure. We then present the results of the intervention on the share of transport costs and subsequently on health service utilization. We conclude the results with an analysis of the effects of road development on the incidence of respiratory illness symptoms.

4.7.1 Sample description

Table 4.2 summarizes the key characteristics of the sample at the time of the baseline survey in 2010. A total of 1600 households were surveyed at baseline. The number of households reduces to 1306 after excluding households with no record at both baseline and end-line. Defining treatment to include households within 20 kilometers of a road earmarked for upgrading or rehabilitation yields a total of 645 as the treated group and the remaining 661 formed the control. Annual consumption expenditure averaged US$ 450 per household and included expenditure on both food and non-food items. In terms of health care utilization, 62.5% of all households had at least one member falling sick and 60% of these utilized a health service. About 18% of households incurred a financial cost and spent approximately 3 % of their total annual household expenditure on travel to a health facility. The incidence of respiratory illness based on self-reported symptoms is estimated at 20%.

At baseline, road infrastructure in Malawi was reported to be above the average of low-income countries in sub-Saharan Africa(Shkaratan et al. 2011). Average road density calculated as the number of road kilometers per square kilometer of land was 0.156 and is very similar between control and treatment clusters. On average a household is located 7.2 kilometers from what is classified as a major road (includes main, primary, and tertiary roads). Households in control clusters averaged 3 kilometers further away from a major road compared to treated clusters. For about half of the households in the sample, the nearest major road is unpaved.

Table 4.2: Descriptive statistics

Variable	Full sample	Control	Treatment
Consumption expenditure	450.99	411.20	478.09
Prop. of transport costs	0.030	0.042	0.030
Healthcare utilization rate	0.600	0.59	0.610
Respiratory illness incidence	0.202	0.210	0.170
Age of head	41.910	42.293	41.639
Head is male	0.753	0.743	0.760
Prop. of male members	0.593	0.601	0.585
Prop. of hh members 0-5 years	0.169	0.178	0.162
Prop. of hh members 6-18 years	0.314	0.326	0.305
Prop. of hh members 19-45 years	0.371	0.330	0.402
Prop. of hh members older than 45	0.146	0.166	0.131
Household size	4.703	4.767	4.657
Education of head			
Primary	0.610	0.707	0.542
Secondary	0.258	0.172	0.319
Tertiary	0.132	0.122	0.139
Urban residence	0.265	0.201	0.416
Household asset index	0.913	0.955	0.883
Household negative shock	0.0817	0.0869	0.0781
Chronic illness	0.0829	0.0819	0.0836
Distance to major road (KM)	7.251	9.008	6.009
Nearest road is paved	0.446	0.294	0.569
Road density (KM/SQ KM)	0.156	0.157	0.155
Nearest health facility (KM)	2.935	3.330	2.656
Multidimensional poverty index	0.237	0.242	0.232
Distance to nearest market	23.156	25.665	22.437
Distance to nearest admarc	7.054	8.040	6.293
Distance to Pop Center with 20'000	30.148	33.152	28.888
Distance to district Headquarters	59.586	50.672	56.462
Average annual rainfall (mm)	597.052	620.88	580.200
Number of observations	1306	661	645

4.7.2 Matching results

Three data balancing procedures were performed out of which two relied on propensity score estimates. In the first step, we use logistic regression to estimate a propensity score for each household based on household and area characteristics at baseline. Since the estimations are performed with treatment defined at 20km and 10km from the road project respectively, the propensity scores are generated for each treatment definition. Table 4.3 shows the propensity scores for the 20km treatment definition which we use in the main model specification. The logistic regression estimation suggests that road condition, and rural or urban classification were the strongest predictors of whether the area was selected for a road project. Urban clusters were more likely to be located within 20km of a road development project as were clusters whose nearest road was unpaved confirming that roads that were gravel or in bad condition were likely to be prioritised for rehabilitation or upgrading. At the same time, the results suggest that urban road infrastructure development is prioritised despite the road density being relatively higher in urban areas. The results also indicate that clusters that were located closer to a market, an Agricultural Development and Marketing Corporation (ADMARC) centre, or a population centre with more than 2000 people, were prioritised for treatment. The estimates also suggest that clusters further away from a major road or district headquarters and those with longer distances to the nearest health facility were likely to be treated. The factors which turn out to be significant predictors are largely in line with road project selection criterion in most countries which aims to increase access to social and economic services.

Table 4.3: Propensity scores

Variable	**Coefficient (se)**	**Variable**	**Coefficient (se)**
Age of head	0.0008	Average annual rainfall (mm)	-0.0334***
	(0.0110)		(0.00368)
Head is male	-0.2862	Multidimensional poverty index	3.068
	(0.2719)		(2.5910)
Household size	0.1210**	Road density (km/sqkm)	-1.3991
	(0.0580)		(2.1552)
Fraction of males	-1.0435**	Distance to major road (baseline)	0.0318***
	(0.4750)		(0.0109)
Fraction hh members 0-5 years old	-0.9733	Nearest is road paved (baseline)	-0.683***
	(0.9427)	Nearest health facility (KM)	0.0452**
Fraction hh members 6-18 years old	-0.958		
	(0.7562)		(0.2531)
Fraction hh members 19-45 years	0.4264	Distance to nearest market (baseline)	-0.0117***
	(0.7010)		(0.0030)
Fraction hh members older than 45	0.8910	Distance to nearest admarc (baseline)	-0.0483*
	(0.2010)		(0.0263)
Urban residence	1.9630***	Distance to Pop Center with 20'000 (baseline)	-0.0490***
	(0.568)		(0.0073)
Education: secondary	0.6380**	Distance to district Headquarters (baseline)	0.0234***
	(0.276)		(0.0044)
Education: Tertiary	0.229*		
	(0.7280)		
Household asset index	-1.4570		
	(1.3011)		
Household negative shock	0.1861		
	(0.2123)		
Constant	22.5600***		
	(2.9730)		
Observations	1,038		1,038

Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

In nearest neighbour propensity matching, we obtain a suitable control group by dropping all observations that are not on common support. Figure C2 shows graphs of common support at the baseline and end line. To assess balance after matching, a balancing test that compares differences in the means of the covariates between control and treated groups is conducted. The balance test in table C3 of the appendix shows the level of the match achieved. Of the 20 baseline characteristics, balance on all but two variables is achieved which means for most covariates there are no significant differences between treated and control groups. The two variables, age of household head and household size are not balanced and we further control for these in the DiD regression estimation. A genetic matching approach yields a closer match but also results in the loss of more observations relative to the NNP matching. Figure C3 plots SMD before and after matching for each of the covariates. There are evident reductions in mean differences after matching.

Table 4.4: Summary outcome variables

	All	**Control**		**Treatment**		
Outcomes	**Mean**	**Mean**	**SD**	**Mean**	**SD**	**SMD**
Consumption expenditure						
Raw sample before matching	450.99	411.20	318.48	478.09	201.08	-0.33
Matched sample after genetic matching	413.17	410.00	200.40	415.00	105.78	-0.01
Prop. of transport costs						
Raw sample before matching	0.036	0.042	0.24	0.029	0.01	0.50
Matched sample after genetic matching	0.033	0.031	0.04	0.034	0.11	-0.11
Healthcare utilization rate						
Raw sample before matching	0.60	0.59	0.50	0.61	0.50	0.13
Matched sample after genetic matching	0.59	0.61	0.49	0.58	0.50	-0.06
Respiratory illness incidence						
Raw sample before matching	0.20	0.21	0.41	0.17	0.38	0.11
Matched sample after genetic matching	0.19	0.21	0.40	0.180	0.40	0.08

In Table 4.4, we show the mean outcome variables in treatment and control before and after genetic matching. The average annual consumption expenditure was US$ 450. At baseline, the mean is higher in the treatment group by more than US$ 50 and this variance between groups is reduced to US$ 5 with matching. In terms of expenditure on transport, on average, a household spent about 3% of their total household expenditure on transport to seek health services. The low mean proportion suggests most households use transport modes that do not require financial payment before use. Healthcare utilisation following an illness, in this dataset, is estimated at 60%. This estimate is close to what has been reported in previous studies in Malawi(National Statistical Office of Malawi and ICF Macro 2011).

IPW sample

Table C4 provides the results of the inverse probability weighting for the baseline dataset. Of the 23 balancing variables used we attain balance on 19 variables. We do not achieve balance on the tertiary arm of education level, the age of head, household index, and the proportion of household members aged over 45 years. All the covariates on which balance is not attained through weighting and matching processes are all controlled for in the regression.

4.7.3 Impact on consumption

In the first step toward estimating the welfare impact of road development projects on households, we analyze the effect on consumption expenditure. We described in the methods section that; the level of consumption expenditure is adopted as a proxy measure of whether households were better off following the completion of roads in project areas. The link between expenditure on consumption and welfare is such that since low-income households spend almost all their earnings on consumption, an increase in consumption expenditure would represent an upward adjustment in the amount consumed and subsequently an increase in welfare. We eliminate the inflationary effects on the welfare measure by deflating the 2019 consumption figures using the consumer price index. We use the world bank reported estimates of CPI in Malawi. Further, all expenditure figures were converted from Malawi Kwacha to US dollars. At baseline, in the control group, the average respondent spent 411 USD per year, and a similar set of households in areas that received road projects spent slightly more.

Table 4.5 shows the results of the difference in difference models which estimates the change in consumption expenditure attributable to road development projects. Five variants of the model are estimated; columns 1 and 2 estimate a basic difference in difference on the unmatched data, without and with control variables respectively. Column 3 shows the results estimated on a matched dataset using nearest neighborhood propensity score matching. Columns 4 and 5 show DID estimates on weighted and genetically matched datasets respectively.

Table 4.5: Impact on Consumption expenditure

	Dependent variable: Log of consumption expenditure				
Independent variables	(1) DiD	(2) DiD with controls	(3) PSM+DiD	(4) IPW+DiD	(5) Gen-match+DiD
After	0.0210**	0.0448***	0.0496	0.0260*	0.0382***
	(0.00914)	(0.0145)	(0.0558)	(0.0141)	(0.0142)
Road development	0.603***	0.504***	0.5061***	0.970***	0.263***
	(0.0216)	(0.0290)	(0.0422)	(0.0198)	(0.0194)
Road development x After	0.0498***	0.0583***	0.0550	0.0441**	0.0343**
	(0.0192)	(0.0210)	(0.0573)	(0.0189)	(0.0167)
Age of head		-0.00176**	-0.0041***	-0.00119*	-0.00107*
		(0.000786)	(0.0012)	(0.000723)	(0.000551)
Head is male		0.0997***	0.0424	0.0564***	0.0421**
		(0.0278)	(0.0371)	(0.0184)	(0.0199)
Urban residence		0.325***	0.1559***	0.0509**	0.245***
		(0.0299)	(0.0569)	(0.0203)	(0.0229)
Education: secondary		0.0279	0.0613	0.0731***	0.0142
		(0.0238)	(0.0476)	(0.0231)	(0.0156)
Education: Tertiary		-0.0365	-0.0864**	-0.0186	-0.0247
		(0.0263)	(0.0424)	(0.0271)	(0.0201)
Household size		0.00704	0.0094	0.0124***	0.0140***
		(0.00430)	(0.0062)	(0.00306)	(0.00324)
Fraction of males		-0.0327	-0.0132	-0.0347**	-0.00383
		(0.0280)	(0.0452)	(0.0162)	(0.0207)
Fraction hh members 0-5 years old		-0.00506	-0.0284	-0.0676***	-0.0429
		(0.0308)	(0.0519)	(0.0247)	(0.0265)
Fraction hh members 6-18 years old		0.0252	0.0073	0.00908	0.00975
		(0.0193)	(0.0334)	(0.0159)	(0.0174)
Fraction hh members 19-45 years old		0.00466	-0.0050	0.00949	0.0161
		(0.0173)	(0.0312)	(0.0158)	(0.0133)
Fraction hh members older than 45 years		-0.0613*	-0.0343	-0.0808***	-0.0113
		(0.0324)	(0.0646)	(0.0283)	(0.0263)
Household asset index		-0.253***	-0.4616**	-0.732***	-1.022***
		(0.0709)	(0.2006)	(0.0751)	(0.0532)
Distance to major road (KM)		-0.00294***	-0.0036***	-0.00166**	-0.0025***
		(0.00111)	(0.0013)	(0.0006)	(0.0003)
Household negative shock		0.0260	0.0391	0.00579	0.0239*
		(0.0183)	(0.0396)	(0.0193)	(0.0144)
Multidimensional poverty index		0.0582	-0.2599	-0.256***	-0.0211
		(0.0950)	(0.2222)	(0.0946)	(0.0795)
Road density (KM/SQKM)		-0.277	-0.4515	-0.0662	-0.128
		(0.179)	(0.3308)	(0.132)	(0.122)
Average annual rainfall (mm)		-6.90e-05	-0.0004***	-9.05e-06	-8.49e-05
		(7.18e-05)	(0.0001)	(5.35e-05)	(6.10e-05)
Constant	0.987***	1.394***	2.0617***	1.390***	1.674***
	(0.0163)	(0.102)	(0.2416)	(0.0915)	(0.0746)
Number of observations	2,104	2,104	2,027	2,104	1,682
R-squared	0.428	0.510	0.3782	0.845	0.689

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; Column label (1) is a difference in difference estimation on consumption expenditure using unmatched dataset and with no controls. Column label (2) is difference in difference estimation on consumption expenditure using unmatched dataset and with controls. Colum label (3) is difference in difference estimation on matched dataset and using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset and using Genetic matching approach.

The estimated effect of the road development projects shown in the table is positive in all models and range between 3% and 6%. We mainly focus the interpretation on the results model (5) in which we use Genetic matching before estimating DiD. Based on this model, households that are in areas where a road development project was undertaken, experienced a 3% increase in consumption expenditure compared to similar households in the control group. When we analyze the impact of roads using a redefined treatment group that includes only households that were within 10 kilometers of a road project (results in appendix), the effects appear stronger than when the treatment threshold is set at 20 kilometers.

4.7.4 Impact on transportation cost

We begin our analysis of the road development impact on transport costs to a health facility with a note that the majority of respondents did not incur a financial cost for transportation to seek a health service. An average household in Malawi relies on bicycles and walking as the primary mode of transport to a health facility (Varela et al. 2019). To determine whether road projects impacted transport costs to the health facility, a key factor to account for is the fact that the cost of transport could also change if a new health facility is brought nearer to the people by constructing more health facilities. For this reason, the distance to the nearest health facility was one of the key variables we matched on and controlled for in the regression models. To estimate the effect of the intervention on transportation costs, a two-part model of expenditure on transport costs to a health facility in a year was estimated. In the first part, we model the impact of road infrastructure development on the likelihood that a household would incur transport costs presented in form of exponentiated coefficients. The second part estimates the effect on the average amount spent conditional on a positive amount. Table 4.6 show combined marginal effects estimated from a two-part model of transport expenditure. Overall, road development projects did not have any significant effect on the likelihood of incurring and magnitude of transport costs.

The coefficients are consistently not statistically different from zero all models apart from the estimates on unmatched data and without controls show a significant effect, but we do not interpret this result since we cannot rule out attributing effects to differences in household characteristics at baseline.

Table 4.6: Combined average marginal effects

Approach	dy/dx	Delta-method std. err
DiD with no controls	-0.0326*	0.0151
DiD with controls	-0.106	0.418
PSM+DiD	-0.0303	0.0162
IPW+DiD	-0.0219	0.0153
Genmatch+DiD	-0.6700	0.7931

*** p<0.001, ** p<0.01, * p<0.05

4.7.5 Health care utilisation

Before we analyse the impact of road developmental projects on health care utilisation, it might be informative to assess how various transport and related covariates are associated with health care utilisation. These results are presented in Table 4.7. Across all models, we consistently observe that households in areas with a higher road density were more likely to utilise health care as were households in areas with a lower multidimensional poverty index. The distance to the nearest health facility is also found to influence the likelihood of utilizing health care with a decrease of between 1.5% and 2.1% for every kilometer increase in distance to a health facility. Other factors include household size which is associated with a higher likelihood of utilizing health care and the higher fraction of children in a household that are aged between 0 and five years also increased the likelihood of utilization.

Table 4.7: Impact on health care utilization

	Dependent: Binary variable for health care utilisation				
	(1)	(2)	(3)	(4)	(5)
Independent	DiD	DiD with controls	PSM+DiD	IPW+DiD	Gen-match+DiD
After	-0.0816**	-0.110***	-0.0726	-0.121**	-0.0967**
	(0.0377)	(0.0418)	(0.0476)	(0.0522)	(0.0487)
Road development	0.0229	-0.00598	-0.0142	-0.0380	0.0208
	(0.0355)	(0.0386)	(0.0372)	(0.0517)	(0.0434)
Road development x After	0.0378	0.0765	0.109	0.203**	0.0536
	(0.0504)	(0.0509)	(0.0598)	(0.0687)	(0.0575)
Age of head		-0.000646	-0.00285*	-0.00137	-0.000720
		(0.00118)	(0.00152)	(0.00146)	(0.00131)
Head is male		-0.00185	0.0123	0.0101	-0.00183
		(0.0345)	(0.0444)	(0.0413)	(0.0422)
Urban residence		-0.0457	-0.0822	-0.134**	-0.0242
		(0.0442)	(0.0524)	(0.0630)	(0.0489)
Education: secondary		0.00773	-0.0362	-0.0342	-0.00678
		(0.0330)	(0.0412)	(0.0550)	(0.0360)
Education: Tertiary		0.0347	-0.0462	0.0578	0.0662
		(0.0425)	(0.0527)	(0.0517)	(0.0480)
Household size		0.0206***	0.0158*	0.0169**	0.0202***
		(0.00543)	(0.00809)	(0.00705)	(0.00599)
Fraction of males		-0.00124	-0.0319	-0.0171	-0.0121
		(0.0477)	(0.0627)	(0.0530)	(0.0512)
Fraction hh members 0-5 years old		0.157***	0.277***	0.115*	0.152**
		(0.0552)	(0.0709)	(0.0654)	(0.0663)
Fraction hh members 6-18 years old		0.0128	0.0504	0.0339	0.0127
		(0.0296)	(0.0394)	(0.0342)	(0.0359)
Fraction members 19-45 years old		-0.0424	-0.105**	-0.0498	-0.0358
		(0.0287)	(0.0513)	(0.0337)	(0.0312)
Fraction hh members > 45 years		-0.0847	-0.00402	-0.0775	-0.0895
		(0.0638)	(0.0936)	(0.0783)	(0.0706)
Household asset index		-0.0810	-0.597***	-0.358**	-0.0467
		(0.114)	(0.170)	(0.173)	(0.118)
Distance to major road (km)		-0.00125	-0.00162	-0.00254	-0.00192
		(0.00152)	(0.00187)	(0.00169)	(0.00188)
Household negative shock		0.0138	-0.00305	0.0921	0.0138
		(0.0349)	(0.0396)	(0.0591)	(0.0383)
Multidimensional pov. index		-0.357*	-0.384*	-0.236**	-0.307*
		(0.183)	(0.238)	(0.255)	(0.199)
Road density (km/sqkm)		0.622**	0.845**	0.156	0.723**
		(0.266)	(0.337)	(0.632)	(0.287)
Nearest health facility (km)		-0.0159**	-0.0188**	-0.0213**	-0.00484
		(0.00688)	(0.00797)	(0.00868)	(0.00902)
Constant	0.729***	0.785***	1.372***	1.157***	0.689***
	(0.0267)	(0.151)	(0.206)	(0.203)	(0.158)
Observations	1,319	1,319	946	1,319	1,043
R-squared	0.007	0.055	0.081	0.073	0.053

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; Column label (1) is a difference in difference estimation on health care utilisation using unmatched dataset and with no controls. Column label (2) is difference in difference estimation on consumption expenditure using unmatched dataset and with controls. Colum label (3) is difference in difference estimation on matched dataset using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset using Genetic matching approach.

With regard to the impact of the identified road projects, the hypothesis that we sought to test is that road development led to an increase in health care utilization by facilitating access to health facilities. Therefore, ideally, the first question would be whether the investments in roads led to improvement in the level of access. While the HIS data did not directly capture the respondents' access to health facilities, one way to examine the effects of roads on access would be to consider the impact on the distance to the nearest health facility. However, considering our interventions did not involve the construction of new roads but upgrading and rehabilitation of existing roads, a change in distance to the nearest health facility cannot be expected after accounting for newly constructed health facilities. We thus go straight to analysing the effect of the intervention on households' likelihood to utilize health services.

Based on our theoretical framework, we expect road development to affect health care utilization by lowering the cost of transportation, or indirectly through an increased ability to afford transportation through better living conditions overall. Results in the prior sections have shown that households in project areas have seen an increase in consumption expenditure which signals a possibility of relatively improved welfare. At the same time, we observed no significant impact on financial transportation cost, there is also the possibility of an effect on the non-financial transport cost through lower travel time which we do not investigate. The impact of road development on the utilization of health care (estimates in Table 4.7) shows no significant difference between treatment and control. In Table C10, we report coefficients from the same regressions as Table 4.7, but with the treatment group limited to households that are located within 10km of a road project. We observe a weak result which suggests the intervention did positively affect health care utilization at some level. We extend this analysis to a subgroup that includes only households residing in areas classified as rural. Estimates based on this subsample, which makes up 75% of the sample, show that road development contributed led to a higher level of health service utilisation (Table C13)

4.7.6 Respiratory health symptoms

Table 4.4 shows the incidence of respiratory illness symptoms at baseline. The overall incidence of respiratory symptoms was 19%. In the control areas, the proportion of households with at least one household member reporting respiratory illness was relatively higher at 21% in comparison to 18% among treated households. Regression results in Table 4.8C11 show that other than the treatment, there are factors that significantly affected the incidence of respiratory illness symptoms. Households that are larger in size were likely to be affected by illness; confirming that respiratory illnesses spread and thrive in residential areas with more people. The type of cooking fuel is another factor, households reliant on wood for cooking fuel were more prone to illness. We also find that a higher road density and urban residence are positively associated with suffering from respiratory illness.

Table 4.8: Impact on incidence of respiratory health symptoms

	Dependent: Binary variable for respiratory illness				
	(1)	(2)	(3)	(4)	(5)
Variables	DiD	DiD with controls	PSM+DiD	IPW+DiD	Gen-match+DiD
After	-0.0717***	-0.0561**	-0.135***	-0.112**	-0.0566*
	(0.0244)	(0.0282)	(0.0267)	(0.0488)	(0.0323)
Road development	-0.0417*	-0.0236	-0.0648***	-0.0465	-0.0254
	(0.0248)	(0.0270)	(0.0235)	(0.0411)	(0.0304)
Road development x After	0.0550*	0.0550	0.113***	0.0789*	0.0514*
	(0.0327)	(0.0340)	(0.0338)	(0.0458)	(0.0381)
Age of head		-0.000702	-0.00188**	-0.00122	-0.000580
		(0.0007)	(0.0008)	(0.0009)	(0.0008)
Head is male		0.0158	0.0171	0.00678	0.0378
		(0.0218)	(0.0271)	(0.0231)	(0.0251)
Urban residence		-0.0390	-0.0838***	-0.0524	-0.0132
		(0.0273)	(0.0284)	(0.0362)	(0.0304)
Education: secondary		0.0159	0.00250	0.0232	0.00628
		(0.0231)	(0.0217)	(0.0323)	(0.0245)
Education: Tertiary		0.0275	0.00862	0.00858	0.0431
		(0.0251)	(0.0283)	(0.0503)	(0.0268)
Household size		0.00734*	0.0105**	0.00642	0.00656
		(0.00417)	(0.00463)	(0.00489)	(0.00454)
Fraction of males		-0.0261	-0.0588*	-0.0328	-0.0144
		(0.0245)	(0.0311)	(0.0209)	(0.0257)
Fraction hh members 0-5 years old		0.00716	0.0444	0.0494	0.00316
		(0.0309)	(0.0402)	(0.0376)	(0.0328)
Fraction hh members 6-18 years old		0.00849	0.0309	0.0146	0.00454
		(0.0159)	(0.0244)	(0.0193)	(0.0193)
Fraction hh members 19-45 years		0.00711	0.0152	0.000763	0.00197
		(0.0176)	(0.0255)	(0.0200)	(0.0186)
Fraction hh members older than 45		0.0141	0.0487	0.0252	0.0137
		(0.0324)	(0.0427)	(0.0355)	(0.0356)
Household asset index		-0.00202	-0.0194	-0.0164	-0.0141
		(0.0810)	(0.0778)	(0.109)	(0.0883)
Distance to major road (km)		0.00153	0.000589	0.00155	2.71e-05
		(0.00104)	(0.000967)	(0.00103)	(0.00111)
Household negative shock		0.0246	0.0681***	0.0345	0.0277
		(0.0214)	(0.0217)	(0.0357)	(0.0235)
Multidimensional pov. index		-0.207*	-0.560***	-0.336**	-0.153
		(0.112)	(0.116)	(0.169)	(0.120)
Road density (km/sqkm)		0.372**	0.260	0.372**	0.320**
		(0.145)	(0.208)	(0.161)	(0.155)
Cooking fuel: firewood		0.0192	0.0459*	0.0247**	0.0183*
		(0.0261)	(0.0266)	(0.0414)	(0.0286)
Floor type: mud/dung/soil		0.00246	0.00461	0.0249	0.0152
		(0.0260)	(0.0262)	(0.0278)	(0.0271)
Roof type: Grass/asbestos		0.00519	0.0289	0.00576	0.00278
		(0.0230)	(0.0247)	(0.0263)	(0.0251)
Constant	0.212***	0.253**	0.434***	0.365**	0.234**
	(0.0193)	(0.105)	(0.108)	(0.168)	(0.116)
Observations	2,104	2,104	2,059	2,104	1,682
R-squared	0.005	0.019	0.042	0.035	0.016

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; Column label (1) is a difference in difference estimation using unmatched dataset and with no controls. Column label (2) is difference in difference estimation on consumption expenditure using unmatched dataset and with controls. Colum label (3) is difference in difference estimation on matched dataset using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset using Genetic matching approach.

The main variable of interest, road development in the context of upgrading gravel roads to bituminous standards presented a possibility of competing effects on respiratory health symptoms. On one hand, it was expected that tarring of previously gravel roads would lead to a reduction in respiratory health symptoms associated with exposure to dust environments around the road. On the other, upgrading roads tends to stimulate and increase traffic which increases exposure to TRAP. After controlling for factors linked to indoor exposure to air pollution, we find that the incidence of respiratory illness symptoms was higher in project areas which in this case would signal increased exposure to TRAP among treated households. Further, we note that respiratory illness symptoms analysed in this paper are self-reported and may be subject to recall bias.

4.8 Discussion

This chapter investigated how Malawi's road development projects have affected the health and welfare of households. Before explaining the estimated effects on outcome variables, we note evidence that points to the possibility that the selection of road projects for upgrading, and rehabilitation largely align with the general objective of investing in projects with the highest return in terms of affording access to social and economic opportunities. The placement of road developments seems to target areas that would facilitate access to markets and social services. However, questions remain in terms of commitment to rural road development; investments in RD were more likely in urban areas.

Turning to the impact on welfare, the estimates suggest a 3% positive effect of road development on welfare. While the data available does unfortunately not allow us to precisely identify the mechanism underlying this impact, prior studies have identified increased opportunities to supply labour and generate an earning that appears to be the most plausible causal pathway. Nakamura et al. (2020) found that once the roads were developed Ethiopian households started to engage in wage jobs, particularly noting an increase in the share of female and young members with wage jobs. Road development has also been linked to new business opportunities for small-scale traders. Women in the communities gained employment through the sale of food to road construction workers not only during the road construction phase (Khanani et al. 2021). Even after construction is completed, some of them continue earning income for their livelihoods through small businesses by the roadside like welding, and vegetable vending, among others (Pradhan & Bagchi 2013, Khanani et al. 2021). In some regions, particularly in east Africa, road development has led to start-up operations or an increase of motorcycles to ferry people from one place to another (Khanani et al. 2021).

The observed increase in consumption expenditure is in line with several studies that report a positive welfare effect of road development (Nguyen 2019, Edmonds et al. 2018). Khandker et al. (2009) estimates an 11% increase in annual consumption, an effect which is much higher and expectedly so if the project involves the construction of new road projects in previously unconnected areas. However, there are also studies that have found that road development does not always benefit households located in project areas (Vanclay 2017, Khanani et al. 2021). They argue that businesses and households that are displaced during the construction phase suffer permanent loss and it is common for households to be displaced with no alternative settlement provided (Vanclay 2017). Further, road development tends to push the cost of living up, a replacement with housing typical of higher income groups than those present in the area means that the values of housing so that low-income households will no longer afford to purchase or rent housing in these areas and move further to remote areas with affordable housing (López-Morales 2015, Krijnen 2018). This displacement of low-income residents adversely affected their already established social networks and source of livelihood. This effect is unlikely in our study since we use a panel dataset that compares the same households before and after road development.

A key consideration when deciding on investment in roads, whether new or upgrading and rehabilitation of existing roads, is the expected improvement in access to social services. The selected investments are premised on future returns in terms of reduced financial and nonfinancial travel costs. The understanding is that once a better road is constructed, the costs of transportation will fall. The vehicle operating costs including expenditures on fuel and maintenance and a cut down on travel time is expected. In the case of the road upgrading and rehabilitation, it is argued that the roughness of the road surface can affect vehicle operating costs by affecting rolling resistance; rough surfaces reduce speed, require greater fuel consumption, increase wear on tires, and generally increase maintenance costs (Chatti & Zaabar 2012, Zaabar & Chatti 2014). The reduced operating costs would not only benefit motorist but also makes it possible to charge lower transport while maintaining a similar profit margin.

Our estimates relating to the proportion of households' expenditure on travel to seek health care do not support this theory and instead show no significant difference in transportation costs in the project versus non-project areas. Several possibilities could explain this result. Firstly, most people who incurred transport costs do so through payment of transport fares on public transportation and it is established that public transport fares tend to be sticky downwards thus limiting the trickledown effect to end users (Bruun et al. 2015, Kerr 2017). The effect of lower transportation costs for the few patients who are also vehicle owners is not sufficient to drive the overall result. A second possibility which we, unfortunately, could not test, is that with improved access following road development, the patients who otherwise would seek health care at the nearest health facility would now choose to visit health facilities located further away in search of more advanced or better-quality health care. If this happens, their transport cost may not go down, and may in fact go up (Aggarwal 2021). Thirdly, the weak effect on transport expenditure to seek health care raises the possibility of patients who before the roads are developed could choose not to travel and therefore have zero cost. In this case, the average post-road development transport costs would likely be much lower compared to the amounts incurred pre-intervention. It is also noteworthy that, although improvements in road infrastructure can be expected to higher transportation costs per trip, the possibility that overall expenditure on transport may increase exists if households choose to make more journeys on better roads.

This result does not imply an overall lack of travel cost reduction, the estimates we present are limited to the amount paid for transportation in monetary form. There is still a possibility that travel time reduced which is also a cost saving on the part of the patients even though the monetary transport cost remained unchanged. The extension of this analysis would consider what the impact of road upgrading and rehabilitation was on the patients' travel time from their residences to the nearest health facility. This analysis is necessary to capture the benefits of not only cost reductions linked to vehicle operating costs but also the benefits accrued to pedestrians and cyclists.

In terms of effects on health care utilisation, road development affects both supply and demand sides. On the supply side, an improved road network would positively impact the delivery of drug supplies and makes it easier for health workers to travel to work impacting the quality of health service. In our estimations, a positive relationship between road development and health care utilisation is observed, although the effect is not significant. Our result is contrary to findings reported in some previous studies on the subject which suggest a significant increase in service utilisation (Adukia et al. 2020, Aggarwal 2021).

With longer distances and high travel costs being cited as barriers to health care utilisation in our study setting (Varela et al. 2019), the non-significant result of road development needs contextualizing. While we control for household-level determinants of health-seeking behaviour in our analysis, we do not control for supply-side factors such as the quality of health care at the nearest health facility which is one of the factors that determine rate of health care utilisation (Nambiar et al. 2017, Kim et al. 2019, Liu, Leslie, Joshua & Kruk 2019) as well as behavioral and socio- cultural barriers which still exist (Chibwana et al. 2009). Considerations of these and other factors that affect health care utilisation is beyond scope of the current study. Notwithstanding these limitations, the non-significant casual effect of road development on health care utilization was also reported in a case study setting in Kenya, stating that dramatic improvements in the road network were not matched by concomitant changes in hospital utilization (Airey 1992). They attribute this result to institutional barriers, singling out the financial cost of hospital treatment as a major constraint to realisation of the full benefits of what they described as a successful road construction project.

Generally, although a positive impact on health and welfare can be expected after investment in road projects, we also find evidence of possible negative externality suggesting deterioration in respiratory health of residents. Specifically, reports of respiratory illness symptoms are found to be higher in project areas. While it is difficult to state cause and effect with certainty, the closes explanation of this result is in the literature that has linked traffic-related pollution and respiratory health.

Upgrading road projects from earthen to bitumen standard means the roads which were previously seasonal are now in use throughout the year and this implies an increase in traffic and traffic-related air pollution exposure in these areas. Traffic exposures in areas closest to roads have been linked with wheezing bronchitic symptoms, and general coughs and flu (Brauer et al. 2002, Gauderman et al. 2005, Bayer-Oglesby et al. 2006). However, it is noted that distance from the pollutant is a crude measure of exposure to pollution and effects from traffic emissions or resuspensions thus tend to be obscured and biased toward no effect estimates (Hazenkamp-von Arx et al. 2011). The observed effects can be largely attributable to TRAP if road upgrading and rehabilitation caused an increase in traffic count in the project area, either through traffic diversion to motorists preferring to use new roads or de-seasoning roads and increased frequency of use among existing motorists. Otherwise, respiratory illness symptoms can be linked to non-traffic-related pollution. For example, if road projects and associated economic opportunities attract people to project areas, the increase in population in project areas tends to create conditions where airborne illnesses could easily spread and thrive.

4.9 Conclusion

We evaluate the impact of road infrastructure development on household consumption, transportation cost to a health facility, health care utilisation, and respiratory illness symptoms using Household survey datasets, facility location datasets, and road development data in Malawi. The estimation approach combines propensity score matching and weighting with a difference in difference approach. We find that households located in areas close to road development projects experienced higher consumption levels which suggests an improvement in welfare.

Contrary to existing studies on the subject, we find that road improvements did not result in lower monetary transportation costs and neither did they lead to higher utilization of health services. Our conclusion raises two considerations, firstly, road improvements alone do not guarantee transportation benefits for low-income households; most benefits associated with lower vehicle operating costs are accrued to vehicle owners who are the minority in our setting. Secondly, improvements in access to health and other social services must be considered together with improvements in the quality of health care and the cost of obtaining health services. Regarding effects on respiratory health, our findings emphasize the need to implement measures to offset negative externalities, alongside road improvements, for example, regulations to limit TRAP and injuries could include limiting the importation of vehicles above a certain age and or vehicles without emission-limiting technologies.

Chapter 5

An economic evaluation of road infrastructure investment as an intervention for preventing health loss

5.1 Introduction

Selection and prioritization of public infrastructure projects is a critical decision-making problem encountered by governments. Broadly, public infrastructure is funded through public resources, and this implies the investment selection criteria should aim to maximise the welfare of the public. However, in practice, the selection of infrastructure projects is often a complex process as governments seek to achieve multiple objectives. In addition to financial, economic, and social viability, project ranking and selection are influenced by political goals (e.g. prospect for election success)(United Nations 2021). Nevertheless, the general expectation is that public infrastructure investment decisions are informed by CBA, CEA, or another form of economic evaluation. CBA and CEA provide a transparent, systematic way to account for costs and outcomes that might arise from the implementation of a particular intervention. For large projects, an Economic Impact Analysis (EIA) can be considered as a complement to CBA or CEA, in order to capture dynamic macroeconomic effects which are not well represented by the estimated shadow prices (Florio 2008). In a CBA all costs and outcomes are valued in a common unit (monetary), and often the sum of costs and outcomes forms a basis to objectively compare alternatives and select ones which maximize the benefits of public funding (Boardman et al. 2017). Alternatively, CEA compares costs to outcomes measured in non-monetary units, which in the field of health is often DALYS or QALYS.

For the transport sector, the CBA has been the predominant economic evaluation approach. Over time, economic evaluation manuals have been developed in some countries to give guidance on how to perform an economic evaluation of transport projects, which impacts to be included, and methods for estimating these impacts e.g (Adler 1971, Mackie et al. 2005, Namibia Roads Authority 2014). The guides assume an ideal scenario taking a multi-sector approach to economic evaluation of transport projects encompassing important impacts regardless of the sector the impacts are falling on. In practice this is too ambitious (Mackie et al. 2005), the scope of evaluations is determined by two factors; Firstly, the availability of good quality and complete data on the expected impacts of the project (Dutra et al. 2014). Secondly, the decision maker may decide the scope based on their sector of primary interest. For example, in appraising a road transport project, a transport planner's primary consideration may be improving the efficiency of the transport system, while health impacts are secondary. A health planner's primary interest may be the costs and effectiveness of investing in road infrastructure as an intervention for preventing health loss. An environmentalist may be more interested in the pollution reduction aspects of the project while a central planner may rank projects that yield the highest net benefit after considering impacts across sectors. The dimensions that are included in the evaluation and their assigned weights may result in different valuations of similar interventions and thus different recommendations. To demonstrate the implications of these considerations on decision-making, we analyse the Kampala city Road Rehabilitation and decongestion Project (KRRP), a project with the potential to impact outcomes in multiple sectors.

The current chapter builds on the findings of chapter 2 that highlighted variance in the way health impacts are treated in transport economic evaluations. An economic analysis of the impact of a road transport project is conducted from the perspectives of a transport decision-maker, health decision-maker, and more broadly a "central" planner with responsibility across sectors. The primary interest is first to assess whether the inclusion of health impact frequently omitted in transport economic evaluations would lead to a different recommendation. Secondly, to determine, in a CEA framework, whether a transport project would be valuable if solely considered as an intervention to prevent future health loss, and costs on the health system. The CEA measures project outcomes in DALYs/QALYs and relaxes the need to impose a particular monetary valuation of health impacts. Thus, the specific objectives of the chapter are to:

1. Conduct a cost-benefit analysis (CBA), an approach primarily used in transport economic evaluations but accounting for additional health impacts.

2. Analyze broader impacts of the project accounting for both transport and health sectors as well as indirect productivity and consumption effects

3. Determine the cost-effectiveness of KRRP as an intervention for preventing health loss through reduction in road traffic injuries and further traffic-related air pollution, and active transport health effects associated with constructing networks of walkways and cycling tracks - aspects usually excluded in traditional CBA. This analysis could inform considerations on the maximum contribution a health planner could make to the infrastructure development scheme.

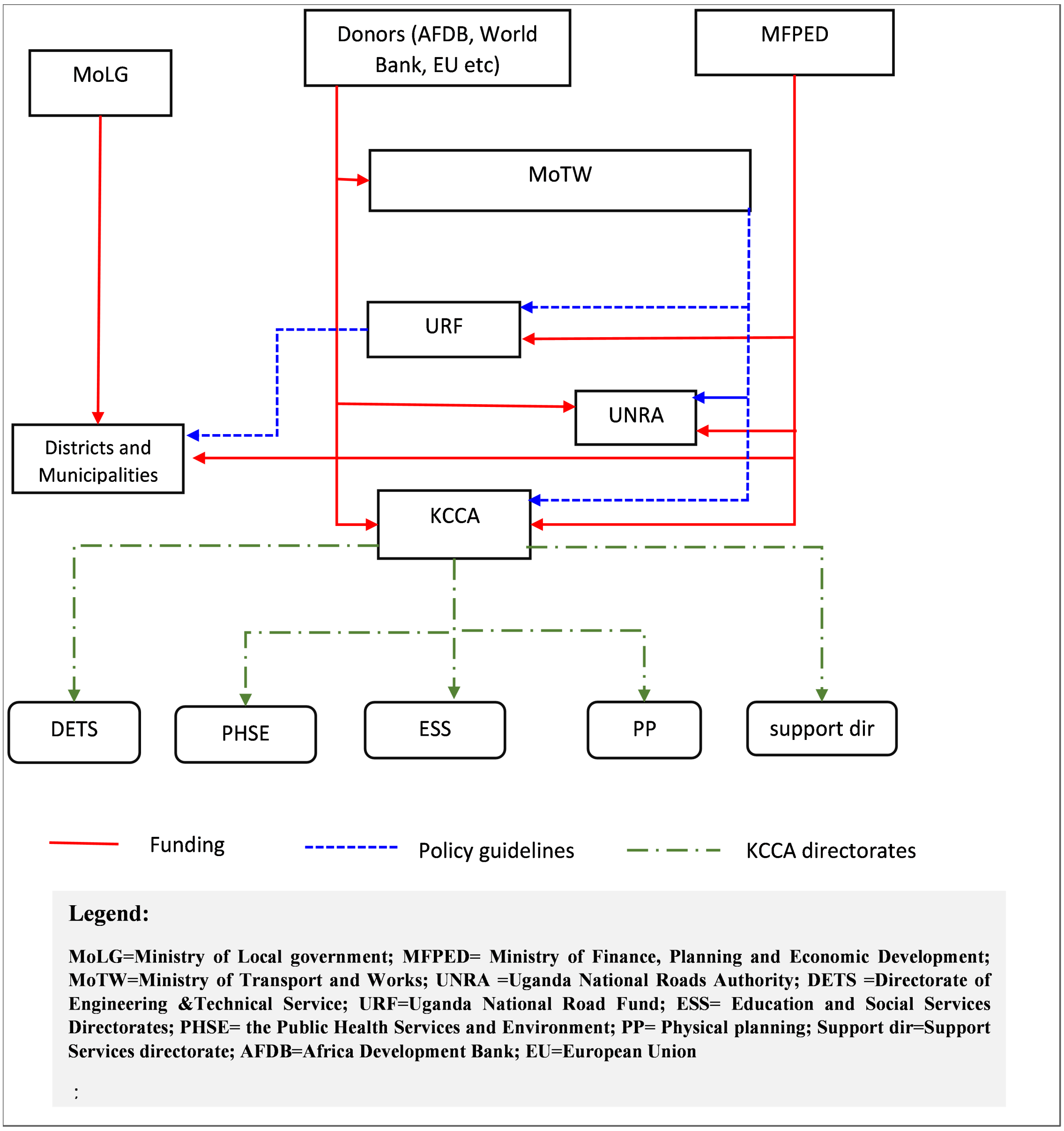
5.2 Setting

5.2.1 Road infrastructure decision making in Uganda

In many country settings, the decisions around resource allocation for transport investment involves multiple players. For Uganda, first, the Ministry of Finance, Planning and Economic Development (MFPED), which is responsible for financial planning for all sectors, allocates funds earmarked for roads transport infrastructure as part of capital expenditure. Funds for the road sector are then channelled through the three main implementing groups of institutions; (i) the Uganda National Roads Authority (UNRA) which oversees the national road network (ii) the Uganda National Road Fund (URF), which is responsible for collecting road user charges and planning for road maintenance, and the (iii) Districts, Municipalities and sub-counties which are responsible for district, urban, and community access roads respectively. The Kampala City Council Authority (KCCA) is responsible for roads in Kampala. Within the KCCA, the Directorate of Engineering Technical

Service (DETS) is responsible for Planning, designing, and managing the construction, rehabilitation, upgrading, and periodic maintenance of the city Roads including road marking and signage. For cross-cutting projects, the DETS (Transport planner) might work with other directorates such as the Physical planning (PP), the Education and Social Services directorates (ESS) as well as the Public Health Services and Environment (PHSE) which is responsible for ensuring a health and productive citizenry. For donor-funded projects, such as those funded by the World Bank, African Development Bank (AfDB), and the European Union, the donor may have input into the specific projects to be invested in. The donor agreements on which road projects to fund may be done with either the Ministry of Transport and Works (MoTW) or the KCCA. The Ministry of Works and Transport retains the coordinating role for the entire works and transport sector. Figure 5.1 summarises these relationships between entities with an interest in the road infrastructure sector in Uganda.

Figure 5.1: Financing and reporting structure



5.2.2 The Kampala city roads rehabilitation and decongestion project

In response to a large and growing commuter traffic in Kampala coupled with the need for a better organized public transport system in the city, the Kampala Capital City Authority (KCCA) planned to undertake major roads rehabilitation and decongestion project as part of the citywide infrastructural improvement program. The KRRP is aimed at tackling congestion in Kampala city through the improvement of the road network, construction of cycle and walking lanes, and upgrading of traffic junctions. A detailed project description, based on the Template for Intervention Description and Replication (TIDierR) checklist, is presented in Table 5.1.

Table 5.1: Description of the Kampala Road rehabilitation project

Checklist item	Item description	Page in the report
Brief name	Kampala City Roads Rehabilitation Project	Title page
Why	Kampala has a road network of 2,110km out of which only 30% is paved. Mobility needs in Kampala remain most acute today in the wake of increasing motorization and worsening congestion. Commuters spend between 1-2 hours commuting to work for average journey lengths of less than 10km, while heightened competition between minibuses and motorbike taxis on the limited road network has increased traffic incident risk, worsened air quality, and reduced travel choices for non-drivers. This intervention will strengthen the foundations for higher productivity by increasing stock of reliable infrastructure and ensuring improved vehicle operating speeds resulting in reduced air polluting emissions and as a consequence, improved air quality in the city. This is expected to translate to greater urban efficiencies thereby making Kampala a better city to live in.	Preliminary page IV
What	The project involves the improvement of 121 Kilometers (km) of roads, construction of 123km of non-motorized traffic facilities, provision of street lighting, and provision of scheduled eco bus services. The project is expected to directly benefit residents of Kampala including commuters, businesses, and transporters passing through the city regularly through improved transport efficiency. By reducing congestion, travel time is expected to reduce by half, Vehicle operating costs will also reduce. In terms of health-related outcomes, the construction of cycle and walking lanes is expected to reduce the number of road traffic incidents while promoting the use of active transport. The provision of eco bus services is expected to lead to a reduction in levels of traffic-related air pollution. The project is expected to create both short-term (during the construction phase) and long-term jobs that will result from a more efficient and less costly transport system. Specific impacts include: (i)an expected 15% reduction in the number road traffic incidents after project completion, (ii)elimination of traffic delays at major junctions and improve transport efficient with average travel time reducing from 65 minutes in 2019 to 30 minutes in 2025 (iii)Create 1671 new jobs over the ten-year period (iv) Increase household incomes by 2 to 3 % (v)Reduce the level of traffic related air pollution by about 41% (vi)Reduce vehicle operating costs	Preliminary page V, Page 9,
How	The project is jointly funded by the African Development Bank, the Global Environmental Fund, (GEF) and the Government of Uganda (GoU). The Bank Group is contributing USD 248 million in loans, representing more than 95 % of the total project cost. The balance of USD 2 million is from GEF grant and GoU. The Kampala city council is the executing agency for the project under the oversight role of the Ministry of transport and Works.	Preliminary page V, Page 9,

Checklist item	Item description	Page in the report
Who provided	KCCA is the overall executing agency for the project. The management of KCCA nominated a Project Coordinator acceptable to the Bank, for the day-to-day management of the project. Further, a project implementation team comprising of a civil engineer, procurement expert, an accountant, an environmentalist, and a socio-economist was constituted. Project Oversight Committee which provides supervisory support consisted of the Permanent Secretary of MoWT, and other key stakeholders including MoFPED, KCCA, the Uganda Power distribution company, Kampala Water and Sewerage Company, civil society representatives, UNRA and other agencies with an interest in the project.	Page 13
Where	The KRRP area of influence is largely in the central division of the city of Kampala made up of five divisions: Central, Nakawa, Kawempe, Rubaga, and Makindye. The area has an estimated population of over 1.5 million. The direct and indirect beneficiaries of the project are more if residents including those that work in the city but live outside of the project area of influence are considered. Exposure to the project impacts varies by impact type, for some impacts such as jobs created, only a small number will directly benefit, other impacts like impact on traffic-related air pollution will benefit a wider population. The economic impact assessment of the Kampala City Road Rehabilitation project demonstrates that there are significant economic gains to the population directly and indirectly served by the proposed intervention.	Page 7
When and how often	The implementation period is 5 years (2020–2024). And the project is assumed to remain effective for 10 years period post project completion. There will be annual maintenance expenses throughout the project life.	Preliminary page iv, Page 4
Planned variation	Sensitivity analysis was undertaken assuming the project implementation suffers considerable delays by up to two years combined with a 30% cost escalation. Lack of sustainable funding mechanism to finance maintenance of newly rehabilitated roads/streets and meet recurrent costs of eco-bus service to ensure sustained results under the project in the long-term. Proposed mitigation measures to address the anticipated impacts shall include provision of road and drainage maintenance equipment to enhance in-house capacity of KCCA to undertake routine maintenance of their infrastructure systems, and to also reduce response times in emergency situations.	Page 10

The decision to invest in the KRRP was determined based on a cost-benefit analysis (CBA) done prior to project commencement. The CBA compared the intervention against the “do nothing alternative”. The cost-benefit analysis was complemented by an EIA. The EIA is conducted to determine how a project or policy affects the amount and type of economic activity in a region and focuses on the economic growth prospects of a project (African Development Bank group 2019), it shows the expected overall change in the level of output for every US dollar of construction expenditure invested in the KRRP.

The results of the CBA and EIA indicate that: (i) the project benefits generated within the region outweigh the costs of project implementation, and (ii) the cost savings accruing to the city of Kampala will increase its regional productivity and serve as a generator of jobs within the region. These results were based on projected project costs and benefits. After accounting for expected additional yearly cost of maintenance that would occur besides the base initial outlay of implementing the project, the total project cost is estimated at USD 275 million. On the benefits side, the project benefit streams that were considered in the analysis included traveller time savings, savings from reduced vehicle operating costs, travel time savings and savings from reduction in road traffic incidents. A comprehensive compilation of project benefit streams that were included in the original CBA is shown in Table 5.2. The table also shows additional impacts accounted for in the extended CBAs and CEA that we conduct.

In the original CBA, the future values of benefits and costs were discounted at a rate of 11% to generate economic indicators of the Economic Internal Rate of Return (EIRR) and Benefit-Cost ratio for the project. The 11% discount rate was adopted due to the following reasons: (i) it represents the rate of central bank borrowing for Uganda; and (ii) it emphasizes projects with more immediate impacts, by applying a heavier weighting in favour of streams of costs/benefits which occur in earlier periods, implicitly favouring projects which pay for themselves within a short time frame. The project implementation period is assumed to start in June 2020 and be completed over a period of 5 years.

By design, cost–benefit analysis aggregates the costs and benefits generated by a transport project into net benefits (or net losses). This implies only quantifiable and monetizable impacts are included. However, market imperfections may mean that prices and costs used in appraisals do not correctly reflect the economic value of the resources used/saved attributable to the project. This can potentially result in incorrect findings of an evaluation. This may occur in several ways – for example, where transport involves costs which are not reflected in market prices (e.g. conges-

Table 5.2: Project benefit streams

Impact	Original CBA	Extended CBA	CEA
Cost of Travel			
Change in travel time	✓	✓	
Change in vehicle operating costs	✓	✓	
Employment and Economic benefits			
New jobs created		✓	
Change in household income		✓	
Road Traffic incidents			
Medical costs saved	✓	✓	
Lost production of RTI victim	✓	✓	
Production/Consumption loss of care givers		✓	
Human costs (VOSL)		✓	
Administrative costs (police, courts and insurance processing)		✓	
Property damage costs		✓	
DALYs averted due to			
Reduction in RTIs			✓
Reduction in Traffic related air pollution (TRAP)			✓
Reduction in Physical Inactivity (PI)			✓
Improved access to health services	✓	✓	✓

tion or pollution) the costs of a project may be understated. The original CBA did not factor into the analysis of health impacts through traffic-related air pollution, and the health benefits linked to an increased level of active transport. While road traffic incidents are included, these were only partially valued based on medical costs saved and the RTI victim's productivity loss avoided. We take a step further to include the lost consumption of caregivers while also accounting for administrative costs associated with road traffic injuries, as indicated in Table 5.2. Additionally, the extended CBA also analyses the non-health benefit of creating new jobs and increases in household income levels. In terms of discounting, a uniform discount rate of 11% was applied, which is higher than would be used in other sectors such as health. The impacts on health through TRAP and PI are analysed in a CEA framework. Allowing for these adjustments in the analysis might contribute towards answering the questions of interest to the health planner such as (i) The influence of choosing a given RTI valuation method on investment decisions (ii)the maximum amount the health sector may contribute towards this intervention if it were jointly funded by transport and health sectors (iii) whether the intervention is cost-effective solely as an intervention for preventing health loss.

5.3 Methods

5.3.1 Methods overview

This economic evaluation involved two main components: A cost-benefit analysis of the KRRP from the perspective of the transport sector and an extended version of CBA that includes impacts that are of secondary importance to transport sector decisions making. The major difference with the CBA that was done prior to the decision to invest in KRRP is in the way we treat the valuation of road traffic injuries that incorporates not only medical costs and lost production but also the production and consumption losses of caregivers of RTI victims, administration costs linked to RTIs and a component to represent human costs linked to injuries. Under the extended version of CBA, the value of reducing road traffic incidents goes beyond costs linked to injuries to include reduction in costs linked to property damages. Other impacts accounted for in the extended CBA include the monetary value of jobs expected to be created by the KRRP estimated in the form of wages and the change in household income levels. The second component is the cost-effectiveness analysis of KRRP as an intervention for preventing health loss. This analysis is conducted from the health perspective and thus forgoes other projects' impacts focusing on only the impacts of primary interest to the health sector. The intervention costs are considered under two scenarios; the full project cost and then a fraction of total project costs based on the monetary value of health impacts estimated by the CBA.

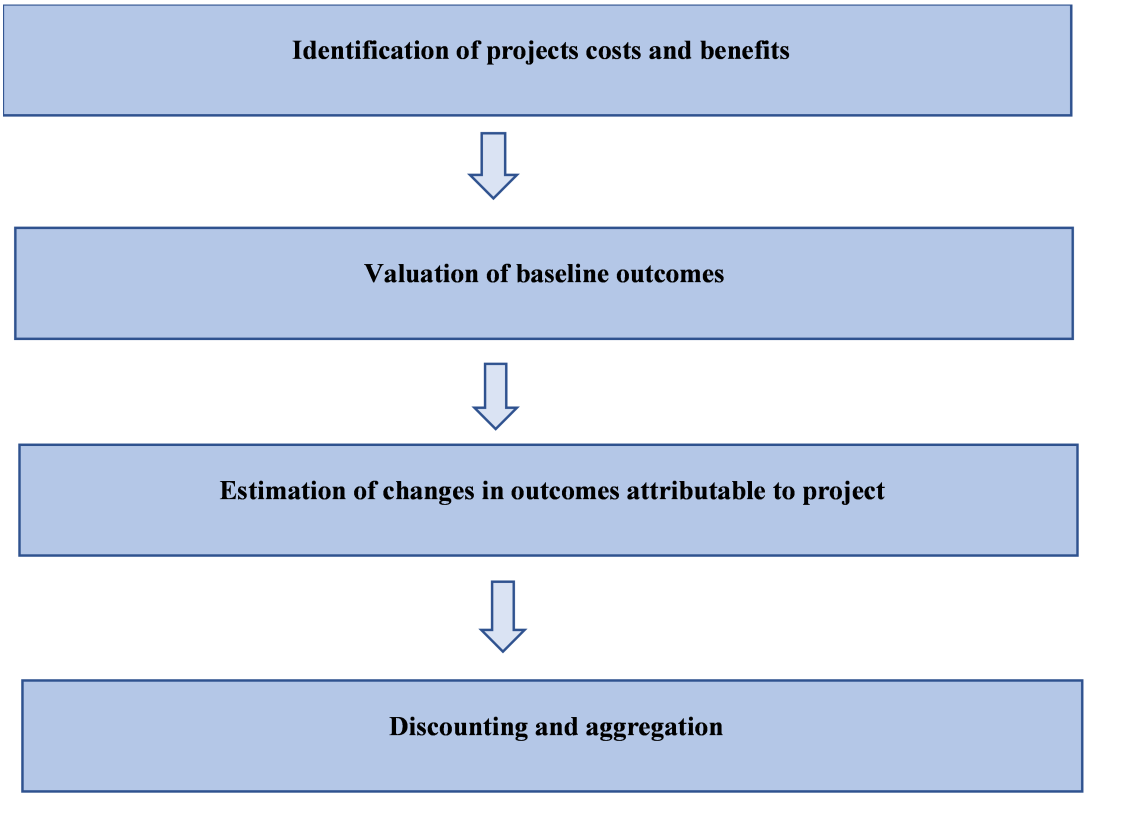
A decision model was developed for both the CBA and CEA in line with the stated objectives. For health impacts, a lifetime time horizon was applied and costs and benefits were discounted at 11% (baseline scenario) to 2019 values. The 11% discount rate is the local discount rate and was used in the initial KRRP economic analysis (African Development Bank group 2019) . In alternative scenarios, a 3%

discount rate was applied to health benefits. The 3% discount rate for health is recommended and widely used in other settings (Claxton et al. 2011, Wilkinson et al. 2014, Johns et al. 2019). The model was developed in Microsoft Excel® (2016; Microsoft Corporation, Redmond, WA, USA)

5.3.2 Model structure and assumptions-CBA

The Cost-benefit model is developed that compares the intervention- KRRP project against the reference baseline or do-nothing case. This is a standard CBA model based on a static setting. Generally, CBA analyses are not dynamic and thus do not answer the question of optimal timing (Godinho & Dias 2012). This means that while the CBA does inform whether a new infrastructure should be built, it does not allow the conclusion regarding if it would be preferable to build it right now or in the future. The approach to CBA followed an established procedure distilled down into a set of specific steps. Figure 5.2 outlines the key steps implemented in the model and the approach that was taken. The first step involves the identification of relevant project costs and outcomes. The second stage involves obtaining baseline values for the outcomes of interest. The third step estimates project impacts per person per year and further expanded to the relevant subpopulation. This is done separately for each channel of the project impact. The final step aggregates over impact channels and over time before discounting all project impacts to their present values.

Figure 5.2: Key steps in developing CBA model



Before detailing how the remaining three stages were completed, Table 5.3 states key assumptions that guided the estimation and analysis of some components of the model. These assumptions are made on either the relationships between variables or the parameter values assumed by specific variables at baseline. A change to alternative assumptions might change the final model results as demonstrated in the sensitivity check. The information used in completing each step was drawn from both the publicly accessible project reports and the literature.

5.3.3 Valuation of project impacts

In this section a detailed account of how each project impact was estimated. In this analysis, reduction in effects that negatively impacts health, transport, and other economic outcomes are accounted for on the benefits side of the equation rather than a reduction on the cost side of the project. For each impact, the method for valuing the outcome is outlined first before describing the approach to estimating the change in the level of that outcome due to the project.

Table 5.3: CBA assumptions

#	Step	Assumptions
1	Estimate change in travel time & traffic incidents	The reduction in travel time and road traffic incidents remained constant over the project life
2	Value time savings per person	The time saved from travelling is channelled to either work or leisure. At the margin, the monetary value of an hour spent working is equal to the utility equivalent derived from an hour of leisure.
3	Estimate the value of traffic incidents per person	No repeat events per individual Each RTI, at a given level of severity, has the same cost and health impact, The baseline risk of being involved in a traffic incident remained the same throughout the project life.
4	Estimate Change in vehicle operating costs	Travel behaviour in terms of the number kilometres driven before and after the project remained the same while the vehicle operating cost changed. This is a strong assumption as the project is also linked to increased active travel. Nevertheless, for the lack of reliable data on the switch between travel modes, the assumption is maintained.
5	Estimate the number and value of jobs created and increase in household income level	That all job opportunities created by the project will be taken The value of a job is measured only in terms of wages and not other factors such as job satisfaction.
6	Adjust parameters	Some values were produced/obtained outside the model itself, and those values from past years are adjusted forward so they are all on a common year basis. The GDP growth rate is used as the basis for adjustment
7	Aggregate benefits over their relevant populations	The level of impact remained the same in all project years.
8	Calculate the present value of road-user benefits and costs	That the same discount rate applies to both health and non-health outcomes. Differential discount rates are applied in a sensitivity analysis.
9	Estimate value of Construction Costs	A uniform amount (10% of total project cost) was spent on maintenance annually

Value of time savings

The first step to estimating the value of travel time at baseline is the determination of trip distribution based on the purpose of the trip. Travel for work is distinguished from travel for leisure or in search of leisure-related activities. This step is important in case different values are given for each activity. Thereafter an income or consumption approach is applied to assign a monetary value to a unit of time spent travelling rather than working or leisure. Often, the same patterns hold if consumption is used instead of income as a measure of labour returns and value of leisure (McCullough 2017). In settings where the agricultural sector significantly contributes to the share of jobs, the consumption approach may be a more appropriate measure of returns to labour. However, In this analysis, the income approach is preferred on the consideration that our study setting, Kampala, is predominantly urban with subsistence agriculture at less than 10% of total employment (Merotto 2020). Thus, the value of an hour of travel time to work is estimated using the formula:

$$VOT_W = \frac{Average\ annual\ wage}{Number\ of\ hours\ worked\ per\ person\ per\ year} \tag{5.1}$$

In the absence of micro survey data eliciting the values, one way to value leisure is to approximate as some proportion of by the average annual income,δ, to reflect the difference in value from time spent working (Andronis et al. 2019). However, rather than arbitrarily decide the value of δ, we apply the reasoning of the neoclassical labour theory which argues that at the utility maximisation point, the value of an hour spent supplying labour is equal to the value derived from an hour of leisure. Based on this theory, the marginal value of leisure time corresponds to the wage rate of the individual (Sendi & Brouwer 2004), so that $\delta = 1$.

The second step is the determination of the amount of time that would be saved by each person. To do this the baseline mean number of trips an average Kampala resident makes per day is obtained (estimated as 2.1 trips Baertsch (2020)). Before the project undertaking, an average single trip would take 65 minutes. The KRRP is expected to lower this to about 30 minutes per trip. The projected change is based on several factors including projected usage growth, congestion reduction, and speed limit adjustments, among other factors influenced by the project. Ultimately, the reduction in travel time is explained by increased trip efficiency after the project compared to travel under the existing road configuration. The third step involves the conversion of the saved time into money terms. This is estimated by multiplying the number of hours of travel time saved as a result of the investment by the hourly value of time. This value is then applied to the projected population size for Kampala over the project life to transform the individual-level estimate into a population-level estimate.

Savings from vehicle operating costs

Besides reduction in congestion and improvements in travel speed, this road construction, and rehabilitation project is also projected to affect vehicle operating expenses. In general, travel at a consistent speed will save fuel consumption and lower the rate of vehicle depreciation. Vehicle operating costs (mainly vehicle fuel and maintenance costs) apply to individuals that use private transport. In this analysis, we use an estimated baseline aggregate vehicle operating cost associated with each kilometre driven per vehicle. This parameter is based on estimated VOC from a Highway Development and Management (HDM-4) model with input data calibrated for Uganda. The project is expected to lower the VOC for each kilometre of travel. Thus, the average vehicle operating cost per vehicle kilometre after the project is estimated at half the pre-intervention cost. The magnitude of the reduction in VOC is based on what is reported in past similar evaluations for Uganda. Based on this reduced parameter, the change in VOC per vehicle per year is approximated as:

$$\begin{aligned} \Delta VoC\ per\ vehicle = \Delta VoC\ per\ km\ * (Average\ number\ of\ trips\ per \\ vehicle * average\ trip\ length\ in\ km) \end{aligned} \tag{5.2}$$

The total change in vehicle operating (equation 5.3) costs is then estimated to reflect the number of vehicles in Kampala which we proxy by the vehicle ownership rate in Kampala.

$$Total\ \Delta VoC = \Delta VoC\ per\ vehicle * (Number\ of\ vehicles) \tag{5.3}$$

The vehicle ownership rate is assumed to remain steady throughout the project life. However, the number of vehicles on which the total VOC is based changes with population growth.

Value of road traffic incidents

Derivation of the monetary value associated with a reduction in road traffic incidents was done in two main steps. Firstly, we obtain the baseline values for medical costs of treating RTIs as well as the value attached to a day spent engaged in productive activity. The number of production days lost is determined based on the distribution of RTIs which are classified into fatal, serious, and non-serious injuries. A similar procedure is followed when valuation is based on the Human cost approach with the difference being that rather than using disaggregated components linked to medical costs, and production losses, a value of statistical life and fractions of, is applied for fatal, and serious and slight injuries respectively. In the second stage, the treatment effect is applied to the baseline and endline rates of RTIs to determine the pre and after-risk levels or the likelihood of an individual sustaining an RTI. Thereafter, the difference in the pre and post-intervention risk levels is multiplied by the average medical costs and value of production loss incurred per RTI sustained to obtain the value of costs and losses averted. Property damage costs which are non-health costs (i.e they are not linked to RTIs but broadly to road traffic incidents) are included in a category separate from the cost of RTIs. The sections that follow detail the procedure for estimating the baseline outcome values related to RTIs.

Estimating medical costs

A comprehensive aggregation of medical costs includes treatment costs incurred by hospitals and also non-hospital treatment costs, such as the costs of treatment provided through rehabilitation centres, general practitioners, physiotherapy, and home care. The cost items that go into total medical costs include first aid at the crash location, transportation costs of victims to the hospital, treatment costs at the emergency department of hospitals, costs linked to in-patient stay at the hospital, patients' aids, and appliances (Wijnen et al. 2017). The approach used to estimate medical costs is based on the actual costs of medical treatment, a process called the Restitution Costs (RC) method (Wijnen et al. 2009). Inpatient hospital treatment makes up the largest cost component. The actual costs components that are ultimately included vary widely from one setting to another based on data availability. In Uganda, costing studies have approximated medical costs using the cost of hospital stay per night and General practitioner costs. For this study, we adopt the approach used in previous costing studies and inflate the estimates of the medical costs reported in (Sebaggala et al. 2017)

$$MC_i = DST_i * HC_i + GP_i \tag{5.4}$$

MC_i is the medical cost of a serious or slight injury causality; DST_i is the duration of stay, (days of hospitalization) for the injury victim HC_i is daily hospital costs for injury causality; and GP_i is general practitioner costs for the injury victim. Estimating medical costs incurred based mainly on inpatient costs may underestimate the true unit cost of obtaining health services. Alongside these unit costs, data on RTI mix (fatal,severe and slight) and the number of cases treated or expected to be treated per year, a total annual medical cost is estimated.

Estimating value of lost production

Lost economic output forms a significant component of the costs of road traffic injuries. In this evaluation, the human capital approach is used to estimate the value of lost production, while the human cost estimates are provided as a sensitivity check. The human capital approach generally involves multiplying the amount of time that an individual was not able to work by an estimated value of what could be produced per unit of time. With regards to potential productive time, a distinction is made between fatalities and injuries, for fatalities and the permanently disabled, we use the remaining number of productive years until retirement and discounted to their present value. For injured victims the relevant time is set at 7 days for slight and 30 days for serious injuries (Tesfay et al. 2019). A major weakness of this approach is its focus on production only while not considering potential utility loss from activities such as leisure which the RTI victims would otherwise enjoy. Further, it does not capture non-market production prior to or beyond the retirement age. These limitations may be a source of inconsistency when compared to how travel time is valued, which accounts for leisure time.

There are two options when estimating the value of lost production; that is to base the estimate on actual or potential production. The difference between the two is that actual production loss would only focus on traffic incident victims who were in employment at the time of the traffic incident and thus excludes non-market labour. Potential production loss accounts for the fact that the loss of productive capacities of unemployed people as well as future production of children also should be valued. Between the two, potential productivity loss is recommended based on the reasoning that whether employed or not, loss of human capital implies that the productive capacities of an economy are reduced, which is regarded as a socio-economic cost. Further, potential production loss is considered an indirect way to compensate for the non-inclusion of the value from non-market production activities that unemployed persons may engage in such as household chores and unpaid family work (Wijnen et al. 2017). Estimating the value of lost production also requires distinguishing gross and net loss in productive capacity (less consumption loss). Often the appropriate measure is the gross value as consumption losses are usually accounted for alongside human costs such as grief and pain in the estimated value of statistical life year (VOSL) (Wijnen & Stipdonk 2016).

To derive the estimated value of production loss potentially averted and attributable to the KRRP, the average wage was used as reflective of the individuals' production value. Considering that project benefits accrue over an extended period, under ideal conditions, a growth rate ought to be applied to account for the possibility that (real) productivity per person might grow over time. A difficulty is that productivity growth is uncertain, especially for distant future periods, (Trawén et al. 2002). We make a simplifying assumption that the average productivity per person remained unchanged. To reflect the fact that people show a preference for present value and assign a higher value to available goods now than goods in the future, estimates of production losses avoided are discounted alongside other benefits. Thus, for the proportion of fatal injuries and permanent disability, we estimated lost production using the equation:

$$LP = \sum_{j=1}^{N} \frac{w(1+g)^i}{(1+r)^i} \tag{5.5}$$

Where N represents the number of individuals who avoided an RTI because of KRRP, w is the average annual wage; r is equal to the discount rate; g is the growth rate of the economy (assumed equal to 0); i is the average number of years of lost output per fatal traffic incident estimated as the difference between Uganda's Life expectancy and the average age of an RTI victim. For non-fatal injuries causing loss of workdays, the formula is adjusted to reflect only the productive time lost. RTI estimated as serious takes up to a month's value in lost production and non-serious injuries take a week.

Besides lost production of the injured victim, road traffic crashes impact welfare household members who act as informal caregivers. There is no payment or possibility of receiving some form of carers' benefit (Bobinac et al. 2010). We estimate the loss in the welfare of household members following a road traffic injury to one of the members based on consumption forgone. The actual amount of consumption forgone that we adopt is based on the SSA region average estimates that we obtain from chapter 2 of the thesis which examined the impact of RTI on household welfare. The estimated consumption forgone corresponds to the first year of injury, we apply similar assumptions regarding the growth and discount rates to obtain the present value over the life of the project.

Estimating Human costs

The estimates of Human costs due to RTIs are based on the results of a WTP study which is then used to derive the value of a statistical life (VOSL), a monetary measure. The procedure employed to obtain VOSL for Uganda follows a standard benefit transfer approach recommended in Viscusi & Masterman (2017). Implementation of this approach requires the estimation of two critical inputs, a base VOSL and the income elasticity of the VOSL. In this study, the authors recommend use of US base VOSL of $9.6 million. The value is calculated using labour market (revealed preference) estimates from a meta-analysis of existing VOSL studies that used the U.S. Census of Fatal Occupation Injuries data series after controlling for publication selection bias. A much lower alternative base VOSL of $3.8 million is estimated by the World Bank (Narain & Sall 2016). The world bank estimate is the mean of a set of stated preference studies and is thus susceptible to hypothetical bias (Murphy et al. 2005). The income elasticity of the VOSL for developing countries is estimated to be just above one Viscusi & Masterman (2017). To obtain the VOSL for Uganda, the base VOSL estimate is multiplied by the ratio of average income in Uganda to income in the United States (Equation below). Per capita Gross National Income estimates are obtained from World Bank data(World Health Organization 2022).

$$VOSL_{UG} = VoSL_{US} * \left(\frac{GNI_{UG}}{GNI_{US}}\right)^{\tau} \tag{5.6}$$

$VOSL_{UG}$, denotes the Value of statistical life for Uganda, GNI_{UG} is the country's Per capita Gross National Income and τ denotes the income elasticity of the VOSL for Uganda. The estimated $VOSL_{UG}$ is multiplied by the number of road traffic crash deaths avoided to yield the estimate of monetized health loss averted for each year.

Our choice to base the Uganda VOSL on the US VOSL is motivated by two factors. Firstly, the calculations utilize a base U.S. VOSL that is itself derived from a meta-analysis of VSL estimates utilizing estimates that accounted for publication selection bias[cite]. Alternative base VOSL that are much lower exist, for example, the World Bank uses a base VSL of $3.8 million while the Organisation for Economic Co-operation and Development (OECD) uses a base mean of $3.0 million (Narain & Sall 2016, Publishing et al. 2012). Each of the World Bank and OECD values is derived by taking the mean of a set of studies that meet a certain threshold for reliability. A meta-analytic approach is preferable to the approach of constraining the set of studies and taking a mean of the constrained set because constraining induces potential biases in terms of the selection of studies (Viscusi & Masterman 2017).

While the VOSL estimates may a good indication of the monetary value of the human cost of fatal injuries, obtaining similar estimates regarding non-fatal injuries is more complex. Among other reasons, there is large variations in the severity of injuries and the level of impact of these injuries on quality of life and hence human costs. There are examples of studies that have used the WTP approach to estimate human costs of non-fatal injuries (Persson 2004, O'Reilly et al. 1994). In these studies, the approach is to first estimate WTP for reducing the risk of a fatal injury and then approximate the value of non-fatal injuries relative to the WTP for reducing fatal risk. The reported values per serious and slight injury as a percentage of the VOSL range from 10-16% for serious injuries and 0.9-1.6% for slight injuries. Accounting for non-fatal injuries is particularly important as they form a large share total number of injuries reported in LMICs. Estimates of these proportions are not available for Uganda, we use the midpoint of values reported for other countries thus adopting 13.0% of VOSL for serious injuries and 1.3% for slight injuries. We do not separately account for Human costs for relatives and friends, the cost of grief. The general assumption is that people consider human costs for relatives and friends when stating their WTP for reducing crash risk, hence already incorporated in the values that result from WTP studies.

Property and administrative costs

Property damage, and insurance and police administrative costs are not necessarily health costs but are included in more broad measures of valuing reduction in road traffic incidents. We accounted for damages to property that includes damaged vehicles, parts of the roadside infrastructure, and goods damaged in transit. A basic estimate of damages to property requires information on the average damage cost per traffic crash, the proportion of traffic incidents involving property damage and the total change in the number of crashes expected over the project period. We use a regional average of damages per traffic crash and combine it with Uganda's country-level statistics on the number of traffic incidents involving damages. We also adopt from previous studies in Uganda the number of vehicles involved in any given traffic incident.

Administrative costs associated with traffic crashes include court costs and costs of insurance companies in handling insurance claims and police services incurred because of traffic crashes. Computation of administrative costs is usually based on actual costs incurred by respective institutions and would thus demand a lot of research effort to calculate estimates because institutions like the police do not keep systematic records of such costs while insurance companies opt to keep such records confidential. Considering that administration costs are likely to make up a relatively smaller component of crash costs, an alternative approach involves estimating administration costs based on the reported average ratio of administration costs to the total costs in crash-costing studies conducted in other similar countries. We use estimates adopted from studies in Ethiopia and Ghana, which report a proportion of between 5 and 7% (Tukela et al. n.d., Kudebong et al. 2011)

Estimating value of employment created

The KRRP is expected to positively change the productive capacity of the economy by inducing new private investments in the city. It is projected that the change in the attractiveness of the city would affect households' and firms' location decisions, leading to at least 450 jobs created in existing firms and further, the creation of about 100 more new small and medium firms. It is further expected that the project will induce an increase in households' income by 2-3 % by 2025. We estimate the monetary value of the productivity benefit of newly created jobs, and the increase in general household income levels using the respective expressions:

1. Number of firms * Average number of employees in firm * Average wage
2. Number of households * Average household income * % change in income

Accounting for employment benefits at the city or regional level is a crude approximation due to the possibility that if there is no change in the supply of labour at the national level, increased employment in one firm, locality or region will be at the expense of others, a case of labour displacement. However, this concern may be less relevant in areas with positive unemployment figures as is the case for the context of this study (World Health Organization 2022).

5.3.4 Model structure and assumptions-CEA

Boardman et al. (2017) elaborates two core reasons that motivate the use of CEA rather than CBA in transport sector Economic evaluations: The first is the inability to monetise the most significant impacts of a project, and the second is when a particular effectiveness measure does not capture all of the benefits of each alternative, but the remaining benefits, such as improvements in access to a school or health facility, are difficult to monetise. The major hindrance is often that insufficient data are available to monetise the impacts of road projects so that any attempt to do so would be highly subjective and speculative. Under these circumstances, CEA is a commonly applied alternative to CBA to evaluate and rank projects. In addition to challenges associated with monetisation, we apply the CEA to this part of the analysis because it allows measuring effectiveness in terms of DALYs or QALYs, metrics commonly used in the health sector. Although the intention behind used of either QALYs or DALYs in CEAs is similar, the theoretical and technical underpinnings of the two metrics is different (Neumann et al. 2018). On one hand, the concept of the QALY represents the product of years lived and the associated utility values, ranging from 0 (dead) to 1 (perfect health). On the other hand, the disability weights used for DALYs are inverse to that of utility weights, with “0” referring to no disability and “1” representing the dead state (Gold et al. 2002). In terms of application, the QALY-based measure has been recommended by many health technology assessment agencies in HICs, whereas the DALY-based measure is generally preferred in LMICs (Feng et al. 2020). A possible reason is that disability weights required for estimating DALYs are publicly available which reduces the cost of conducting CEA.

Because CEA does not monetise project benefits, two measures are necessary: the effectiveness measure and the project costs. Costs are reported as the financial cost of a project and the outcomes will be represented in DALYs. The incomparable metrics for costs and outcomes mean that it is hard to derive a single measurement of net benefits. The ratio of indicators, however, offers the basis for screening and ranking alternative proposals. This ratio can be represented as a cost-effectiveness ratio (CE ratio), which is the cost of an option divided by its effectiveness measure. To provide a basis for comparison across projects, the incremental cost-effectiveness ratio, which represents the ratio of the difference in costs to the difference in outcomes between two interventions is used. The incremental cost-effectiveness ratio (ICER) for the intervention is determined by comparing model outcomes based on present levels of health impacts with those anticipated after project completion. Considering the case of two projects, i and j. The cost-effectiveness ratio of project i relative to project j, CE_{ij}, is given by the formula:

$$CE_{ij} = \frac{C_i - C_j}{E_i - E_j} \tag{5.7}$$

where C_i is the cost of alternative i, C_j is the cost of alternative j, E_i is the effectiveness units produced by alternative i, and E_j is the effectiveness units produced by alternative j. In our case, the comparison alternative, j, is a scenario where no project is undertaken, and the status quo continues.

The effectiveness of KRRP impact on the population's health is estimated through three impact channels: road traffic incidents, traffic-related air pollution, and health impacts through the increase in uptake of active transportation mode-walking and cycling. The outcomes of the model are expressed in terms of Disability Adjusted Years (DALYs). The DALY provides a summary measure combining estimates of the loss of health from both mortality and morbidity. The CEA was done in four stages (1) The first step was to establish the expected reduction in road traffic incidents, level of traffic air pollution, and level of physical inactivity (2) translation of the expected changes in the three dimensions of health impacts into the number of DALYs averted (3) estimate the costs of constructing and maintaining the KRRP (4) derive an estimate of the economic value of investing in KRRP by preventing loss of health in terms of the cost per DALY averted.

Estimating project effectiveness on reducing RTI

To estimate the change in expected reduction in health loss linked to the prevention of traffic incidents, the DALY metric aimed to capture the health gap that combines lifetime lost due to premature mortality and non-fatal conditions of traffic incidents. This is measured as a sum of Years of Life Lost (YLL) and the equivalent Years of life Lost from Disability (YLD) for people that did not die in a traffic incident but living with its consequences on their health:

$$DALY = YLL + YLD \tag{5.8}$$

The component YLL is estimated as

$$YLL = D(age, sex, cause) * L(age, sex) \tag{5.9}$$

where D refers to the number of deaths disaggregated by age, sex, and cause. The cause specifies whether the injury was sustained as a pedestrian, motorist bicyclist, bus truck or other. L is the standard life expectancy; the number of years people surviving to that age are expected to live. The standard reference table for life expectancy that we use is extracted from the World Health Organisation life tables for Uganda for the year 2019.

Estimating the non-fatal health impact of injuries on health requires more detailed data on the incidence of injuries by age and sex, injury types (traumatic brain injury, fractured hand or wrist, etc) and their external causes (pedestrian, motorist etc). In our setting information on the incidence of injuries for each external cause are available. However, country-level estimates of the health conditions developed as a result of RTIs (sequela) are not available. We base our estimate of health loss attributable to injury on the mapping provided in the Global Burden of Disease (GBD 2010) that linked each external cause to injury sequelae. The mappings are estimates of the probability that a health event, that is an injury incident, due to a particular external cause will result in a particular injury-related health condition and is represented as:

$$N = I(age, sex, ext.cause) * p(age, sex, ext.cause, sequelae) \tag{5.10}$$

N is the incidence of particular sequelae, I is the incidence of external causes of injuries and p is the probability of the occurrence of any given sequela. The

GBD study developed these mappings based on large hospital administrative and surveillance databases from 28 countries from South-East Asia; East Sub-Saharan Africa Central, Eastern and Western Europe; Central, Southern and Tropical Latin America; North Africa and the Middle East (Bhalla & Harrison 2016). The details of the mapping methods are described in GBD 2010 reports (Murray et al. 2012). Using the estimated N, the YLD is then estimated based on the equation:

$$YLD = N * p_{PD} * DW_{PD} * L + N * (1 - p_{PD}) * DW_{ST} * D_{ST} \tag{5.11}$$

were N is the number of incident cases of each sequela, p_{PD} is the proportion of cases that will have permanent disability; DW_{PD} and DW_{ST} are long-term and short-term disability weights for a wide range of nature-of-injury categories that can arise from each cause of injury. Disability weight reflects the magnitude of the health loss associated with an outcome and it has a value that is anchored between 0, equivalent to full health, and 1, equivalent to death (Salomon et al. 2015). D_{ST} is the short-term duration of the disabling event, and L is the life expectancy of the population. The values for disability weights, the percentage of incident cases that develop a persisting disability, and the duration of disability of cases that have a short-term disability are global estimates extracted from GBD studies. Disability weights used in our model are based on the values used in GBD-2019 and we check the sensitivity of burden estimates to disability weights using the 2017 weights.

To estimate the annual number of DALYs averted due to the intervention by reducing the RTI incidence data that is input in the model by the projected reduction of 15% in all injury types. The incidence of injury estimates disaggregated by age, sex, injury severity and injury cause is obtained from the Uganda annual crime and road safety reports. We assume the reduction in the incidence of injuries over project life while holding injury distribution by severity and cause constant. Total DALYs averted over the project life are a projection of year one DALYs multiplied by effective years of the intervention. It is further assumed that the intervention effectiveness remained uniform across project years.

Estimating project effectiveness on TRAP

Estimating the DALYs attributable to TRAP requires estimating and accounting for several factors: establishing the counterfactual level of the theoretical minimum risk exposure, estimates of spatial and temporal population-weighted exposure, and estimation of relative risk from exposure. The data for relative risk and estimates of the exposure of the population are combined to generate the Population Attribution Function (PAF), a proportion of DALYs in a population that can be attributed to exposure (air pollution) above theoretical minimum risk exposure level (Cohen et al. 2017). For this study, we do not estimate DALYs averted using primary data sources. We extract the number of DALYS attributed to air pollution using the Global Health Data Exchange GBD Results Tool for Uganda in the year 2019. The reported DALYs are for the whole country. We use the proportion of vehicles in Kampala as an indicator of the level of contribution and concentration of TRAP in the city, relative to the rest of the country.

In the second step, we account for the fact that ambient air pollution emanates from varied sources including open-air burning of refuse and biomass, industrial operations, and domestic cooking fires (Landrigan 2017). Thus, the proportion of DALYs linked to traffic air pollution needed to be extracted as a proportion of total DALYs attributed to ambient air pollution. Estimates indicate that 43% of urban air pollution in rapidly growing cities in developing countries is attributable to motor vehicle emissions (Skaalvik et al. 2011), so while there are many sources of air pollution in Kampala, motor vehicles play a critical role in the problem (Kinney et al. 2011). The assumption we make is that the contribution of TRAP to ambient air pollution is on scale to the proportion of DALYs lost due to TRAP, so that 43% of DALYs linked to ambient air pollutants are attributed to TRAP. We then estimate the reduction in DALYs that could be associated with the 43% reduction in TRAP emissions after the intervention.

Estimating project effectiveness on Physical Activity (PA)

Estimating DALYs averted due to improved physical activity through increased use of active transport demands accounting for interactions between change in the level of active transport use and increased level of exposure to traffic-related air pollution and road traffic injury risk. Consideration of interactions between the positive effects of exercise through active transport and such negative effects requires detailed microdata to estimate a set of dose relationships among the three outcomes. Generally, studies have shown that overall, the positive health effects of active transport often outweigh the negative effects of air pollution and road crashes suffered by pedestrians and cyclists by large margins (Mueller et al. 2015, Tainio et al. 2016).

In this study, the relationships between these outcomes are not entirely built but rely on an already existing model which accounts for these interactions. For this evaluation, the intervention involves the introduction and expansion of dedicated cycle and walking lane transport which may promote physical activity. We estimate the number of lives that could be saved through increased uptake of active transport modes using the World Health Organization's Health economic assessment tool (HEAT version 5.0) (Kahlmeier et al. 2017). The HEAT is designed to assess the economic effects of a given state using single-point data or the effects of an intervention using before-and-after data. The tool is founded on the premise that physical activity has a continuous linear dose–response relationship with most health outcomes so that each increase in physical activity is associated with additional health benefits. A comparative risk assessment approach is used in the HEAT so that the risk of interest (mortality or premature deaths) is compared between two cases: with and without the intervention. The difference in mortality between the two cases is the impact of interest. To estimate the difference in mortality, the HEAT employs well-established epidemiological relationships between exposure (amount of walking or cycling) and a health outcome (all-cause mortality). The effect of being exposed is first expressed as a relative risk, comparing the risk of death among people who are exposed (walk or cycle regularly) to the risk if they are not exposed, taking into account the increase in the risk of RTIs and TRAPs. The HEAT's actual estimates of relative risk are derived from the literature and then scaled to local levels of walking or cycling using the formulas shown in box 5.1.

Box 5.1 : Mortality risks

1. **Physical activity benefit**: Reduced mortality risk from walking and/or cycling is estimated as:

$$\left(\frac{local\ volume\ of\ active\ mode}{reference\ volume\ of\ active\ mode}\right) * (1 - RR) \tag{5.12}$$

2. **Air pollution risk**: Mortality risk when walking and/or cycling is as:

$$\left(\frac{AP\ exposure\ of\ active\ mode\ users}{reference\ for\ AP\ exposure}\right) * (1 - RR) \tag{5.13}$$

3. **Crash risk**: Mortality risk when cycling is based on the equation:

$$\left(\frac{Countrywide\ fatal\ crashes}{Countrywide\ volume\ of\ active\ mode}\right) * local\ volume\ of\ active\ mode \tag{5.14}$$

The HEAT impact calculations for physical activity and air pollution apply a population-attributable fraction formula. This formula is used to relate the mortality rate for the general population MR_{pop} to the two groups compared in comparative risk assessment: the exposed group (reference group),e, and unexposed group (comparison group) u. In HEAT, exposure refers to the assessed amount of cycling or walking. The MR_{pop} is the weighted average of the mortality rate in the exposed MR_e and unexposed populations. MR_{pop} depends on the contrast in mortality risk between the two groups as well as the size of the two groups.

The population-attributable proportion (PAF) is used in the HEAT impact estimates for physical activity and air pollution. PAF is used to determine the relationship between the mortality rate for the general population MR_{pop} and that of the groups being compared; the exposed (e) and the unexposed group (u). In HEAT, exposure refers to the quantity of estimated cycling or walking. The MR pop is the weighted average of the mortality rates in the exposed MR_e and unexposed MR_u populations. Thus, MR_{pop} depends on the disparity in mortality risk between the two groups as well as the size of the two groups, P_u, and P_e.

$$MR_pop = MR_u * P_u + MR_e * P_e \tag{5.15}$$

Epidemiological studies estimate the contrast in mortality risk and express it as a relative risk (RR)

$$RR = \frac{MR_e}{MR_u} \tag{5.16}$$

In the HEAT context, the size of the assessed population cycling, and or walking is estimated relative to the size of the total population (all inhabitants of a country 20–74 years old). MR_u and MR_e are then multiplied by the assessed population to derive the number of deaths in the exposed group and unexposed group (the hypothetical counterfactual of the same population not being exposed: not or with lower levels of cycling or walking). The difference between the two groups reflects the number of deaths attributed to the exposure or the impact of the exposure. If the impact is smaller among exposed people, the exposure prevents deaths. To use HEAT, core data inputs include (i) an estimate of the size of the study population. The population size must reflect the age range being assessed, such as excluding people younger than 20 years, which HEAT does not consider; and (ii) an estimate of the average amount of walking or cycling in the study population. The tool has an option for specifying the country for which the assessment is done and whether the assessment is at the country or city level.

We draw estimates from country studies showing that walking and bicycling modes of transport constitute above 70% of all trips undertaken in Uganda (Janusz et al. 2019) and the average number of minutes of walking and bicycling per Kampala resident per week for transportation purposes from Nalusiba (2017). We consider these estimates to represent the baseline scenario prior to project implementation. Studies which estimate the impact of introducing cycling and walking lanes on the uptake of active transport are unavailable in Uganda and Africa. Thus, we base our statistic on a study conducted in UK which evaluated the effects of providing new, traffic-free routes for walking and cycling on overall levels of walking, cycling, and physical activity (Goodman et al. 2014). Considering that most people in Uganda already use bicycles and/or walk, we use a conservative lower end of reported estimates. Population estimates in Kampala city were obtained from Census reports provided by the Uganda Bureau of statistics. The population size is adjusted to reflect the age group for which the HEAT tool was developed, those aged between 20 and 74 years. A notable limitation of the approach we apply is that HEAT does not provide for other health outcomes other than mortality and the exact type of relationship is still uncertain (Kahlmeier et al. 2017). We thus do not account for the health burden due to morbidity.

5.3.5 Intervention costs

The intervention was defined as the rehabilitation of 121 Kilometres (km) of roads, construction of 123km of non-motorized traffic facilities, provision of street lighting, and provision of scheduled eco bus services in Kampala. The installation, design, and planning costs were assumed to have occurred in the first year of the intervention with a financial cost of the initial project investment amounting to 250 million US dollars. Alongside the initial capital cost, periodic maintenance costs were included, assuming a 10-year life for the project from the date of completion.

Parameter sources

Table 5.4 summarises the input parameters used in the analysis. Parameters describing the base scenario and expected impact of the project are obtained from both the project documents and the general literature.

Table 5.4: Summary of parameters used in the models

Parameter	Value	Source
Effective lifetime of intervention	10 years	Kampala City Roads Rehabilitation Project Appraisal Report; African Development Bank (2019)
Discount rate for costs and benefits	11%%	Kampala City Roads Rehabilitation Project Appraisal Report; African Development Bank (2019)
GDP per capita	USD 794.45	World Bank (2019)
Vehicle operating cost /km before project	USD 0.68/veh-km	African Development Bank (2007)
Vehicle operating cost /km after project	USD 0.314/veh-km	African Development Bank (2007)
Average length of private trip	11km	Kampala capital city Authority (2018)
Share of private vehicle trips	8-10%	Traffic survey; JICA (2011)
Travel time per trip before	65 minutes	Traffic survey; JICA (2011)
Travel time per trip after	30 minutes	Traffic survey; JICA (2011)
Walking trips (000 trips/day)	1,964,210	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)
Bicycle trips (000 trips/day)	302,480	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)
Motorbike trips (000 trips/day)	485,416	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)
Passenger car trips (000 trips/day)	19,495	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)
Small bus trips (000 trips/day)	37,251	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)
Large bustrips (000 trips/day)	13,858	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)
Truck trips (000 trips/day)	14,761	Projections for Kampala based on primary study and inflated to 2019 using population growth JICA (2011)

Parameter	Value	Source
Travelling time related to culture, leisure, mass-media and sports practices (hours per day per person)	0.7	Time Use Survey; Uganda Bureau of statistics (2018)
Travelling and commuting for employment	0.9	Time Use Survey; Uganda Bureau of statistics (2018)
Average medical cost per RTI	USD 325.23	The Cost of Motorcycle Accidents in Uganda; Sebaggala et al (2014)
Median monthly wage per person	UG 200,000	Annual Labour Force Survey; Uganda Bureau of Statistics (2019)
Average number of employees in a small medium enterprise	5	National Small Business Survey of Uganda; Financial Sector deepening (2015)
% of working population as share of working age	81	Annual Labour Force Survey; Uganda Bureau of Statistics (2019)
% of people in wage employment in Kampala	19	Annual Labour Force Survey; Uganda Bureau of Statistics (2019)
Number of households in Kampala	418,787	Annual Labour Force Survey; Uganda Bureau of Statistics (2019)
Median monthly household income in Kampala	UGX 667,000	National Labour Force Survey; Uganda Bureau of Statistics (2017)
Base Value of statistical life	$9.6 million	Viscusi and Masterman (2017)
RTI incidence reduction	15 % annually	Kampala City Roads Rehabilitation Project Appraisal Report; African Development Bank (2019)
Age standardized ambient air pollution attributed death rate per 100, 000 in Uganda [Confidence interval]	68.8 [58.01-80.28]	The Global health observatory; World Health organisation (2021)
Baseline emission levels in Kampala	170µm/m3 (2019)	Kampala City Roads Rehabilitation Project Appraisal Report; African Development Bank (2019)
Targeted level of emissions after project completion	100µm/m3 in 2026	Kampala City Roads Rehabilitation Project Appraisal Report; African Development Bank (2019
Walking and bicycling per person per week for transportation purposes	30 minutes	Nalusiba (2017)
Change in minutes walked /cycled post project	+24 to +45 minutes per week	Goodman et al 2014

Parameter	Value	Source
Total cost of construction and maintenance of intervention	US 250 million	Kampala City Roads Rehabilitation Project Appraisal Report; AFDB (2019)

5.4 Results

5.4.1 Cost Benefit Analysis: base-case and alternative scenarios

Table 5.5 show the estimation results for the base case and alternative scenarios. The cost of construction and maintenance of the KRRP was worth USD 255,058,260.84 in 2019 USD values, approximately twice KCCA's annual budget in the same year (Harman et al. 2021). This investment is expected to yield a stream of benefits across, transport, health sectors, and the wider economy in Kampala. The expected benefits are estimated independently and tabulated in the table. The first component of results in the table answers the question of whether the project is viable from the perspective of a transport planner who is only concerned about the two core outcomes for transport infrastructure investment: reduction in travel time and vehicle operating costs. The aggregate value of these benefits is approximately USD 240 million, a value that falls below the cost of the investment.

Thus, from a pure transport sector perspective (concerned only about transport system efficiency), the project is not cost-beneficial. However, the project also has a benefit stream that is of primary interest to the health sector, a reduction in RTIs. The monetised value of a 15% reduction in RTIs has an estimated present value of USD 24,192,645.98. This amount is a sum of the present values of the costs averted due to the reduction in RTIs. From Table 5.5, this includes a reduction in medical costs, productivity losses for both victims and caregivers, and administration costs linked to RTIs. The amount represents the maximum amount the Public health department of the Kampala city council would be willing to contribute to this project if it were a departmental co-financed investment. When considered in isolation, the health benefits through RTIs avoided yielding a negative net present value. However, combining the transport and health sector benefit streams yields a total benefit above project costs indicating that the project becomes cost beneficial if the value of the reduction in RTIs is accounted for and comprehensively valued under the human capital approach. The surplus of benefits above benefits is about USD 5 million. This amount rises significantly if the impact stock of the project is expanded to also consider the effects of KRRP on job creation and improvements in household income level.

The CBA results are extremely sensitive to some of the assumptions made in the analysis; A change of the discount rate from 11 to 5% leads to a positive NPV when only transport benefit streams are accounted for. Applying a 15% discount rate results in a negative present value for transport, and health benefits streams combined. The benefit value remains below the cost of investments even after accounting for jobs and increases in household income. A second sensitivity assessment uses a different approach to attaching a monetary value to averted RTIs; the value of statistical life. The estimated value of RTIs under this approach is significantly higher than the value obtained using the Human capital approach. The observed large differences between the two approaches could be attributed to the differences in contexts; while the Uganda VOSL is derived from an estimated US-based Value of statistical life, the Human Capital approach mostly applied local/regional parameters. The annual wage in Uganda averages about USD 660. This wage combined with the average age of RTI victims of 30 years and retirement of age of 60 years, results in an estimated productivity loss of USD 19800 for each fatal RTI. This amount is below the derived VOSL for Uganda based on the USA VOSL of USD 9,600,000. Consequently, if the VOSL is used, the KRRP turns out cost-beneficial when considered as an intervention to exclusively lower the incidence of RTIs.

Table 5.5: Cost benefit results

Dimension	Benefits	Costs	Net present value
Costs			
Project capital cost		-250,000,000	
Project operating expenses		-7,471,353.94	
Expected benefits			
Reduction in Travel time	175,995,687.80		
Reduction in vehicle operating costs	60,129,929.56		
NPV (Transport only)			-21,345,736.54
Reduction in RTI linked medical costs	37,777.56		
Avoided productivity loss (Fatal RTI)	19,417,029.21		
Avoided productivity loss (Serious RTI)	184,293.99		
Avoided productivity loss (Non-serious RTI)	32,524.49		
Administration costs linked to RTIs	3,461,149.14		
Property damage linked to traffic incidents	2,941,976.77		
Production loss of RTI victims' care givers	1,059,871.58		
NPV (Health only)			-230,336,731.19
NPV (Transport + Health)			5,788,886.21
Increase in household income	199680076.2		
Earnings from new jobs	64468.67635		
NPV (Transport+Health+Wider economy)			205,533,431.07
Alternative scenario: Discount rate 5%			
NPV (Transport only)			186,882,692.67
NPV (Health only)			-212,237,703.99
NPV (Transport+Health)			238,703,018.29
NPV (Transport+Health+Wider economy)			620,165,014.35
Alternative scenario: Discount rate 20%			
NPV (Transport only)			-153,900,106.73
NPV (Health only)			-241,792,647.52
NPV (Transport+Health)			-142,488,462.22
NPV (Transport+Health+Wider economy)			-58,484,576.85
Alternative scenario: Discount health 3% and the rest at 11%			
NPV (Transport only)			-21,345,736.54
NPV (Health only)			-201,247,526.21
NPV (Transport+Health)			34,878,091.19
NPV (Transport+Health+Wider economy)			234,622,636.05

5.4.2 Cost-effectiveness analysis: base-case and alternative scenarios

The CEA results of Table 5.6 considers the entire project's costs against health outcomes, that is, the DALYs averted through KRRP impact on rate of RTIs, level of TRAP and level of physical activity through active transport use. The DALYs averted are through each of the health impact channels are reported in separate rows alongside different combinations.

To decide whether the project would result in adequate health gains than if

Table 5.6: Cost effectiveness estimates

Impact channel	Total intervention costs at 11% discount rate	Total intervention costs at 3% discount rate	ICER at 11 % discount rate	ICER at 3% discount rate	ICER discounting intervention costs at 11% and Health outcomes at 3%
RTI reduction only	257,471,353.94	267,597,760.64	8,987.67	3965.9055	3,815.83
TRAP reduction only	257,471,353.94	267,597,760.64	10,341.32	4563.2199	4,390.54
PI reduction only	257,471,353.94	267,597,760.64	19,368.89	8546.7362	8,223.31
RTI+TRAP reduction	257,471,353.94	267,597,760.64	4,808.55	2121.8235	2,041.53
RTI+PI reduction	257,471,353.94	267,597,760.64	6,139.01	2708.9042	2,606.39
TRAP+PI reduction	257,471,353.94	267,597,760.64	6,741.79	2974.8869	2,862.31
RTI+TRAP+PI reduction	257,471,353.94	267,597,760.64	3,852.20	1699.8233	1,635.50

resources were to be invested elsewhere, an incremental cost-effectiveness ratio is estimated. Considering that the comparison is a do-nothing scenario, the costs, and benefits of the comparator are assumed to equal zero. The ICER is compared to the percapita Uganda's per capita GDP estimated at USD 794 which is used as a CEA threshold. An alternative threshold range is obtained from Woods et al (2015) who estimate the CEA threshold range for the health sector in Uganda to be in the range USD 28 - USD 725.

Results in Table 5.6 show that if considered as an intervention for preventing health loss, the KRRP did not represent a valuable investment. Different combinations of impact channels show that the cost per DALY averted were way above both CEA threshold. Combining DALY averted from RTIs, TRAP, and PA gives a total of USD 66,837.56 DALYs transforming into a USD 3,852.20 cost per DALY at 11% discount rate. Applying a discount rate of 3%, a rate that is similar to what has been used in other settings for health sector interventions' economics evaluations, brings down the cost per DALY to about USD 1699 and is still cost ineffective. Similarly discounting the health impacts at 3% and intervention costs at 11% still yields a consistent result with an estimated cost per DALY above the threshold. Regardless of the assumptions made around the appropriate discount rate, the estimated cost per DALY averted lies well above the GDP per capita threshold of USD 794 and outside the alternative CEA threshold range (USD 28 - USD728), indicating that from the health perspective, the intervention represents poor value for money.

The finding that the KRRP is not cost-effective as an intervention for preventing health means a decision maker with a primary interest in health outcomes would decide against the intervention. However, the key consideration here is that the costs of the intervention were considered in their entirety. An alternative way to analyse the viability of KRRP as a public health intervention is to determine the proportion of the investment that could be attributable to the health sector. From the CBA estimations, it is estimated that the maximum amount that the public health department would be willing to contribute towards the KRRP is 24,192,645.98. Would this amount of investment represent a cost-effective option for the health sector given the CEA thresholds for Uganda?

Table D2 presents the cost-effectiveness results for KRRP based on the maximum willingness to contribute for public health benefits. At 11% discount rate for both intervention costs and DALYs show that the intervention is still not cost-effective with cost per DALY averted estimated at 1,137.98. This value is above both per capita GDP and the upper limit of the alternative threshold range. A discount rate of 3% for both cost and outcomes changes the result: a combination of health outcomes from any two impact arms yields a cost-effective result with the costs per DALY ranging between 300 and 600, these amounts are below the percapita GDP threshold and also within the CEA threshold range of between USD 28 and USD 728. Aggregating all estimated health impacts give a value of 339.96 which is almost twice the per capita GDP threshold and well below the upper limit of the threshold range estimated by (Woods et al. 2016).

The choice of discount rates has important implications for the outcomes of economic evaluations of health interventions. Discounting is essentially adjusting for differences in the timing of costs (expenditures) compared to health benefits (outcomes). A higher discount rate produces lower net present value. Countries that may choose to set high discount rates may do so to prioritise interventions or national policy that promises to respond to their immediate health problems. Other than the level of discount rate adopted, there is a question that emerges from this practice is whether health benefits ought to be discounted using the same discount rate or if at all they should be discounted at all. Proponents of differential discounting argue that health is a unique commodity, which cannot be traded over time and, hence, it cannot be invested elsewhere at some real rate of return, like most other resources (Chapman 2002). However, it is also argued that healthcare transforms resources into health and because it is possible to trade healthcare resources over time, the same should hold for health (Claxton et al. 2006). Based on this argument, healthcare resources are ultimately transformed into health, implying that if healthcare resources are being discounted, then so should health effects and at the same rate. Applying differential discount rates (11% discount rate for costs and 3% for health outcomes) shows a similar pattern in results, however, this set of results shows the intervention is slightly more cost-effective.

Sensitivity analysis

The results of both the CBA and CEA models are sensitive to a number of key parameters used in the modelling exercise. One of the key parameters deriving the results is the estimated impact of the interventions on the incidence of RTIs (Estimated at 15%). In appendix D2 and D4, we show the results in event that that the intervention was only 50% effective, that is RTI incidence reduction attributable to intervention is 7.5% rather than 15%. The results of the CBA (Table D2) show that the investment is only viable in the scenario where all three categories of outcomes are considered (Transport, Health and Wider economy). In the CEA model (Table D4), this level of intervention effectiveness on RTIs does not result in sufficient DALYs averted relative to the cost.

5.5 Discussion

While investing in road infrastructure is important in supporting the smooth operation of the economy, these investments have significant cross-sectoral impacts which if included or excludes have the potential to change the outlook of the investment in terms of their cost-benefit or effectiveness. In this chapter, the road rehabilitation and decongestion project was analysed to first consider how the decision to invest is influenced by inclusion or exclusion and measurement of health outcomes. Secondly to analyse the viability of interventions implemented in the transport sector to prevent health loss. The results show that health benefits constitute a major benefits category for this intervention, in the CBA, about 20% of the monetized total benefits were attributed to a reduction in road traffic injuries. The exclusion of this benefits stream automatically makes the project not beneficial given the cost. Notwithstanding the data limitations, economic evaluations would more accurately indicate value for money if the impact stock is expanded and consistently consider the externalities imposed on outcomes in other sectors.

In advocating for the inclusion of all relevant impacts, our study does not claim completeness. The analysis is limited to the outcomes that could be monetised with reasonable accuracy. For example, while it is expected that the intervention will improve access to health services, this impact is excluded from the CBA because of the difficulties associated with the impact estimation process for this variable and the heavy data requirements needed to estimate and monetise changes in access. Other health benefits, including improvement in the level of physical activity and reduction in the burden of disease linked to lower levels of traffic-related pollution, have not been included in the CBA because we lack data to monetise these even though it is known from project documents how much the project will impact these two risk factors. Thus, one cannot conclude from this work that investing in a road rehabilitation and decongestion project is not cost-beneficial per se from the health perspective. A more complete evaluation would reflect the value of all relevant outcomes.

A second point illustrated in the CBA analysis is that the decision on the approach chosen for estimating and monetizing benefits is just as important as the decisions regarding which impacts to include. We demonstrate this point by comparing the value obtained for the reduction of road traffic injuries using Human capital versus Human cost (Value of statistical life). The monetary value of the same set of injuries estimated using the VOSL for Uganda is significantly higher to the extent that the CBA which includes only the value of injuries averted on the benefits stream and excludes all transport sector outcomes, still yields a positive net present value. There are significant differences in the theoretical underpinnings of the two approaches and consequently capture different things in their valuation. The key difference is that while Human capital approach aims to estimate the societal value of the loss of productive capacities of road casualties, the willingness-to-pay (WTP) approach estimates the amount individuals are willing to pay for reducing risks. The focus of this analysis was not to show which approach is better than the other but to demonstrate the importance of consistency in choice of the valuation approaches. The inclusion of primary or recommended methods in economic evaluation manuals and guidelines may help minimise these inconsistencies.

Results of the cost-effectiveness model show that KRRP does not avert enough DALYs if the aim is to invest for public health gains. This conclusion does not imply that the project as a whole was unviable. Other impacts, which are non-health, were excluded retaining the focus on outcomes that could be expressed in terms of DALYs. For this intervention, the largest amount of DALYs is from avoided RTIs while the expected increase in the level of physical activity generated the lowest number. When aggregated, each DALY averted would cost USD 3,852.20, which is several times above the cost-effectiveness threshold.

Other studies investigating cost-effectiveness of road sector interventions to improve health outcomes have reported more favourable results. Veerman et al. (2016) focusing on assessing the cost-effectiveness of increasing sidewalk availability as one means of encouraging walking found that installing sidewalks in high population density neighbourhoods as a single intervention is likely to cost-effectively improve health. Peters & Anderson (2013) conducted a cost-benefit analysis alongside a cost-utility analysis of mandatory 20 mph zones as an intervention to prevent the occurrence and severity of road traffic injuries, while the intervention was not cost-effective regardless of approach in low-density areas, they conclude that mandatory 20 mph zones may be cost-effective in high casualty areas when a CBA from a societal perspective is considered.

An important note to make in the CEA analysis is that while we focus on health outcomes, the investment was not a deliberate investment to improve population health. To get a more complete picture we subset the cost and use a component that could be considered attributable to health to construct an alternative CEA estimate. From the CBA it was established that in the hypothetical context where the different departments were to allocate resources from joint implementation of cross-sectoral interventions, the public health department would be willing to pay a maximum proportion of 20% of the total project costs. This estimate is based only on the health impacts that could be monetised, reduction in RTIs in this case. Working with this 20% as the project cost, we estimated the DALYs that would be averted through a reduction in TRAP, RTIs, and Physical inactivity. The results, depending on the assumptions around the discount rate, show that this would be a worthwhile intervention for the department of public health to contribute to as long as the total contribution does not exceed 20% of the financial cost.

5.5.1 Study limitations

The study has a number of limitations, first is that most of the analysis is informed by data that was collected some years back, thus there may be inaccuracies in our estimates if the trajectory of variables changed over time. Related to this is the challenge that there is very little data or no data in the Uganda context to inform a number of the key parameters; a few key parameters were borrowed from other settings and are generic. Although we try to use parameters from within the East African region where available, the results should be interpreted with caution. A major weakness of the CBA which we conduct, and generally all CBA models, is that there is no provision for incorporating the difficult-to-monetise impacts. While recognising that the KRRP impacted health through three main channels, only one channel could be monetised with reasonable accuracy, the other two, linked to TRAP and PA, were excluded. Finally, the assumption that the risk of being involved in a traffic incident remained the same throughout the project life is another major limitation of this chapter. In reality, several opposing factors can be expected to influence the incidence of RTIs including the number of KMs driven, population growth, motor vehicle population and the overall state of road infrastructure.

5.6 Conclusion

This work adds to an evidence base examining the cost-effectiveness and benefits of intervening in the road transport sector as a means to increase transport efficiency and improve public health outcomes. The study points to the potential that rehabilitating and decongesting township roads is one way to improve the health of residents. What this chapter has shown is that the decisions to invest may be largely influenced by the selection of the cross-sectoral costs and impacts that the evaluator chooses or is able to include in the model. The study also highlights the importance of being consistent with approaches applied in obtaining values for the intervention impact. In particular, the choice of methods to value road traffic injuries might be the determining factor of whether the intervention turns out cost-beneficial.

Chapter 6

Conclusion

This thesis explores the effects of transport infrastructure and externalities on household welfare in Low- and middle-income countries focusing mainly on impacts on health. In all chapters, the central aim is to examine how road transport impacts health and related outcomes and in turn how health impacts affect transport decisions. In Chapter 3, I build on the road transport externalities literature by analysing how road traffic injuries affect the various dimensions of household economic well-being in ten countries in the SSA region. In a region with a large number of households living below or close to the poverty line like SSA, RTIs can have significant welfare effects on the entire household beyond the RTI victim. Overall, I find that road traffic injuries place a significant burden on households in a number of ways when compared to similar households that did not report an RTI. The primary channel seems to be the RTI's incremental effect on out-of-pocket health expenditure which is estimated to be more than a third higher among RTI-affected households. This result is in line with expectations considering that at the time of the survey, 7 of the 10 countries represented in the sample analysed, charged user fees before a patient could access health services (Masiye et al. 2010, Van Rooy et al. 2012, Obare et al. 2018, Bicaba et al. 2020). Although the estimated increase in OOP in this study is modest relative to previous findings in other regions where it is reported that RTI experience caused health-related expenditure to more than double Gururaj et al. (2004), Mohanan (2013), it represents an amount that could potentially push health expenditures above set catastrophic levels, especially for low-income households (Wagstaff & Doorslaer 2003, Xu et al. 2003).

The analysis further shows evidence that households may have responded to the

RTI experience by adopting a variety of strategies including a reduction in food consumption, expenditure on household amenities, and education. Reduction of non-medical consumption in the face of economic shocks introduced by road traffic injuries is a phenomenon that has drawn varied conclusions in the literature. Our finding is similar to that of Gururaj et al. (2004), Mohanan (2013) who concludes that when faced with shock-related expenditures, households were able to smooth consumption on food and housing amenities (Mohanan 2013). One possibility for the variance in conclusions is the varying definitions and scope of what is analysed as non-health consumption expenditure. For example, a broader definition that includes transport-related expenditure would likely increase following an RTI as because of transport costs linked to health seeking. Because OOP expenses on health care are significantly increased in road traffic injury-affected households, the added expenses may partly have been financed from increased borrowing. Our analysis points to some level of reliance on borrowing among RTI-affected households to meet expenditures required to obtain health care relative to control households. The likelihood to borrow to finance health expenditure was higher by about 23% among RTI-affected households. A disadvantage with the WHS data set that we analyse is that it only has information on whether households borrowed to finance health care, and not how much they borrowed. Thus, our results may underestimate this category by not showing the extent of the amounts borrowed and interest paid.

The findings in this thesis further suggest that households met unanticipated health expenses mainly through borrowing and reductions in consumption rather than adjusting labour supply or depletion of assets. We do not find any evidence of a negative association between road traffic injuries and our indicator of labour force participation. In this regard, our findings are aligned with those of Alam & Mahal (2016). Indeed, there is strong evidence from previous research of labour supply effects of household shocks, especially among poorer sections of society (Razzak et al. 2011, Nithershini et al. 2012, Mohanan 2013). However, it is important to note the possibility that the sample I analyse included all levels of injury severity and not only serious injuries that warranted a hospital admission. Thus, it is probable that our road traffic injury cases might not be severe enough to lead to a significant decline in labour supplied. Further, the observed results could be due to the possibility that RTIs did not compel affected individuals to entirely leave the labour force but rather reduce on the number of hours that our data was unable to capture.

Without controlling for travel habits in the analysis, a likelihood exists that there is a competing effect, that dilutes the hypothesis, that individuals in the labour force are more likely to be involved in a road traffic incident as they are more exposed when going to work or looking for work. I find no evidence to support the hypothesis that households that experienced RTI were more likely to have depleted assets. The results still hold after excluding from analysis vehicles, motorcycles, and bicycles, assets considered as road incident risk factors. While selling assets is a plausible option in times of injury or illness, often, the assets sold may mainly include kitchen utensils and small jewellery items among other minor items Mohanan (2013), which were not among assets considered for the construction of the asset index. Our study makes an important contribution by being the first study that comes closer to estimating, using econometric methods, the effect of RTIs on an array of five indicators of household welfare using data in SSA region. A further strength of the dataset we analyse is its multi-country nature consisting of ten countries, thus the sample and estimated effects are potentially representative of households at the regional level and not driven by unique macroeconomic conditions unique to any of the countries included in the sample. However, our findings are subject to a number of limitations; a major restriction to exploring further relationships using this dataset is the small sample of households that reported RTISs. With a larger sample, the structure that we estimate in this chapter can be modified to take advantage of a potential natural nesting of data at more than two levels. Future work exploring this topic using similar methods and a sufficiently large number of treated households could explore estimating a three-level model, such that at the third level would be countries, at the second level would be rural/urban residences, and at the first level would be households. Such a model is more efficient and uses more of the available information by further exploring the heterogeneities within the dataset. A second limitation has to do with the possibility that the effects of injuries on household welfare in some cases extend beyond one year, notably for fatal injuries. Consequently, an intertemporal choice model would be a valuable tool for describing how current decisions influence future options. As a result of the cross-sectional character of the data, we do not estimate a two-period model. Future research could explore conducting a similar kind of analysis but using a panel dataset or repeated cross-section to further understand the impact of RTIs beyond the period of incidence. With regards to our estimates of RTI impact on likelihood of borrowing, it must be noted that we do not estimate the impact on the actual amount of funds borrowed which would be different depending on the severity of injury and length of treatment. Throughout the analysis and applicable to estimated impact on all five outcomes, a caveat is that we make no distinction based on the position of the injured person within the household; if the RTI victim is the breadwinner, the economic impact on the household could be greater. Another concern might be that our sample size is not large enough to enable us to conduct subgroup analysis for the poor and rich households. One way of identifying poor and rich households is by categorisation into five quintiles based on income or consumption levels so that the top and bottom 20 percent comprise of the rich and poor households respectively. We have tried to address this issue by using splitting the sample into two groups: top half as richer and bottom half as poorer households.

While road transport has demonstrable negative consequences on health through various pathways, road infrastructure development can have important implications on households' health and welfare. The expected effects of road infrastructure development on households are generally agreed in theory. Yet, causal evidence is limited as no study was found to have evaluated the potential impact of upgrading road on household health and non-health outcomes in the region. I focused the analysis on whether upgrading dusty and often seasonal roads to bitumen standards has impacted the cost of travel to seek health services, the level of health service utilization, the incidence of Respiratory Illness (RI), and the level of household consumption expenditure. I applied a difference-in-differences strategy to compare households that were located within a certain radius of a recently upgraded road to similar households residing further away from the road project areas using a panel dataset. Results suggest that households nearer to a road development project reported higher consumption but were more prone to RIs. The effects on transportation costs and level of health care utilisation were negligible.

These results not only highlight the importance of sustained investments in transport infrastructure, particularly for developing countries but also points to the importance of mitigating unintended effects of road development. While steps have been taken to minimise road traffic incidents, less is being done in terms of pollution-related externalities. Our findings are comparable to studies focusing on TRAP exposure, adding to evidence that prolonged and cumulative exposures to TRAP affect respiratory health (Beatty and Shimshack 2014, Janke 2014, Filippini, Masiero et al. 2019, Liu and Ao 2021). These findings support efforts to restrict residential developments near major roadways and other TRAP sources. Complimentary measures could include enforcing age limits for vehicles as older vehicles are associated with higher levels of emissions or alternatively, increasing carbon taxes already charged in most countries. The positive impact of road development on welfare, which we also find in this analysis is one of the generally expected impacts of such investments. Prior studies have identified an array of pathways that road development links to higher household consumption including increased opportunities to supply labour and generate an earning (Nakamura et al. 2020). Road development, particularly rural roads, has also been shown to have a catalytic effect on creation of new business opportunities for small-scale traders (Khanani et al. 2021, Pradhan & Bagchi 2013). Despite the evidence pointing to welfare improvements, we find no evidence to support the hypothesis of lower transportation expenditure on trips to seek health care. This result opens a possible line of inquiry into health-seeking and travel behaviour. This is the possibility that with improved access following road development, the patients who otherwise would seek health care at the nearest health facility would now choose to visit health facilities located further away in search of more advanced or better-quality health care. If this happens, their transport cost may not go down, and may in fact go up. Unfortunately, with the data available at the time of the analysis this hypothesis could not be tested. In this case, the increased health benefits attributable to efforts to lower transportation costs may be offset by new transport costs. Future studies could further explore this co-dependence phenomenon by collecting more targeted datasets. The issue of poor quality of health services also partially explains the conclusion that utilisation of health services did not improve in the intervention areas. Extensive public health literature has shown supply-side factors such as quality of health care at the nearest health facility are critical factors determining the rate of health care utilisation (Nambiar et al. 2017, Kim et al. 2019, Liu, Leslie, Joshua & Kruk 2019). The results in this chapter are subject to the limitation that we relied on the distance to the road variable to define the treatment. The challenge with the adopted approach is that the cut-off point for defining treatment is arbitrary. We try to overcome this limitation by adopting and estimating the impact of interventions at various cut-off points. Within the limitations of the datasets analysed, this thesis demonstrate evidence in that emphasizes the critical role of infrastructure development in improving welfare of communities. At the same time, the thesis demonstrates that such interventions must be to be planned with a view to minimise the negative externalities that might work against reversing the welfare gains. Therefore, this calls for further policy efforts to intensify interventions that promote economic activity while minimising risks to health. Specifically, there is a need to prioritise road safety features to reduce the risk of road traffic injuries as well as promotion of technologies that reduce pollution of the surrounding communities. Further, these results provide information is required for policy as well as investment decision-making that allows prioritisation of interventions that yield the largest net benefits across sectors.

Therefore, the last empirical chapter applied some of the estimates in the earlier chapters to analyse, the value of road transport decongestion as an intervention for preventing health loss. The analysis in this chapter is set up in both CBA and CEA frameworks, with one of the questions being whether a transport project would be valuable if solely considered as an intervention to prevent future health loss, and costs on the health system. I present the evidence that suggests that when the entire investment is considered part of costs, a traffic decongestion intervention do not avert enough DALYs, so from the perspective of public health gains the intervention is not cost-effective. However, this conclusion should be understood in the context that, other sector benefits accrue to the project which would make the project viable overall. Assuming a setting where projects are cross-sector funded, the health sector would only incur a fraction of intervention costs. Based on this assumption, the intervention cost per DALY averted was close to but still higher than the CEA threshold. This result signals the potential of similar interventions, it is highly probable that in instances where DALYs averted attributable to all health impacts are estimated, the interventions would present value for money. A concern about the results in this chapter is that they are an output of a static model. We opted for a static model because getting the actual measurement of the interdependencies among parameters can be difficult, especially in environments with limited data. However, opting for a static rather than dynamic model underplays the fact that the effectiveness of intervention over its life does not remain constant. In an evolutionary environment such as road infrastructure, the static CBA/CEA approaches may result in misleading economic outputs since the variations caused to both costs and outcomes by the crucial factor of their interdependencies remain uncaptured. It is also important to note that some of the analysis is informed by data that was collected some years back, thus there may be inaccuracies in our estimates if the trajectory of variables drastically changed over time. Related to this is the challenge that there is very little data or no data in the Uganda context to inform a number of the key parameters, as such few key parameters were borrowed from other settings and are generic. However, we endeavoured to obtain parameters from within the East African region where there are available. A major weakness of the CBA models, such as the one we conduct, difficult-to-monetise impacts are omitted; from the expected health impacts of the KRRP, only one channel (RTIs)could be monetised with reasonable accuracy, impacts through TRAP and PA, were excluded.

Evaluations of interventions such as this one raises the question of which impacts should be considered. On the one hand, it is necessary to understand whether the project is viable from the transportation sector perspective before implementation. On the other hand, it is important know about the secondary impacts falling outside of the transport sector. As more and better-quality data become available, it would be interesting for future research to further examine an expanded set of intersectoral impacts of road sector interventions going beyond the impacts on health to consider other effects on outcomes in sectors such as the environment and agriculture sectors. In terms of policy implications, this thesis emphasizes the need to investigate both the intended and unintended consequences of interventions. Whether positive or negative, these externalities must be highlighted and where possible estimated for inclusion in the decision model. It is critical to go beyond the primary objectives and explicit target of the intervention, to explore unintended effects. These effects have the potential to influence the overall benefits of the intervention and their consideration in the current intervention could pave the way for the design of future policies and the accumulation of data for future impact evaluations.

Chapters 3 and 4 and more generally, the effects or road transport impacts on health would greatly benefit from better-quality datasets. The outlook for future studies relating to the impacts of road transport on health in SSA looks optimistic as efforts to gather more and improved data on road transport externalities have gained pace in the recent past. For example, a group of stakeholders came together under the auspices of the African Road Safety Observatory to formulate and oversee the implementation of the work plan for 2019-2021, with the goal of starting to build a robust body of data that can be used to monitor Africa's road safety performance and improve decision making. With better data research on the costs and impacts of road crashes, future studies could capture more accurately the impact on all aspects including impacts on household poverty, labour supply and schooling among other mechanisms. Comprehensive evaluations of transport sector interventions for the prevention of health loss are lacking in the region, this thesis has provided a foundation on which future studies can build. With more complete datasets which allow a thorough assessment of travel behaviour and shifts in modes of transport before and after the intervention, alternative models such as the Integrated Transport and Health Impact Modelling Tool (ITHIM) can be explored to perform an integrated assessment of the health effects of transport policies and scenarios. Prospective research based on such improved data will be able to advance our understanding of the interaction between transport and health further and improve the quality of policies and decision-making. Future work could also apply the evidence established in this thesis to build a case for enhanced intersectoral collaboration with the aim to improve population health in the SSA region. Following the WHO recommendations, countries have made efforts to set up mechanisms and processes to facilitate collaboration and coordination across sectors. However, progress has been slow with one of the impeding factors being the scanty evidence on the magnitude of cross-sector health impacts which is needed to inform decisions around intersectoral resource allocation, particularly for projects which need resource commitment from different decision-makers with contrasting objectives and with separate budgets.

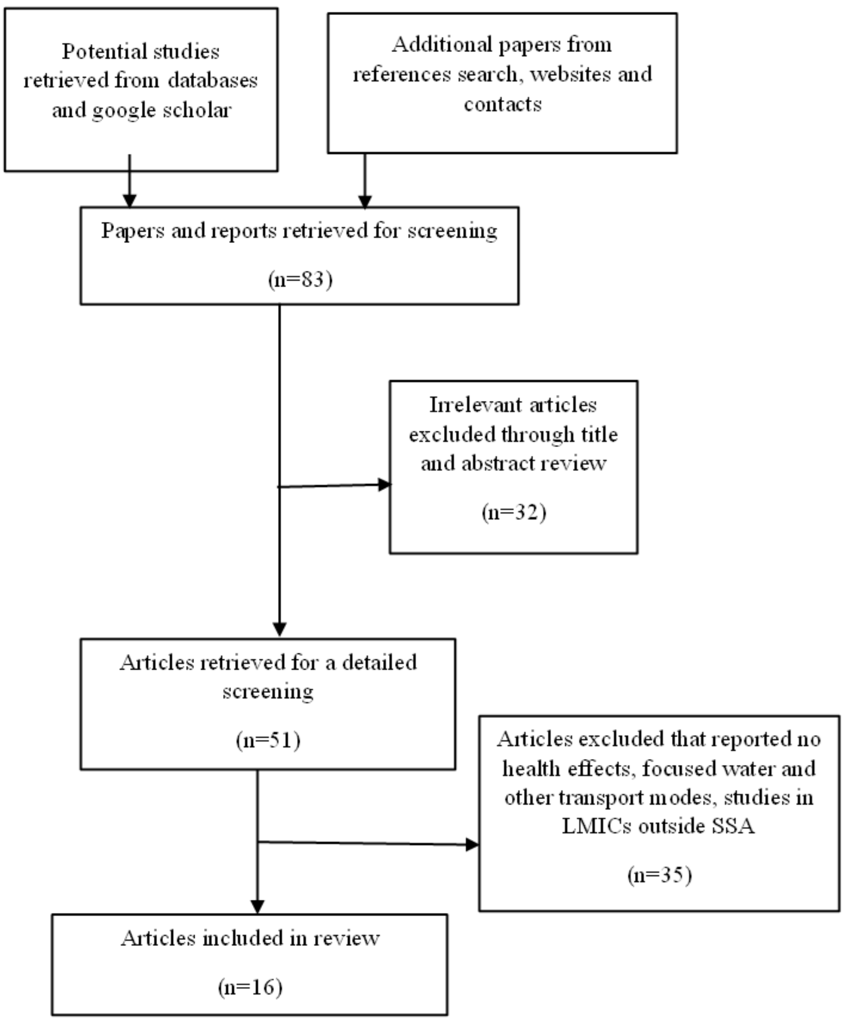
Appendices

Appendix A

Appendix to Chapter 2

A.1 Appendix figures

Figure A.1: Steps in literature selection



A.2 Appendix tables

Table A1: Economic evaluation studies by health effects, methods and country.

Classification	Previous studies
By evaluation method	
Cost Benefit analysis	Pienaar (2008)
	Cooke et al (2017)
	Harris Olukoga (2005)
	Miller (2019)
Cost effectiveness	Bishai et al (2008)
	Ralaidovy et al (2018)
	Chisholm, et al (2012)
	Muchapondwa (2010)
By health effects	
Road incidents	Bishai et al (2008)
	Pienaar (2008)
	Cooke et al (2017)
	Ralaidovy, et al (2018)
	Harris Olukoga (2005)
	Chisholm, et al (2012)
Vehicle emissions	Muchapondwa (2010)
	Miller (2019)
Physical activity	Cooke et al (2017)
By Country/ Region	
South Africa	Muchapondwa (2010)
	Cooke et al (2017)
	Harris Olukoga (2005)
Namibia	Pienaar (2008)
Uganda	Bishai et al (2008)
Nigeria	Miller (2019)
Sub-Saharan Africa	Ralaidovy, Ambinintsoa H., et al (2018)
	Chisholm, et al (2012)

Appendix B

Appendix to Chapter 3

B.1 Appendix tables

Table B1: Two-level glm estimates of RTI effects on economic welfare

	pr(HE>0)	pr(HE/TE>0.1)	HE	NHE	AI	Borrow	LFP
Fixed effects							
Intercept	0.896	0.185***	6.72	35.80***	0.043	0.075*	4.516***
	(0.385)	(0.063)	(1.813)	(11.15)	(0.0062)	(0.022)	(1.612)
Road traffic injury (no)							
yes	1.480***	1.314**	1.393**	0.773***	1.063*	1.251*	0.977
	(0.104)	(0.149)	(0.100)	(0.052)	(0.078)	(0.196)	(0.133)
Sex of h.head (male)							
female	1.064	0.942	0.975	0.922	1.038	1.165	0.249***
	(0.102)	(0.092)	(0.075)	(0.062)	(0.032)	(0.142)	(0.025)
Age of household head	0.988**	0.998	0.999	1.009*	1.006***	1.001	0.996
	(0.004)	(0.004)	(0.003)	(0.003)	(0.001)	(0.005)	(0.004)
Marital status (not married)							
married	0.873	0.914	0.97	1.506***	0.934	0.981	0.270***
	(0.098)	(0.106)	(0.089)	(0.106)	(0.033)	(0.143)	(0.032)
Residence(rural)							
urban	1.135	1.194**	1.272**	1.414***	1.806***	0.871	1.023
	(0.113)	(0.120)	(0.114)	(0.127)	(0.076)	(0.110)	(0.110)
urban#rti	1.175	1.331**	1.230**	0.592	1.913***	0.85	1.166
	(0.021)	(0.190)	(0.087)	(0.065)	(0.128)	(0.135)	(0.200)
urban#no_rti	1.056	1.198*	1.061	1.261	1.039	0.882	0.959
	(0.135)	(0.020)	(0.075)	(0.120)	(0.091)	(0.165)	(0.125)
Household size	1.048**	1.047*	1.013	0.972*	0.978***	1.03	1.046*
	(0.018)	(0.019)	(0.014)	(0.013)	(0.006)	(0.023)	(0.020)
Education level (none)							
primary	1.194	1.233	1.225	1.196	1.395***	0.916	0.903
	(0.136)	(0.141)	(0.134)	(0.147)	(0.082)	(0.132)	(0.109)
secondary	1.109	1.317*	1.567***	1.066	2.040***	0.858	1.142
	(0.148)	(0.178)	(0.168)	(0.125)	(0.115)	(0.146)	(0.163)
tertiary	1.628*	1.169	1.820***	2.565***	2.709***	0.651	2.550***
	(0.340)	(0.250)	(0.230)	(0.287)	(0.165)	(0.198)	(0.637)
Health status (good)							
average	1.567**	1.379**	0.966	0.813	0.881**	1.59***	0.817
	(0.180)	(0.153)	(0.084)	(0.089)	(0.037)	(0.218)	(0.098)
bad	1.438*	1.762**	1.363*	1.136	0.768***	1.838**	0.378***
	(0.258)	(0.306)	(0.179)	(0.230)	(0.137)	(0.040)	(0.006)
Illness (no)							
yes	1.605**	1.351**	1.101	0.668***	1.083*	1.273	0.895
	(0.152)	(0.130)	(0.084)	(0.042)	(0.034)	(0.160)	(0.091)
Alcohol consumption	1.002	1.001	1	0.968***	1.002	1.010*	1.007
	(0.036)	(0.004)	(0.003)	(0.006)	(0.001)	(0.004)	(0.005)
Health insurance (no)							
yes	1.63	0.577**	1.04	3.597***	1.281***	0.800	1.361
	(0.303)	(0.122)	(0.130)	(0.236)	(0.049)	(0.202)	(0.287)
Charged user fees (no)							
yes	1.004	1.478*	1.706*	1.056	1.191	1.236	0.993
	(0.423)	(0.469)	(0.432)	(0.289)	(0.147)	(0.200)	(0.339)
Per-capita gdp (lower)							
higher	0.429	0.629*	1.296	1.838*	1.918***	1.722**	0.788
	(0.194)	(0.216)	(0.346)	(0.512)	(0.248)	(0.298)	(0.289)
Random effects							
(intercept)	0.345	0.178	0.091	0.112	0.026	0.011	0.212
	(0.172)	(0.098)	(0.057)	(0.061)	(0.016)	(0.026)	(0.107)
Observations	2,463	2463	1435	2478	2478	2478	2452

Continuous dependent variables are logged; Coefficients are exponentiated; Standard errors in parentheses; column a=no controls, column b=with controls; HE=health expenditure,
NHE =household non health expenditure, TE=total consumption expenditure LFP=labour force participation,
AI=asset index; p* < 0.05, p** < 0.01, p*** < 0.001

Table B1 shows the GLM estimations with a full set of controls. The level of expenditure (likelihood to spend any amount, catastrophic expenditure, and amount spent) was also affected by household size, health insurance cover, region and country of residence, illness experience in the households, and self-assessed health status of the household head. For non-health expenditure, the table shows that households headed by married persons spent significantly more on household items. Households in areas classified as urban spent about a third more than rural ones. Education level makes a difference only at the tertiary level, Other significant factors associated with non-health consumption expenditure include alcohol consumption which is negatively associated, and health insurance which is positively associated. There is also a positive association based on whether a household is drawn from a category with higher per capita GDP than the average of the 10 countries.

Table B2: Generalised Linear Model estimates -sub samples

Outcome variable	**Full sample**	**Sub sample**	**Sub sample**
	(all RTIs)	(RTI six months or less)	(RTI more than six months)
Positive health expenditure	1.480***	1.536**	1.255**
	(0.104)	(0.032)	(0.091)
Catastrophic health expenditure	1.314**	1.350**	1.110**
	(0.149)	(0.138)	(0.027)
Magnitude of health expenditure†	1.393***	1.432**	1.303**
	(0.100)	(0. 171)	(0.116)
Non health expenditure†	0.773***	0.789***	0.745***
	(0.052)	(0.123)	(0.191)
Asset index†	1.063*	1.087*	1.06
	(0.078)	(0.259)	(0.092)
Borrowed funds	1.251**	1.458***	1.431**
	(0.196)	(1.331)	(0.279)
Labour force participation	0.977	1.136*	0.835
	(0.133)	(0.491)	(0.137)

† indicates log-transformed continuous dependent variables, the rest are binary outcomes; all coefficients are exponentiated; Standard errors in parentheses ;
$p^* < 0.05$, $p^{**} < 0.01$, $p^{***} < 0.001$

B.2 Asset index construction

The asset index is constructed based on ownership of 11 assets: a bicycle, motor vehicle, refrigerator, washing machine, dishwasher, sewing machine, telephone, cell phone, computer, Television set, and radio. We then use Multiple Correspondence Analysis (MCA) to construct a composite asset ownership Indicator. With all variables being categorical, MCA a variant of Principal Component Analysis is preferred as it makes fewer assumptions on the underlying distributions of variables (Asselin 2009). MCA is a data combination technique based on correlation patterns over a set of variables described by a single component, the principal components. Principal components are unobserved variables that account for the maximum variance of a given set of other variables (Joliffe & Morgan 1992). The first principal component represents a latent variable that captures the highest variance of all observed variables used in the analysis and is therefore the best single-dimensional candidate to represent all the variables considered (Ezzrari & Verme 2013). The resulting composite indicator is normalized to make it meaningful and comparable across households. A min-max normalization technique shown in equation 2.5 is used to convert the negative values of the composite indicator to non-negative. This technique has previously been applied in the construction of indices such as the Human Development Index (HDI) (Sen & Anand 1994).

$$Normalised\ asset\ ownership\ index = \frac{(Composite\ indicator - Minimum\ value)}{(Maximum\ value - minimum\ value)} \tag{B.1}$$

The normalised asset index takes values between zero and one with the higher value suggesting ownership of a higher number of assets. Ownership of fewer assets is assumed to indicate that households either have inadequate funds to purchase assets or sold some of their assets to meet other household demands.

B.3 Missing values in the data

The data is complete for most variables used in the analysis other than the health insurance variable which had more than two-thirds of observations missing. We constructed an alternative health insurance variable based on which households had made payments for health insurance premiums. We then run Little (1988) tests on the pattern of the remaining missing values, which suggests that the data were missing completely at random. We deal with missing values through listwise deletion reducing the number of observations from 39,158 to 38,161 households. The remaining sample is sufficiently large to abate concerns over reduced statistical power.

B.4 Choice of matching approach

We explore four matching approaches: exact matching, coarsened exact matching, propensity score matching, and genetic matching. All the matching procedures are conducted using the statistical software R. To assess the comparability of treatment and control groups after matching, we use a measure of balance which makes a joint comparison of the standard deviation of covariates and their means, the standardized difference in means (SMD). SMD estimates the distance between standardized means between treatment and control groups and is defined for continuous variables as;

$$SMD = \frac{\bar{X_T} - \bar{X_C}}{\sqrt{\frac{S_T^2 - S_C^2}{2}}} \tag{B.2}$$

where $\bar{X_T}$ and $\bar{X_C}$ are the sample means for the treated and control groups, respectively; S_T^2 and S_C^2 are sample variance for the treated and control groups. For categorical variables, raw differences in proportion are already on the same scale, hence computing the standardized difference for categorical variables did not provide additional value. SMD is shown to be a robust measure and often dominates other measures of balance (Linden & Samuels 2013). For each covariate, a mean difference statistic is estimated, we also estimate the overall mean difference for the comparison of different matching approaches. Table B.3 shows a summary of matching results, average SMD, and the number of matched treated observations for each matching approach are presented.

Table B3: Summary of matching outputs

Matching methods	**Number of observations dropped**	**Number of observations matched**	**Average standardized adjusted mean differences**
Exact matching	487	336	0
CEM -automatic	430	393	0.0003
CEM-user defined	190	633	0.0027
Propensity score	0	823	0.0065
Genetic matching	0	823	0.0031

Between the different approaches, the differences in mean balancing score are minimal, so our choice is mainly informed by the number of observations matched. Genetic matching produces a relatively more balanced match for this sample and also maintains the full sample of treated households. Therefore, Genetic matching is used to match the sample used in subsequent analysis. Figure B.1 plots the standardized mean differences before and after matching for each of the covariates.

B.5 Appendix figures

Figure B.1: Within country Genetic match balance

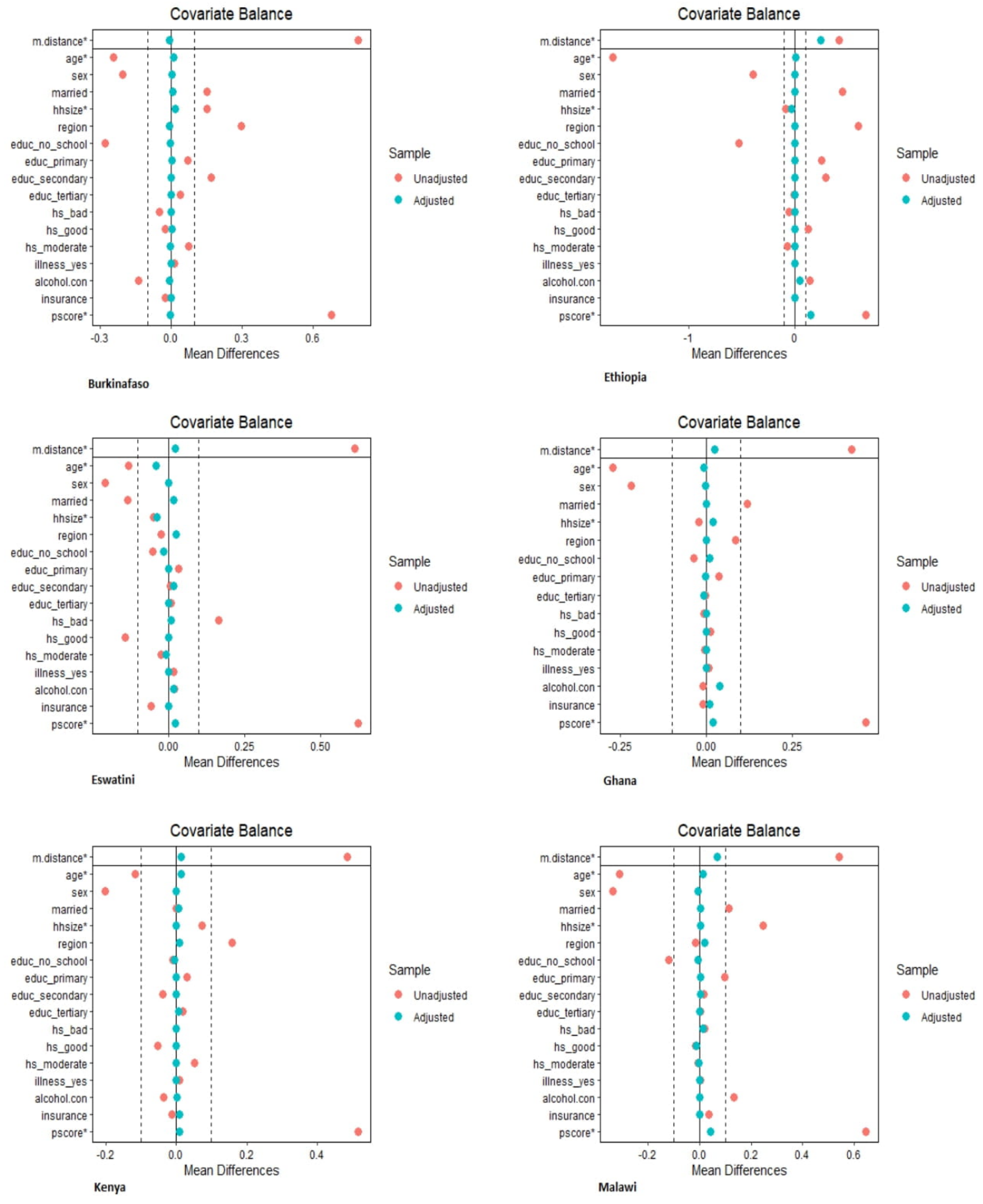
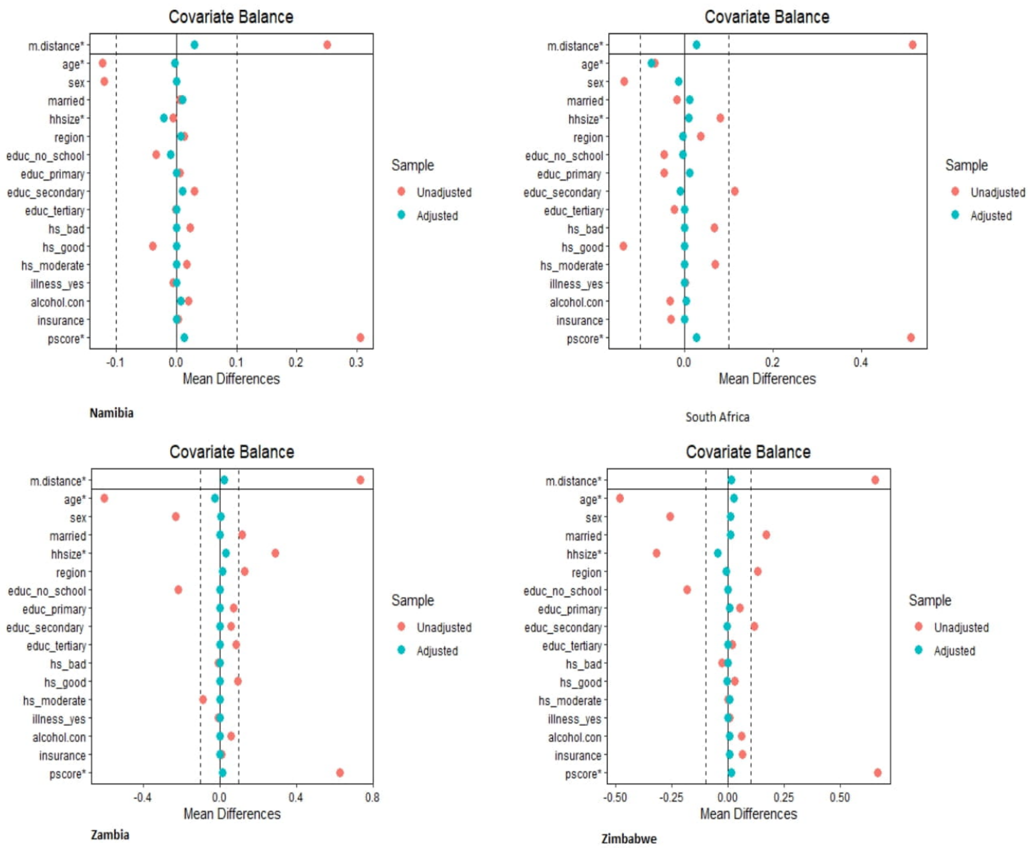


Figure B.2: Within country Genetic match balance cont..



1.hhsize=household size .
2.educ=level of education [none, primary, secondary, tertiary]
3.hs=health status [bad, moderate, good]

Appendix C

Appendix to Chapter 4

C.1 Appendix tables

Table C1: Road projects between 2016 and 2018 and affected districts

Project name	Description	Completion date	Areas affected	Change in road status
Ugrading: Liwonde-Mangochi road	Involves upgrading of a 75 Km stretch of road to bitumen standard from Liwonde to Bakili Muluzi Bridge at Mangochi Boma	start: January 2015 end: August 2018	Mangochi	unpaved to paved
Ugrading: Lilongwe old airport – Kwanyanda- Santhe and Kasiya spur road project	This is a 95 km long road project starts from the M12 (the Lilongwe to Mchinji road) and joins the M18 at Santhe Trading Centre in Kasungu District. The project involves upgrading of the existing earth road to class 1 bitumen standard, and construction of a four-span bridge across the Bua River and culverts on other river crossings.	start: January 2015 end: August 2018	Mchinji Kasungu Lilongwe	Unpaved to paved
Ugrading: Chikwawa – Chapananga road	This involves upgrading of a 47Km long Chikwawa-Chapamanga stretch which is part of the 109-kilometer Chikwawa Mwanza (S136) road.	Start: 2013 End: September 2017	Mwanza, Chikhwawa	Unpaved to paved
Upgrading: jenda-edingeni road project	The project upgrades of 53 km long road to class 1 bitumen standard class 1 from Jenda to Edingeni.	Start :2011 End: 2017	Mzimba	Unpaved to paved
Upgrading: milepa-chiladzulu road section	The project upgrade the road from gravel surface to class 1 bitumen. This 21.4 km section starts at Milepa and stops at Chiladzulu boma. Also involved construction of a single span reinforced concrete bridge	Start: 2012 end: May 2017	Mulanje	Unpaved to paved status
Upgrading: lirangwe-chingale-machinga road project	The 61.2 km long, Lirangwe-Chingale-Machinga Road designated as S139 starts at Lirangwe Trading Centre in Blantyre District. The road extends northwards passing through Chingale and Chinseu Trading Centres.	Partially complete as of July 2019	Mangochi, Machinga blantyre	Unpaved to paved
Rehabilitation: chikhwawa – ngabu – bangula road	Rehabilitation of 81.74km of road from Chikwawa to Bangula Trading Centre to bitumen class 1 standard with sealed shoulder	Start: 2014 end: 2016	Chikhwawa, Nsanje	Rehabilitation of previously paved road
Rehabilitation: Blantyre-Zomba Road Project	Road rehabilitation and widening from Blantyre through Chiradzulu to Zomba	Start: 2011 end: 2017	Zomba, Chiradzulu, blantrye	Rehabilitation of previously paved road

Table C2: Variable definitions

Variable	Definition [options]	Source
Outcome variables		
Transportation cost	Fraction of total household consumption expenditure that a household spent on travel to and from a health facility during the last 12 months. [continuous variable]	LSMS-HIS
Consumption expenditure	Amount spent on food and non-food expenditure including general transportation expenses [continuous variable]	
Respiratory health	Whether a member of household experienced symptoms of respiratory illness in two weeks before the survey. [0. no 1. yes]	
Utilization of health services	whether members of household received health service from a health facility after falling sick [0. no 1. yes]	
Control variables		
Distance to health facility	distance between household location and the nearest health facility [continuous variable]	Estimates using geo coded health facility data from ministry of health database on health facility location and year facility started operating[1])
Distance to major road	distance between household location and nearest major road (include main, secondary, and tertiary roads and excludes urban and community roads)	LSMS-HIS
Paved road	Nearest major road is paved to bituminous standard. 1. Yes, 0.no	Roads database
Road density	District level road density estimated as the total number of road kilometers over total land area	Roads database
Sex	whether household head is male or female [0. Female, 1. Male]	LSMS-HIS
Prop. of male members	Share of male household members	
Prop. of hh members 0-5 years	Share of household members aged 0 to 5 years	LSMS-HIS
Prop. of hh members 6-18 years	Share of household members aged 6 to 18 years	
Prop. of hh members 19-45 years	Share of household members aged 19 to 45 years	
Prop. of hh members older than 45	Share of household members aged above 45 years	
Age	Age of household head in years [continuous]	LSMS-HIS
Household size	number of people living in the household	
Education	highest level of schooling attended or completed [0. none 1. primary 2. secondary 3. tertiary]	
Urban residence	1.Urban; 0. rural	
Household asset index	index constructed using principal component analysis based on ownership of household durable assets, such as radio, telephone, refrigerator.	

Variable	Definition [options]	Source
Household negative shock	If a household affected negatively by any of the adverse events such death of a member, drought, flood etc.	LSMS-HIS
MDPI	District level Mutidimensional poverty index	Oxford Poverty and Human Development Initiative reports
Household has chronically ill member	There is atleast one person in the household suffering from longterm illness	LSMS-HIS
Distance to business center	distance to nearest business center (includes services such as a shop and a market, school, fuel station [continuous variable in kilometres]	LSMS-HIS
Distance to nearest admarc	distance to agricultural Development and Marketing Corporation [continuous]	
Distance to Pop Center with 20'000	distance to nearest settlement centre with more than 2000 people [continuous variable in kilometres]	LSMS-HIS
Distance to district Headquarters	distance to nearest district headquarters [continuous variable in kilometres]	
Cooking fuel	the type of fuel that the household mainly uses for cooking [0. Clean (electricity, natural gas, biogas) 1. Non-clean (wood, charcoal etc.)]	LSMS-HIS
Housing floor material	main material of the floor of the dwelling [1. finished floor (Parquet, polished wood, Ceramic tiles, Cement Carpet) 1. Natural floor (sand, earth, dung)].	LSMS-HIS
Average annual rainfall (mm)	Amount of rainfall received in a year	
Intervention		
Distance to upgraded road	distance between household location and nearest upgraded road	Estimates based on data from roads authority

Table C3: Nearest neighbour match balance

Variable	Mean control	Mean Treatment	diff
Age of head	41.7	41.29	0.412*
Head is male	0.756	0.736	0.021
Proportion of male members	0.523	0.531	-0.008
Fraction hh members 0-5 years	0.183	0.192	-0.008
Fraction hh members 6-18 years	0.329	0.323	0.005
Fraction hh members 19-45 years	0.366	0.362	0.004
Fraction hh members older than 45	0.168	0.157	0.01
Household size	5.017	4.912	0.105*
Education of head	0.019	0.014	0.005
Primary	0.711	0.655	0.056
Secondary	0.169	0.189	-0.02
Tertiary	0.036	0.036	-0.001
Urban residence	0.113	0.099	0.013
Household asset index	0.964	0.959	0.005
Household negative shock	0.752	0.778	-0.026
Distance to major road (KM)	9.06	9.693	-0.633
Nearest road is paved	0.364	0.347	0.017
Road density (KM/SQKM)	0.157	0.152	0.006
Nearest health facility (KM)	3.549	3.941	-0.392
Multidimensional poverty index	0.296	0.292	0.004

Table C4: Weighted sample statistics

Variable	Full sample	Control	Treatment	raw (diff)	weighted (diff)
Age of head	41.910	42.293	41.639	0.654*	0.421*
Head is male	0.753	0.743	0.760	-0.017	0.014
Proportion of male members	0.593	0.601	0.585	0.016	0.002
Fraction hh members 0-5 years	0.169	0.178	0.162	0.016	0.007
Fraction hh members 6-18 years	0.314	0.326	0.305	0.021*	0.000
Fraction hh members 19-45 years	0.371	0.330	0.402	-0.072	0.000
Fraction hh members older than 45	0.146	0.166	0.131	0.035*	0.013*
Household size	4.703	4.767	4.657	0.110*	0.021
Education of head					
Primary	0.610	0.707	0.542	0.164***	0.019
Secondary	0.258	0.172	0.319	-0.147***	-0.045
Tertiary	0.132	0.122	0.139	-0.017*	0.011**
Urban residence	0.265	0.201	0.416	-0.364***	0.026
Household asset index	0.913	0.955	0.883	0.072***	0.007*
Household negative shock	0.817	0.869	0.781	0.088***	0.011
Distance to major road (km)	7.251	9.008	6.009	2.999***	0.011
Nearest road is paved	0.446	0.294	0.569	-0.275***	0.006
Road density (km/sqkm)	0.156	0.156	0.155	0.001	-0.0009
Nearest health facility (km)	2.935	3.330	2.656	0.673***	0.031
Multidimensional poverty index	0.237	0.242	0.232	0.010	0.000
Distance to nearest market	23.156	25.665	22.437	3.228	0.021
Distance to nearest admarc	7.054	8.040	6.293	1.747	0.199
Distance to Pop Center with 20'000	30.148	33.152	28.888	4.264	0.0.304
Distance to district Headquarters	59.586	50.672	56.462	-5.791	1.041
Average annual rainfall (mm)	597.052	620.88	580.200	40.684***	-4.454

Table C5: Impact on transport expenditure: tpm

	Dependent variable: Expenditure on transport as proportion of total household expenditure				
	(1)	(2)	(3)	(4)	(5)
Independent	DiD	DiD with controls	PSM+DiD	IPW+DiD	Gen-match+DiD
Road development	0.199	0.333	0.346	-0.0320	0.130
	(0.211)	(0.234)	(0.237)	(0.268)	(0.274)
After	0.214	0.351	0.322	0.232	0.441*
	(0.196)	(0.226)	(0.235)	(0.307)	(0.244)
Road development x After	-0.262	-0.287	-0.245	-0.1000	-0.185
	(0.292)	(0.301)	(0.307)	(0.380)	(0.344)
Age of head		-0.00146	-0.00203	-0.00879	-0.00590
		(0.00722)	(0.00735)	(0.0084)	(0.00815)
Head is male		0.508**	0.544**	0.607**	0.146
		(0.242)	(0.247)	(0.285)	(0.271)
Urban residence		0.105	0.136	0.261	0.139
		(0.249)	(0.255)	(0.342)	(0.278)
Education: secondary		-0.00593	-0.00168	0.303	-0.0116
		(0.191)	(0.197)	(0.269)	(0.208)
Education: Tertiary		0.00136	0.0616	0.0964	0.0342
		(0.252)	(0.259)	(0.298)	(0.280)
Household size		-0.167	-0.267	-0.735**	-0.0409
		(0.302)	(0.312)	(0.335)	(0.323)
Fraction of males		0.707**	0.773**	0.825**	0.745*
		(0.358)	(0.375)	(0.379)	(0.385)
Fraction hh members 0-5 years old		-0.434*	-0.318	-0.175	-0.438
		(0.258)	(0.263)	(0.403)	(0.276)
Fraction hh members 6-18 years old		-0.0599	-0.0587	-0.0607	-0.186
		(0.250)	(0.262)	(0.279)	(0.273)
Fraction hh members 19-45 years		0.0321	0.0971	0.866**	0.0576
		(0.368)	(0.376)	(0.421)	(0.401)
Fraction hh members older than 45		0.0316	-0.114	0.675	0.503
		(0.654)	(0.769)	(0.996)	(0.719)
Household asset index		-0.033***	-0.030***	-0.025**	-0.036***
		(0.0108)	(0.0110)	(0.0127)	(0.0137)
Distance to major road (km)		0.372*	0.402*	0.856***	0.240
		(0.206)	(0.213)	(0.282)	(0.224)
Household negative shock		-1.071	-0.826	-0.720	-1.650
		(1.028)	(1.066)	(1.372)	(1.118)
Multidimensional poverty index		-1.205	-1.856	-0.133	-1.443
		(1.756)	(1.834)	(1.761)	(1.902)
Road density (km/sqkm)		0.333	0.346	-0.0320	0.130
		(0.234)	(0.237)	(0.268)	(0.274)
Household has chronically ill member		-2.397**	-2.212*	-3.255**	-1.777
		(1.123)	(1.255)	(1.542)	(1.250)
Nearest health facility (km)		0.0284	0.0101	0.0152	0.0359
		(0.0420)	(0.0432)	(0.0461)	(0.0531)

Continued on next page

	Dependent variable: Expenditure on transport as proportion of total household expenditure				
	(1)	(2)	(3)	(4)	(5)
Independent	DiD	DiD with controls	PSM+DiD	IPW+DiD	Genmatch +DiD
Constant	-2.329***	-2.403***	-2.246**	-3.359***	-2.096**
	(0.145)	(0.894)	(1.007)	(1.268)	(0.986)
Observations	2,104	2,104	1,985	2,104	1,682
Part two					
Road development	1.352***	0.683**	0.645*	0.584**	0.489
	(0.361)	(0.329)	(0.338)	(0.258)	(0.374)
After	1.021***	0.359	0.382	0.311	0.315
	(0.336)	(0.327)	(0.348)	(0.286)	(0.349)
Road development x After	-1.136**	-0.870**	-0.914	-0.780**	-0.569
	(0.500)	(0.440)	(0.456)	(0.379)	(0.506)
Age of head		0.0112	0.0109	0.0144*	0.0169
		(0.0104)	(0.0110)	(0.00778)	(0.0125)
Head is male		-0.236	-0.300	-0.0760	-0.0532
		(0.355)	(0.367)	(0.296)	(0.377)
Urban residence		-0.166	-0.220	-0.0306	-0.0951
		(0.450)	(0.468)	(0.376)	(0.521)
Education: secondary		-0.0531	-0.119	-0.145	-0.0477
		(0.284)	(0.294)	(0.221)	(0.318)
Education: Tertiary		0.441	0.433	0.450	0.327
		(0.369)	(0.389)	(0.380)	(0.409)
Household size		-0.395	-0.312	-0.659*	-0.430
		(0.436)	(0.459)	(0.364)	(0.449)
Fraction of males		-1.830**	-1.909**	-0.965	-2.888***
		(0.790)	(0.836)	(0.703)	(0.890)
Fraction hh members 0-5 years old		0.143	0.0754	0.220	-0.0248
		(0.323)	(0.336)	(0.370)	(0.358)
Fraction hh members 6-18 years old		0.969**	0.947**	0.855**	1.434***
		(0.446)	(0.478)	(0.357)	(0.476)
Fraction hh members 19-45 years		0.812	0.819	0.839*	0.665
		(0.557)	(0.582)	(0.505)	(0.635)
Fraction hh members older than 45		4.990***	4.851***	4.960***	5.404***
		(1.044)	(1.239)	(1.019)	(1.167)
Household asset index		0.0171	0.0171	0.0292*	0.0337
		(0.0149)	(0.0152)	(0.0154)	(0.0215)
Distance to major road (KM)		-0.161	-0.184	-0.0511	-0.355
		(0.298)	(0.313)	(0.316)	(0.323)
Household negative shock		-1.065	-1.306	-1.062	-0.391
		(1.669)	(1.741)	(1.248)	(1.940)
Multidimensional poverty index		-0.941	-0.504	-1.773	-1.409
		(2.722)	(2.917)	(1.313)	(3.003)
Road density (km/sqkm)		0.683**	0.645*	0.584**	0.489
		-0.329	-0.338	-0.258	-0.374

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	Dependent variable: Expenditure on transport as proportion of total household expenditure				
	(1)	(2)	(3)	(4)	(5)
Independent	DiD	DiD with controls	PSM+DiD	IPW+DiD	Genmatch +DiD
Household has chronically ill member		0.0194	0.0189	0.0012	0.0335
		-2.722	-2.917	-1.313	-3.003
Nearest health facility (km)		-0.0713	-0.066	-0.123***	-0.112
		-0.0682	-0.0702	-0.0448	-0.0882
Constant	-2.451***	-6.315***	-6.066***	-6.892***	-6.806***
	-0.25	-1.398	-1.585	-1.107	-1.519
Observations	392	392	157	392	151

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p*<0.1; Part one of the two part model (tpm) is logistic estimation in the DiD framework and part two is a GLM estimation. Column label (1) is a difference in difference estimation on transport expenditure using unmatched dataset and with no controls. Column label (2) is difference in difference estimation on consumption expenditure using unmatched dataset and with controls. Column label (3) is difference in difference estimation on matched dataset using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset using Genetic matching approach.

Table C6: Impact on consumption expenditure (treated is within 10km of interevention)

	Dependent: log of consumption expenditure				
	(1)	(2)	(3)	(4)	(5)
Independent	DiD	DiD with controls	PSM+DiD	IPW+DiD	Gen-match+DiD
After	0.0135**	0.0317***	0.0259	0.0267**	0.0298**
	(0.00572)	(0.00935)	(0.0161)	(0.0122)	(0.0135)
Road devpt	0.815***	0.889***	0.8701***	0.944***	0.495***
	(0.0130)	(0.0143)	(0.0152)	(0.0178)	(0.0180)
Road devpt x After	0.054***	0.0492***	0.0379*	0.0343*	0.0645***
	(0.0155)	(0.0165)	(0.0203)	(0.0192)	(0.0195)
Age of head		-0.00163***	-0.0015***	-0.00122*	-0.000465
		(0.000503)	(0.0005)	(0.000673)	(0.000538)
Head is male		0.0605***	0.0515***	0.0530***	0.0815***
		(0.0158)	(0.0140)	(0.0163)	(0.0179)
Urban residence		-0.0120	-0.0023	-0.0306*	0.151***
		(0.0125)	(0.0210)	(0.0178)	(0.0210)
Education: secondary		0.0444***	0.0520***	0.0470**	0.0699***
		(0.0123)	(0.0146)	(0.0188)	(0.0135)
Education: Tertiary		-0.0525***	-0.0286	-0.00768	0.0940***
		(0.0177)	(0.0190)	(0.0261)	(0.0229)
Household size		0.0146***	0.0129***	0.0112***	0.0165***
		(0.00255)	(0.0024)	(0.00275)	(0.00301)
Fraction of males		-0.00519	-0.0044	-0.0712***	-0.0512***
		(0.0172)	(0.0179)	(0.0171)	(0.0197)
Fraction members 0-5 yrs		-0.0262	-0.0309	-0.0723***	-0.0456*
		(0.0201)	(0.0223)	(0.0213)	(0.0250)
Fraction of members 6-18 yrs		0.00409	0.0146	0.0275*	0.0165
		(0.0128)	(0.0136)	(0.0154)	(0.0155)
Fraction hh members 19-45 yrs		0.0157	0.0045	-0.0214	0.0415**
		(0.0136)	(0.0170)	(0.0144)	(0.0182)
Fraction hh members > 45		-0.0305	-0.0428*	-0.0945***	-0.00513
		(0.0218)	(0.0246)	(0.0254)	(0.0264)
Household asset index		-0.429***	-0.8927***	-0.682***	-0.532***
		(0.0500)	(0.0889)	(0.0736)	(0.0431)
Distance to major road (km)		-0.00220***	-0.0020***	-0.0016***	-0.0028***
		(0.00064)	(0.0006)	(0.00059)	(0.000552)
Household negative shock		0.0157	0.0390**	0.00220	-0.00383
		(0.0113)	(0.0155)	(0.0157)	(0.0135)
Multidimensional pov. index		-0.113*	-0.1596**	-0.190**	-0.0386
		(0.0583)	(0.0800)	(0.0765)	(0.0732)
Road density (km/sqkm)		0.00706	-0.0480	-0.113	0.0802
		(0.119)	(0.1112)	(0.107)	(0.0985)
Rainfall (mm)		6.10e-05	3.12e-05	1.89e-05	1.92e-05
		(4.49e-05)	(4.10e-05)	(4.75e-05)	(5.54e-05)
Constant	0.775***	1.061***	1.574***	1.386***	0.710***
	(0.00495)	(0.0662)	(0.0989)	(0.0879)	(0.0514)
Observations	2,104	2,104	2,027	2,104	1,682
R-squared	0.760	0.802	0.8447	0.888	0.748

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; Column label (1) is a difference in difference estimation using unmatched dataset and with no controls. Column label (2) is difference in difference estimation using unmatched dataset and with controls. Colum label (3) is difference in difference estimation on matched dataset using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset using Genetic matching approach.

Table C7: Impact on health services utilisation (treated is within 10km of intervention)

	Dependent: Binary variable for health care utilisation				
Independent	(1) DiD	(2) DiD with controls	(3) PSM+DiD	(4) IPW+DiD	(5) Gen-match+DiD
After	-0.0687**	-0.0984***	0.0484	-0.121**	-0.0781*
	(0.0326)	(0.0369)	(0.0477)	(0.0522)	(0.0421)
Road development	0.0453	-0.000179	0.0968***	-0.0380	0.0390
	(0.0354)	(0.0425)	(0.0364)	(0.0517)	(0.0465)
Road development x After	0.0208	0.0791	-0.0683	0.203**	0.0325
	(0.0509)	(0.0523)	(0.0593)	(0.0687)	(0.0584)
Age of head		-0.000637	-0.00256	-0.00137	-0.000757
		(0.00119)	(0.00160)	(0.00146)	(0.00132)
Head is male		0.000224	0.0291	0.0101	0.00288
		(0.0345)	(0.0445)	(0.0413)	(0.0426)
Urban residence		-0.0589	-0.0799	-0.134**	-0.0365
		(0.0457)	(0.0490)	(0.0630)	(0.0506)
Education: secondary		0.00810	-0.00108	-0.0342	0.00758
		(0.0331)	(0.0359)	(0.0550)	(0.0361)
Education: Tertiary		0.0352	0.00576	0.0578	0.0658
		(0.0426)	(0.0532)	(0.0517)	(0.0480)
Household size		0.0204***	0.00755	0.0169**	0.0194***
		(0.00542)	(0.00762)	(0.00705)	(0.00595)
Fraction of males		-0.00280	-0.0959*	-0.0171	-0.00824
		(0.0479)	(0.0580)	(0.0530)	(0.0517)
Fraction hh members 0-5 years		0.158***	0.192***	0.115*	0.155**
		(0.0556)	(0.0733)	(0.0654)	(0.0670)
Fraction hh members 6-18 years		0.0159	0.0977***	0.0339	-0.00903
		(0.0293)	(0.0331)	(0.0342)	(0.0365)
Fraction hh members 19-45 years		-0.0437	-0.0408	-0.0498	-0.0361
		(0.0287)	(0.0529)	(0.0337)	(0.0311)
Fraction hh members older than 45		-0.0863	-0.0187	-0.0775	-0.0883
		(0.0641)	(0.0909)	(0.0783)	(0.0708)
Household asset index		-0.0772	-0.878***	-0.358**	-0.0418
		(0.114)	(0.156)	(0.173)	(0.118)
Distance to major road (km)		-0.0012	-0.0053**	-0.0025	-0.0020
		(0.00152)	(0.00213)	(0.00169)	(0.00187)
Household negative shock		0.0139	0.101***	0.0921	0.0153
		(0.0350)	(0.0368)	(0.0591)	(0.0384)
Multidimensional pov. index		-0.379**	-0.0853	-0.236*	-0.305*
		(0.186)	(0.206)	(0.255)	(0.204)
Road density (km/sqkm)		0.602**	0.568*	0.156	0.687**
		(0.264)	(0.333)	(0.632)	(0.286)
Nearest health facility (km)		-0.0158**	-0.00525	-0.0213**	-0.00402
		(0.00684)	(0.00832)	(0.00868)	(0.00890)
Constant	0.724***	0.788***	1.493***	1.157***	0.687***
	(0.0233)	(0.152)	(0.196)	(0.203)	(0.159)
Observations	1,319	1,319	967	1,319	1,043
R-squared	0.008	0.055	0.087	0.073	0.053

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; Column label (1) is a difference in difference estimation using unmatched dataset and with no controls. Column label (2) is difference in difference estimation using unmatched dataset and with controls. Colum label (3) is difference in difference estimation on matched dataset using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset using Genetic matching approach.

Table C8: Impact on respiratory health (Treated within 10km of intervention)

	Dependent: Binary variable for respiratory illness				
	(1)	(2)	(3)	(4)	(5)
Independent	DiD	DiD with controls	PSM+DiD	IPW+DiD	Gen-match+DiD
After	-0.0624***	-0.0473*	-0.107***	-0.0922***	-0.0439
	(0.0212)	(0.0256)	(0.0288)	(0.0351)	(0.0319)
Road development	-0.0394	-0.0220	-0.071***	-0.0372	-0.0243
	(0.0243)	(0.0288)	(0.0246)	(0.0354)	(0.0373)
Road development x After	0.0521	0.0617*	0.124***	0.0807*	0.0658
	(0.0330)	(0.0359)	(0.0361)	(0.0432)	(0.0516)
Age of head		-0.000663	-0.000413	-0.000989	-0.000106
		(0.000727)	(0.00093)	(0.000879)	(0.000943)
Head is male		0.0160	0.0221	0.00643	0.0415
		(0.0219)	(0.0292)	(0.0267)	(0.0280)
Urban residence		-0.0390	-0.0707**	-0.0608*	-0.0162
		(0.0273)	(0.0287)	(0.0349)	(0.0297)
Education: secondary		0.0165	0.061***	0.00485	0.0239
		(0.0231)	(0.0218)	(0.0269)	(0.0311)
Education: Tertiary		-0.0253	-0.0576*	-0.00147	-0.0579*
		(0.0252)	(0.0297)	(0.0384)	(0.0306)
Household size		0.00706*	0.00737	0.00647	0.0907
		(0.00417)	(0.00454)	(0.00482)	(0.00495)
Fraction of males		-0.0275	-0.0486	-0.0239	-0.00670
		(0.0245)	(0.0297)	(0.0216)	(0.0327)
Fraction hh members 0-5 years old		0.00901	0.0529	0.0328	-0.0106
		(0.0309)	(0.0423)	(0.0372)	(0.0382)
Fraction hh members 6-18 years old		0.00945	0.0135	0.00621	-0.0111
		(0.0160)	(0.0208)	(0.0172)	(0.0269)
Fraction hh members 19-45 years		0.00688	0.0245	0.000604	0.00379
		(0.0175)	(0.0250)	(0.0169)	(0.0238)
Fraction hh members older than 45		0.0127	0.0150	0.0124	0.000773
		(0.0324)	(0.0440)	(0.0336)	(0.0414)
Household asset index		0.0131	0.0508	0.114	0.0253
		(0.0805)	(0.0775)	(0.0854)	(0.143)
Distance to major road (KM)		0.00178*	0.00137	0.000383	7.22e-05
		(0.00101)	(0.00121)	(0.00106)	(0.00112)
Household negative shock		0.0283	0.0296	0.0381	0.0327
		(0.0214)	(0.0222)	(0.0233)	(0.0302)
Multidimensional poverty index		-0.164	-0.663***	-0.122	-0.214
		(0.111)	(0.116)	(0.137)	(0.184)
Road density (KM/SQKM)		0.389***	0.00410	0.262	0.454***
		(0.142)	(0.240)	(0.166)	(0.161)
Cooking fuel: firewood		0.0384	0.075***	0.0120**	0.0632*
		(0.0251)	(0.0254)	(0.0299)	(0.0385)
Floor type: mud/dung/soil		0.00167	0.00116	0.00536	0.0255
		(0.0260)	(0.0264)	(0.0293)	(0.0330)
Roof type: Grass/asbestos		0.00696	0.0572**	0.00495	0.00817
		(0.0229)	(0.0259)	(0.0264)	(0.0285)
Constant	0.205***	0.197*	0.316***	0.159	0.248
	(0.0165)	(0.101)	(0.113)	(0.124)	(0.168)
Observations	2,104	2,104	1,973	2,104	1,208
R-squared	0.004	0.018	0.043	0.025	0.020

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; Column label (1) is a difference in difference estimation using unmatched dataset and with no controls. Column label (2) is difference in difference estimation using unmatched dataset and with controls. Colum label (3) is difference in difference estimation on matched dataset using nearest neighbour approach. Column label (4) is difference in difference estimation on inverse probability weighted dataset. Column label (5) is difference in difference estimation on matched dataset using Genetic matching approach.

Table C9: Regression estimations with distance to road project as continuous variable

Variables	(1) Consumption expenditure	(2) Transport expenditure	(3) Health care utilisation	(4) Respiratory illness
Road development	-0.0215***	-5.60e-06	-3.97e-05	5.52e-05***
	(0.00491)	(6.79e-06)	(2.58e-05)	(1.99e-05)
Age of head	0.886***	7.52e-05	0.000711	0.000956*
	(0.133)	(0.000184)	(0.000700)	(0.000544)
Head is male	-55.47***	0.00103	0.0628**	0.0625***
	(5.001)	(0.00695)	(0.0264)	(0.0203)
Household asset index	439.7***	0.0280	-0.0189	-0.103
	(16.23)	(0.0226)	(0.0856)	(0.0737)
Education: secondary	-5.909	-0.0117	7.56e-05	-0.00397
	(5.145)	(0.00715)	(0.0271)	(0.0209)
Education: Tertiary	-25.87**	-0.00599	-0.121**	-0.0445
	(11.43)	(0.0158)	(0.0601)	(0.0460)
Distance to major road (km)	1.792***	-0.000253	-0.00606***	-0.00103
	(0.247)	(0.000349)	(0.00132)	(0.000997)
Household negative shock	-14.25***	0.0145**	0.114***	0.0148
	(4.087)	(0.00565)	(0.0214)	(0.0167)
Multidimensional poverty index	142.2***	-0.0377	-0.108	-0.274***
	(21.74)	(0.0313)	(0.119)	(0.0903)
Road density (km/sqkm)	30.29	0.00592	0.294	-0.176
	(45.10)	(0.0628)	(0.238)	(0.182)
Cooking fuel: firewood				0.116***
				(0.0259)
Floor type: mud/dung/soil				0.0142
				(0.0246)
Roof type: Grass/asbestos				0.00161
				(0.0228)
Nearest health facility (km)		0.000131	-0.00221	
		(0.00162)	(0.00614)	
Constant	-842.0***	-0.00851	0.374***	0.175**
	(18.38)	(0.0254)	(0.0964)	(0.0819)
Observations	2,504	2,504	2,504	2,504
R-squared	0.457	0.007	0.026	0.021

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1;

The results of Table C.9 show the estimates based we also explore predictive linear OLS models estimated on unmatched data with distance from a road project in its continuous form model. The coefficients show a changes in outcome associated with unit change in distance from the road in Kilometers (Multiplying coefficients by 1000 give change in coefficient when distance changes by a metre). In this model, there is positive association between consumption expenditure and road projects and a negative association with respiratory illness symptoms.

Table C10: Estimations for sub sample: rural households (20 KM)

	(1) DiD with no controls	(2) DiD with controls	(3) PSM+DiD	(4) IPW+DiD	(5) Gen-match+DiD
Consumption expenditure					
RD X Period	0.0501**	0.0414	0.0211	0.0564***	0.0251
	(0.0249)	(0.0258)	(0.0612)	(0.0206)	(0.0198)
Observations, n	1,539	1,539	1,435	1,539	1,208
Respiratory illness					
RD X Period	0.0550*	0.0541	0.0956***	0.0917**	0.0300
	(0.0327)	(0.0340)	(0.0341)	(0.0403)	(0.0439)
Observations, n	1,539	1,539	1,435	1,539	1,208
Transport expenditure					
RD X Period†	-0.0456*	-0.0252	-0.0217	-0.0231	-0.0619
	(0.0226)	(0.0278)	(0.0184)	(0.0236)	(0.429)
Observations, n	1539	1539	1539	1499	1539
Healthcare utilisation					
RD X Period	0.122**	0.153***	0.144**	0.259***	0.138**
	(0.0592)	(0.0589)	(0.0660)	(0.0709)	(0.0662)
Observations, n	1,020	1,020	799	1,020	786

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; †represents a combined marginal effect

Table C11: Estimations for sub sample: rural households (10 KM)

	(1) DiD with no controls	(2) DiD with controls	(3) PSM+DiD	(4) IPW+DiD	(5) Gen-match+DiD
Consumption expenditure					
RD X Period	0.0508***	0.0563***	0.0382*	0.0342*	0.0772***
	(0.0187)	(0.0198)	(0.0217)	(0.0189)	(0.0285)
Observations, n	1,493	1,493	1,338	1,493	1,205
Respiratory illness					
RD X Period	0.0521	0.0617*	0.124***	0.0807*	0.0658
	(0.0330)	(0.0359)	(0.0361)	(0.0432)	(0.0516)
Observations, n	1,493	1,493	1,177	1,493	1,205
Transport expenditure					
RD X Period †	-0.0307	-0.00754	-0.00585	-0.0166	-0.570
	(0.0247)	(0.0251)	(0.0214)	(0.0193)	(0.298)
Observations, n	1,493	1,493	1,177	1,493	1,205
Healthcare utilisation					
RD X Period	0.185***	0.250***	0.283***	0.259***	0.192**
	(0.0691)	(0.0682)	(0.0654)	(0.0709)	(0.0785)
Observations, n	1,020	1,020	764	1,020	786

Robust standard errors at cluster level in parentheses; p***<0.01, p**<0.05, p* <0.1; †represents a combined marginal effect

C.2 Appendix figures

Figure C.1: Road density and road status, 2010

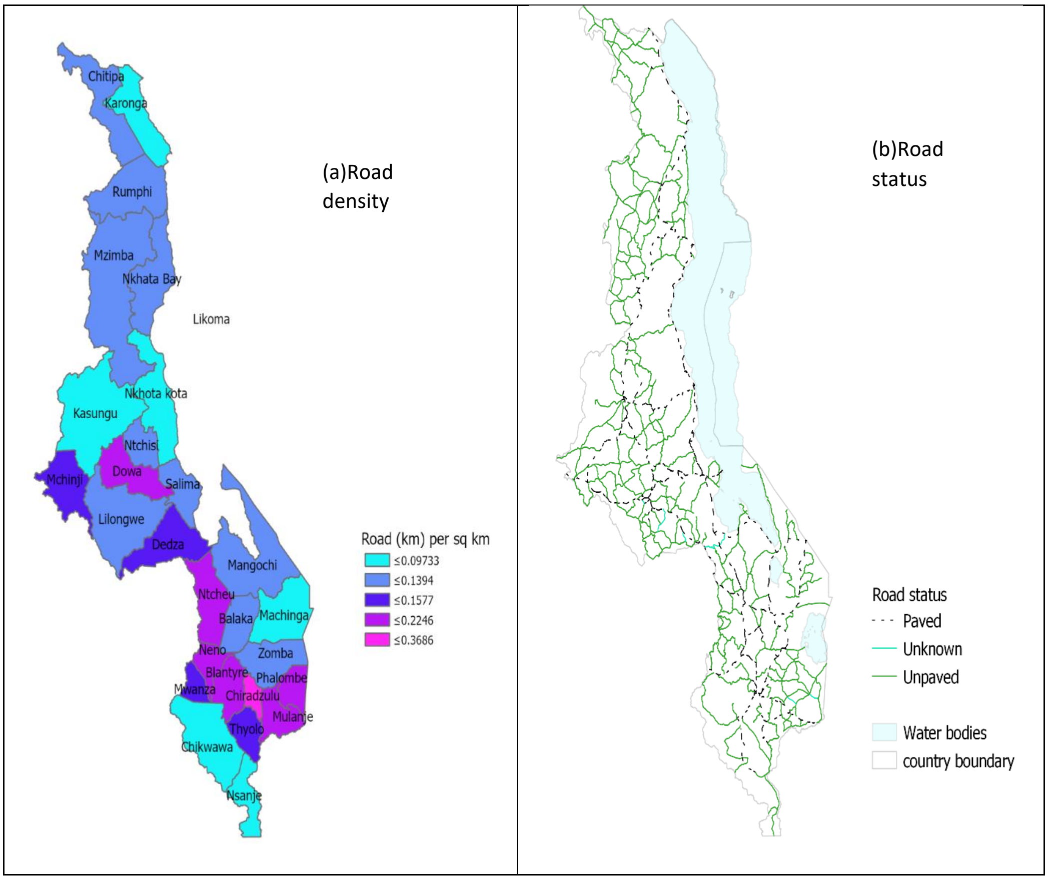


Figure C.2: Common Support Treatment 20km

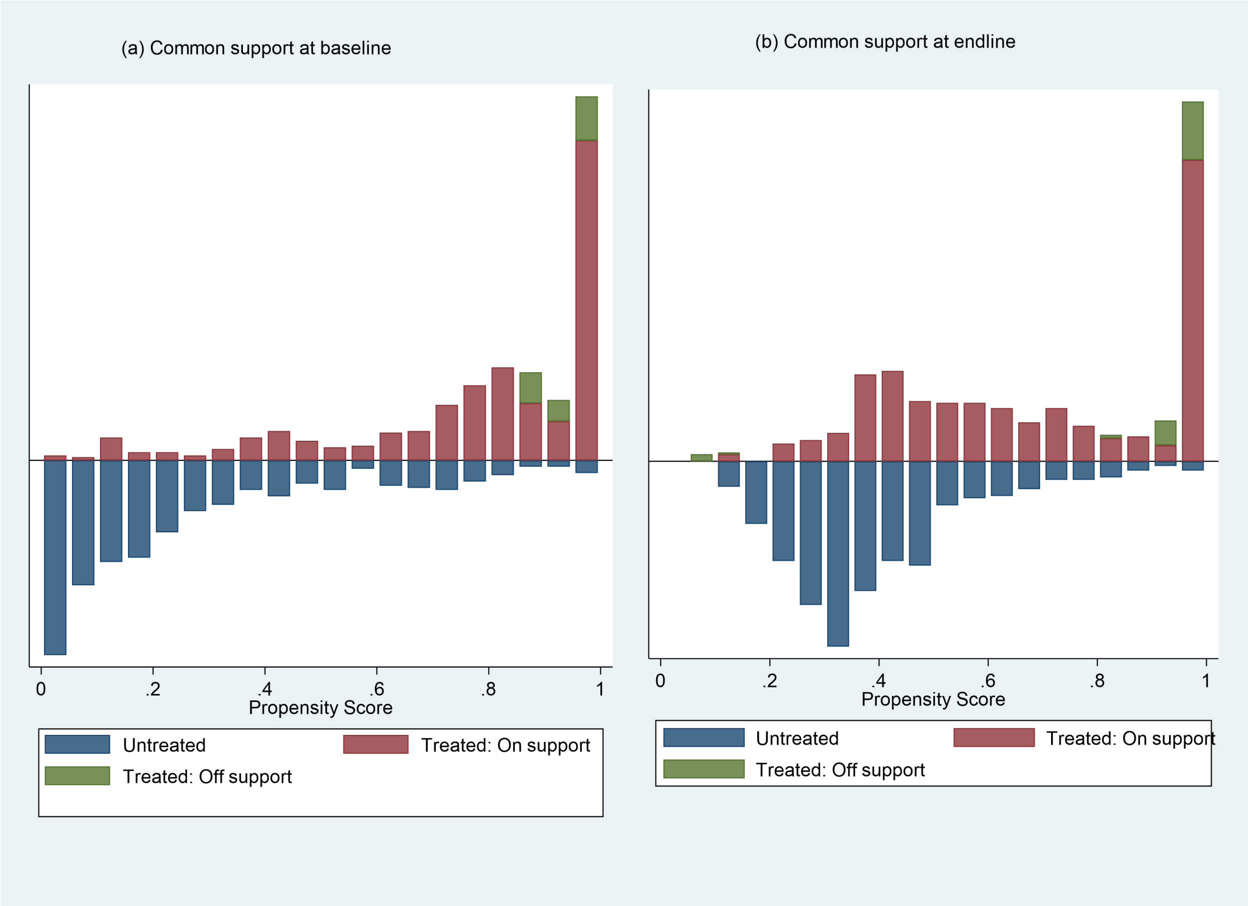
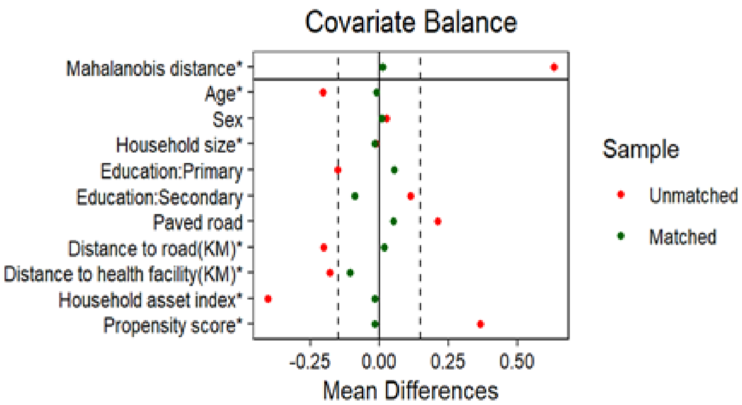


Figure C.3: Genetic matching balance



Appendix D

Appendix to Chapter 5

D.1 Appendix tables

Table D1: CBA alternative scenario: RTIs values using Human costs approach

Dimension	Benefits	Costs	Net present value
Costs			
Project capital cost	-	-250,000,000.0	
Project operating expenses	-	-7,471,353.9	
Expected benefits			
Reduction in Travel time	175,995,687.84		
Reduction in vehicle operating costs	60,129,929.56		
NPV (Transport only)			**-21,345,736.5**
Reduction in RTI linked medical costs	90,784.80		
Human costs avoided (Fatal RTI)	39,617,242,408.97		
Human costs avoided (Serious RTI)	2,916,217.91		
Human costs avoided (Non serious RTI)	224,994.87		
Administration costs linked to RTIs	3,461,149.14		
Costs associated with damage to property due to RTI	2,941,976.77		
Production loss of RTI victims' care givers	2,547,020.44		
NPV (Health only)			**39,371,953,198.95**
NPV (Transport+Health)			**39,608,078,816.35**
Improvements in household economic welfare	199680076.2		
Earnings from new jobs	64468.67635		
NPV (Transport+Health+Wider societal)			**39,807,823,361.21**

Table D2: Cost benefit results with 7.5 % RTI reduction

Dimension	Benefits	Costs	Net present value
Costs			
Project capital cost		-250,000,000	
Project operating expenses		-7,471,353.94	
Expected benefits			
Reduction in Travel time	175,995,687.80		
Reduction in vehicle operating costs	60,129,929.56		
NPV (Transport only)			-21,345,736.54
Reduction in RTI linked medical costs	18888.78		
Avoided productivity loss (Fatal RTI)	9708514.605		
Avoided productivity loss (Serious RTI)	92146.995		
Avoided productivity loss (Non-serious RTI)	16262.245		
Administration costs linked to RTIs	1730574.57		
Property damage linked to traffic incidents	1470988.385		
Production loss of RTI victims' care givers	529935.79		
NPV (Health only)			-243,904,042.57
NPV (Transport + Health)			-7,778,425.21
Increase in household income	199680076.2		
Earnings from new jobs	64468.67635		
NPV (Transport+Health+Wider economy)			191,966,119.67

Table D3: CEA results alternative scenarios

Impact channel	Total costs	DALYs averted	Cost/DALY	Woods et al (2015) threshold range (PPP-USD)	CEA threshold (Percapita GDP, USD)
RTI reduction only	51,494,270.79	19,394.74	2,655.06	28 - 725	$794
TRAP reduction only	51,494,270.79	16,856.01	3,054.95	28 - 725	$794
PI reduction only	51,494,270.79	8,999.66	5,721.80	28 - 725	$794
RTI+TRAP reduction	51,494,270.79	36,250.75	1,420.50	28 - 725	$794
RTI+PI reduction	51,494,270.79	28,394.40	1,813.54	28 - 725	$794
TRAP+PI reduction	51,494,270.79	25,855.67	1,991.60	28 - 725	$794
RTI+TRAP+PI reduction	51,494,270.79	45,250.41	1,137.98	28 - 725	$794
Scenario II : 3 % discount rate					
Impact channel	**Total costs**	**DALYs averted**	**Cost/DALY**	**Woods et al (2015) threshold range (PPP-USD)**	**CEA threshold (Percapita GDP, USD)**
RTI reduction only	53,519,552.13	67,474.57	793.18107	28 - 725	794
TRAP reduction only	53,519,552.13	58,642.31	912.64399	28 - 725	794
PI reduction only	53,519,552.13	31,309.94	1709.3470	28 - 725	794
RTI+TRAP reduction	53,519,552.13	126,116.8	424.36497	28 - 725	794
RTI+PI reduction	53,519,552.13	98,784.50	541.78086	28 - 725	794
TRAP+PI reducttion	53,519,552.13	89,952.25	594.9773	28 - 725	794
RTI+TRAP+PI reduction	53,519,552.13	157,426.8	339.96468	28 - 725	794
Scenario III: 11 % for intervention costs and 3% for Health outcomes					
Impact channel	**Total costs**	**DALYs averted**	**Cost/DALY**	**Woods et al (2015) threshold range (PPP-USD)**	**CEA threshold (Percapita GDP, USD)**
RTI reduction only	51,494,270.79	67,474.57	763.16560	28 - 725	794
TRAP reduction only	51,494,270.79	58,642.31	878.10781	28 - 725	794
PI reduction only	51,494,270.79	31,309.94	1644.6620	28 - 725	794
RTI+TRAP reduction	51,494,270.79	126,116.8	408.30619	28 - 725	794
RTI+PI reduction	51,494,270.79	98,784.50	521.27885	28 - 725	794
TRAP+PI reduction	51,494,270.79	89,952.25	572.46228	28 - 725	794
RTI+TRAP+PI reduction	51,494,270.79	157,426.8	327.09977	28 - 725	794

Table D4: Cost effectiveness estimates with 7.5 % RTI reduction

Impact channel	Total intervention costs at 11% discount rate	Total intervention costs at 3% discount rate	ICER at 11 % discount rate	ICER at 3% discount rate	ICER discounting intervention costs at 11% and Health outcomes at 3%
RTI reduction only	257,471,353.94	267,597,760.64	17,975.33	7931.81	7631.66
TRAP reduction only	257,471,353.94	267,597,760.64	10,341.32	4563.22	4390.54
PI reduction only	257,471,353.94	267,597,760.64	19,368.90	8546.74	8223.31
RTI+TRAP reduction	257,471,353.94	267,597,760.64	6,564.64	2896.72	2787.10
RTI+PI reduction	257,471,353.94	267,597,760.64	9,323.06	4113.90	3958.22
TRAP+PI reduction	257,471,353.94	267,597,760.64	6,741.79	2974.89	2862.31
RTI+TRAP+PI reduction	257,471,353.94	267,597,760.64	4,902.91	2163.46	2081.59

Abbreviations

AAP	Ambient Air Pollution
ADMARC	Agricultural Development and Marketing Corporation
AFDB	Africa Development Bank
BMI	Body Mass Index
CBA	Cost Benefit Analysis
CEA	Cost Effectiveness Analysis
CEAM	Coarsened Exact Matching
CI	Confidence Interval
CPI	Consumer Price Index
DALYS	Disability Adjusted Life Years
DETS	Directorate of Engineering Technical Service
DHS	Demographic Health Surveys
DID	Difference in Difference
EIA	Economic Impact Analysis
EIRR	Economic Internal Rate of Return
ESS	Education and Social Services
MFPED	Ministry of Finance, Planning and Economic Development
GBD	Global Burden of Disease
GDP	Gross Domestic Product
GEF	Global Environmental Fund
GLM	Generalised Linear Model
GPS	Geographical Positioning System
HC	Human capital
HDI	Human Development Index
HDM	Highway Development and Management
HE	Health Expenditure
HEAT	Health Economic Assessment Tool
HHE	Household Health Expenditure
HIS	Household Integrated Surveys
HNHE	Household Non-Health Expenditure
ICC	Intra Class Correlation
ICER	Incremental Cost Effectiveness Ratio
IHS	Integrated Household Survey
IPW	Inverse Probability of Treatment Weighting
IV	Instrumental Variable
KCCA	Kampala City Council Authority

KRRP	Kampala City Road Rehabilitation Project
LMIC	Low- and Middle-Income Countries
LPM	Linear Probability Model
LSMS	Living Standards Measurement Study Surveys
MCA	Multiple Correspondence Analysis
MD	Mahalanobis distance
MDPI	Multidimensional Poverty Index
MFPED	Ministry of Finance, Planning and Economic Development
MR	Mortality Risk
MOTW	Ministry of Transport and Works
NCD	Non-Communicable Disease
NMT	Non-Motorised Transport
NNPM	Nearest Neighbour Propensity Score Matching
NPV	Net Present Value
NSO	National Statistical Office
OLS	Ordinary Least Squares
OOP	Out of Pocket Payments
PA	Physical Activity
PAF	Population Attribution Function
PHSE	Public Health Services and Environment
PI	Physical Inactivity
PP	Physical planning
PPP	Purchasing Power Parity
PSM	Propensity Score Matching
QALY	Quality Adjusted Life Year
RC	Restitution Costs
RD	Road Development
RED	Roads Economic Decision tool
RI	Respiratory Illness
RR	Relative Risk
RTI	Road Traffic Injuries
SDG	Sustainable Development Goals
SMD	Standardised Mean Difference
SSA	Sub-Saharan Africa
THE	Total Health Expenditure
TIDierR	Template for Intervention Description and Replication
TRAP	Traffic Related Air Pollution
UGX	Ugandan Shillings
UK	United Kingdom
UN	United Nations
UNRA	Uganda National Roads Authority
URF	Uganda National Road Fund
USD	United States Dollar
VOC	Vehicle Operating Cost
VOSL	Value Of Statistical Life

WHO	World Health Organisation
WHS	World Health surveys
WTP	Willingness to Pay
YLD	Years of Life lost from Disability
YLL	Years of Life Lost

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