The Effect of Darkness on the Number of Cyclists

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D.)

By:

Maan BALELA

B.Arch., M.Eng.

The University of Sheffield

School of Architecture

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Abstract

Cycling remains a marginal mode of transportation in many countries despite its known benefits and the efforts made by those countries to promote it. Darkness may be one barrier to cycling, as without sufficient light cyclists may experience a reduced sense of safety because it is more difficult to see obstacles in their path and to be seen by other road users like motorists to avoid collisions. The main aim of this thesis is to investigate the effect of darkness on cycling rates.

Previous studies have used a comparison of cyclist counts in case hours (that change between daylight and darkness) and control hours (that remain in the same ambient light condition) to assess the effect of darkness on cycling. These studies tended to use only one to two case and control hour combinations in their analysis, when up to 88 other combinations are possible across their datasets. This thesis shows that the choice of case and control hours significantly impacts the measured effect of darkness. An alternative method is therefore proposed to combine all possible case and control hour combinations into a single measure of the effect of darkness on cycling.

The improved method is then applied to cycling data from 15 cities around the world to investigate the effect of darkness on their cyclists. The findings from this analysis confirm a reduction in cyclist numbers after dark, with the size of this effect varying across cities. When exploring this variance at a city scale, the effect of darkness tended to decrease in cities higher in latitude and stronger in cycling culture; when exploring this variance at the scale of cycling sites within the city, the effect of darkness tended to decrease in sites dominated by utilitarian cycling and closer to the city centre.

Journal papers arising from work reported in this thesis

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Contribution: Conceptualization, Data curation, Writing – review & editing.

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- All materials reproduced in this thesis using Google services (Google Maps, Google Street View, and Google Earth) are the property of Google and are used in accordance with their terms of service. Where the Google logo was not visible due to formatting or cropping, equivalent attribution was provided in text format in the figure caption. Minor graphical adjustments (e.g. desaturation, overlays, or annotations) were applied to enhance clarity and illustrate additional data relevant to the research in this thesis. These adjustments do not alter the maps or images provided by Google.

- Pages saved from Luko's Global Cycling Cities Index 2022 were captured from their website before its removal in 2023. The Luko platform and its website are no longer accessible and now redirect to *Getsafe*, a German digital insurance company, which has acquired Luko in October of 2023. These pages are included here solely for academic and non-commercial purposes to document the data source used in this research and to support reproducibility.

- The observational count experiment by Gorjimahlabani [2025], mentioned as part of the pilot study (see Appendix **G**), was granted ethical approval by the University of Sheffield Research Ethics Committee, with the reference number 043559 (approved 08/10/2021). The author would like to thank Dr. Gorjimahlabani for providing the raw counts from his experiment and giving his permission for its inclusion in this thesis.

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Statement about the use of A.I.

The author acknowledges that Artificial Intelligence (AI) tools were used in a limited manner during the preparation of this thesis, as detailed below:

ChatGPT

- Writing refinement: punctuation correction (e.g. choosing between a colon or a semicolon) and phrasing improvements (e.g. alternative wording for clarity).
- Brainstorming: structural improvements (e.g. reordering subsections for better flow) and critical discussion of methods (e.g. challenging the efficacy of the case-control method)
- Exploration of complex analytical patterns: assistance in preliminary visual identification of trends across 821 combinations of case and control hours from the scatterplots created by the author in **Figure 3.2** to **3.16**.
- Technical assistance: Complex Excel formulas.

Litmaps and Elicit

- Literature discovery: support in identifying additional relevant literature, which was subsequently reviewed by the author.
- Topic summary: *Elicit* was used to generate brief summaries of selected topics to help the author understand recent developments in the field (e.g. the increased risk of fatal cyclist-motorist collisions in roundabouts).

All sources and references mentioned in this thesis were independently reviewed and verified by the author before their inclusion. No AI tools were used to generate original research content, analysis output, or figures. All intellectual contributions presented in this thesis are the author's own unless otherwise noted.

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Chapter 1. Barriers to cycling

1.1. Introduction

While cycling has many benefits, its uptake in some countries remains marginal despite extensive national efforts to promote urban mobility. This is likely because cycling is discouraged by a range of adverse factors. One such factor is darkness [Winters et al., 2011]; the absence or insufficiency of light can significantly reduce visibility for cyclists and those who share the road with them, which may lead cyclists to feel unsafe and opt for an alternative method of transportation that is perceived to be safer for travel after dark.

The research reported in this thesis explores the impact of darkness on cyclist numbers and how any impact of darkness is mediated by factors such as the location of the country, the local cycling culture, and any cycling site attributes (e.g. the presence of street lighting). This chapter discusses the benefits of cycling, the efforts and initiatives made to promote it, and the barriers that may stand in the way of cycling uptake, including darkness.

1.2. Benefits of cycling

Cycling is the utilization of a bicycle for transport, sport, or recreation [Encyclopaedia Britannica, 2024]. Cycling can offer many benefits when compared to motorised transport. The following are examples of such benefits:

- Improved personal health: cycling can improve health and fitness due to the physical exertion associated with it [Hamer & Chida, 2008; World Health Organization, 2010]. This includes improved functional and cardiorespiratory fitness and reduced cancer and obesity-related mortality [Oja et al., 2011].

- Reduced energy consumption: A cyclist travelling at 21 km/h is estimated to consume about 3% of the energy (per kilometre travelled) of a single-occupancy car driving on the motorway [MacKay, 2009, p. 236].

- Reduction of lifecycle CO_2 emissions: It is estimated that cyclists have 84% less life cycle emissions (the sum of emissions produced during the production, operation, and disposal of the vehicle) than users of other modes of transportation. Emissions can be lowered by more than 10 times when compared to driving a fossil fuel powered car [Brand et al., 2021].

- Social benefits: Increased cycling can make streets livelier and increase social interaction which helps strengthen communities and deter crime [Pucher & Beuhler, 2012].

- Economic benefits: Cycling is more affordable and accessible to communities of lower income: 1 km cycled costs 6 times less when compared to the same distance when driven by car [Gössling, 2015] and the overall cost of buying and maintaining a bicycle is approximately 1% - 5% of the cost of buying and maintaining a car [Queensland Health, 2016].

With all these clear benefits from cycling, efforts to promote it have long been a policy focus in many countries. The next section discusses how such promotional efforts can contribute to an increase in cycling and shape cycling future for cities.

1.3. Promotion of cycling

Promotional interventions aiming to increase cycling share can manifest in several forms of government support; this includes funding, education, urban planning regulation, legislation, and pro-cycling initiatives [Emanuel, 2019; Pucher & Beuhler, 2008]. These efforts can contribute to an increase in the number of people cycling [Goodman et al., 2013; Yang et al., 2010].

Countries like The Netherlands, Germany, and Denmark are good examples of how consistent support since the mid 1970's made cycling more accessible and comfortable [Pucher & Buehler, 2008], landing a few of their cities among the highest ranked cycling-friendly cities in multiple global indexes [e.g. Copenhagenize, 2019; Luko, 2022]. Effective efforts observed in these countries (summarized in **Table 1.1**) can make cycling "irresistible" and help maintain its strength as a viable mode of transportation.

Table 1.1 Cycling promotion measures applied in the Netherlands, Germany, and Denmark [Pucher & Buehler, 2008].

Promotional measure	Examples
Well-connected cycling infrastructure network	Separate cycling lanes and cycling streets, enhanced signage systems, integration with public transport.
Traffic control	Protective laws for cyclists, traffic-calming measures in residential neighbourhoods.
Trip-end facilities	Extensive parking throughout the city, enhanced-security parking garages.
Accessibility to bicycles	Affordable and easy to use bike-sharing schemes, tax breaks for bicycle purchases in the Netherlands, discounted fares for 'park and bike' schemes.
Journey planning aid	Ease of access to comprehensive cycling maps, websites, and apps that aid in planning journeys.
Education campaigns	Health-focused public awareness campaigns, cycling festivals and competitions, cycling tours for the elderly, education for motorists.
Feedback loops	Public surveys measuring levels of satisfactions with facilities, integration of public feedback with companies, research bodies, and city councils.

However, despite similar promotional efforts being applied in other countries such as the UK (**Table 1.2**), their cycling shares remain small when compared to the Netherlands, Germany, or Denmark. For example, in 2022 cycling in the UK accounted for 2% of all trips (under 5 miles) made using different transport modes [Walking and Cycling Statistics: Department for Transport, 2023], while in the same year in the Netherlands cycling made up 28% of all trips [Netherlands Institute for Transport, 2023]. This difference between the two countries has been largely consistent throughout the last decade [The European Commission, 2013] – despite an increased budget of £1.2 billion five years earlier in the UK, aiming to double cycling and walking by 2025 [Department for Transport, 2017]. There may be several reasons behind the contrast between cycling in the UK and in countries like the Netherlands. Promotional efforts in the UK (see examples in **Table 1.2**) have often been short-term and limited in geographical scope, relying on competitive local funding and time-bound programmes. In contrast, in the Netherlands (see examples in **Table 1.1**), cycling promotion is embedded in long-term national transport and urban planning strategies that are supported by consistent funding from central governments and implemented by individual municipalities [Pucher & Buehler, 2008]. This type of consistent and coordinated support may boost cycling not only by making it safer (i.e. consistently improving infrastructure), but also by shaping the image of cycling and reinforcing cycling culture, both of which are central in mitigating some of the barriers that cyclists face (e.g. safety concerns, topography, darkness). The variation in the scale and duration of promotional efforts are also relevant to the broader state of knowledge on cycling barriers. Research increasingly recognises that physical, social, and environmental barriers do not operate in isolation but are mediated by the policy and cultural contexts in which cycling occurs. In settings with sustained and coordinated promotions (e.g. The Netherlands), barriers like perceived safety, weather, or darkness may be less influential, as cycling is supported by infrastructure, culture, and policy continuity. Conversely, in places where initiatives are localised and intermittent, the same barriers may exert a stronger deterrent effect. It may therefore be important to examine barriers to cycling across different settings (i.e. different countries) to understand the impact of contextual factors on their relevant significance. Potential barriers to cycling are explored in the next section.

Table 1.2 Examples of promotional efforts applied in the UK in the last two decade [Sustrans, 2017; Department for Transport, 2019; Department for Transport, 2022; Cycling UK, 2024; Betterpoints. n.d.].

Initiative name and year of application	Description	Aim
Cycling Demonstration Towns and cycling cities 2005-2011	An initiative focused on 18 intervention towns	Increase annual spending per person on cycling from £1 up to £17
Cycle to work scheme 1999-ongoing	An initiative offering tax-free bicycle purchase for employers when loaning them to employees for daily commute.	Promote cycling and reduce carbon footprint
Big Bike Revival 2014-ongoing	A campaign led by Cycling UK, offering free repairs, workshops, training, and other benefits.	Increase cycling uptake
Cycling and walking investment strategy II 2017-2025	A government strategy outlining investment plans	Double cycling for shorter journeys
Community programmes (e.g. *Betterpoints*)	Local initiatives offering rewards and incentives for cycling and walking	Promote active travel

1.4. Barriers to cycling uptake

There are several factors that can be considered when exploring barriers to cycling uptake and frequency. These factors are commonly grouped into several themed categories when discussed in previous studies [e.g. Piatkowski and Bopp, 2021; Willis et al., 2015]. **Figure 1.1** summarizes the different factors, grouping overlapping themes into three categories of barriers: i) (inter)personal barriers, which include the individual and social influences, ii) Physical barriers, which include attributes that cyclists may interact with in both the natural and built environments, and iii) Policy, which may influence certain factors within the (inter)personal and physical barriers categories. The three categories are detailed further in the following subsections.

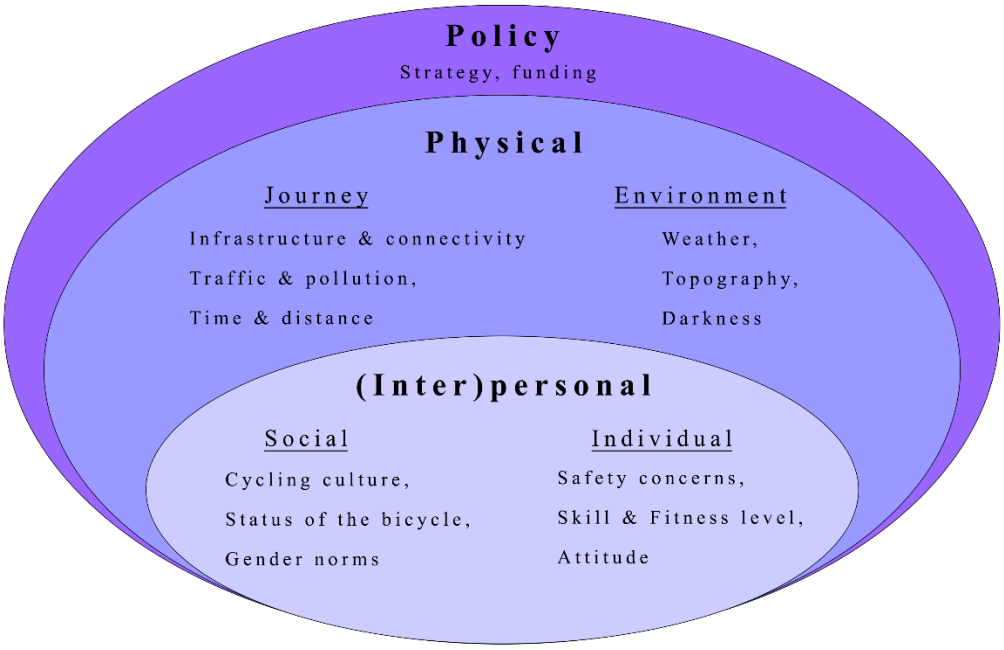


Figure 1.1 Barriers to cycling as summarized from the literature reviewed for this section, adapted into a socio-ecological model.

1.4.1. (Inter)personal barriers

At the most basic level, the decision to cycle may be influenced by personal barriers, such as a person's level of fitness; and interpersonal barriers, such as the cycling culture in a location. While a country's cycling culture isn't something tangible, Carstensen and Ebert [2012] suggest that it is formed of three aspects: legislative, social, and cultural. The legislative aspect of cycling (i.e. policy and planning) is more widely explored in literature than the 'immaterial' social and cultural dimension [Spinney, 2009]. One example of the social and cultural aspects that may deter cycling is the status of the bicycle in a country [Horton, 2007]. Horton discusses how attitudes towards cycling can influence this status; these attitudes are of cyclists towards themselves and of observers towards them. Cycling can sometimes reflect high status and can sometimes be 'stigmatised'. This can depend on multiple things like the appearance of a cyclist, their gear, and attire. Even within different groups of a country's cyclists, attitudes reflect a perceived hierarchy. These attitudes can often shape how cyclists are viewed and treated on the road by other cyclists and road users. Thus, this aspect should be considered when exploring the varying levels of cycling between different locations.

Additionally, individual aspects that may vary from person to person could also obstruct cycling uptake. Cycling requires skill and a certain level of fitness. The absence or lack of confidence in either may deter some people from cycling, particularly for safety concerns (i.e. fear of injury when cycling with traffic) [Gatersleben & Appleton, 2007]. This overlap with physical barriers such as traffic is explored in the next section.

1.4.2. Physical barriers

Safety is a major concern for cyclists [Pucher & Buehler, 2008]. This is because there are several experiences and interactions that may cause cyclists to feel unsafe while travelling. These interactions can be with particular attributes in their journey, such as heavy traffic [Lee & Moudon, 2008; Segadilha & Sanches, 2014]; or with environmental attributes such as harsh topography [Harris et al., 2013; Parkin et al., 2008; Vandenbulcke et al., 2011], weather [Miranda-Moreno & Nosal, 2011], or darkness [Winters et al., 2011]. The following is a discussion of several of these barriers and actions that may be taken by decision makers to mitigate them.

1.4.2.1. Journey attributes

The presence of separate cycling infrastructure is often reported as a key demand by cyclists and potential cyclists [Heesch et al., 2012; Sanders & Cooper, 2013], as cycling next to heavy traffic can be a significant discouragement for them [Gössling et al., 2019; Lee & Moudon, 2008; Segadilha & Sanches, 2014], especially in locations where speed control is not strongly enforced [Segadilha & Sanches, 2014]. This can cause cyclists to choose alternative routes that may be longer in distance just to avoid the risk of injury, noise, and air pollution commonly associated with heavy traffic [Gössling et al., 2019]. This perceived fear is a reasonable concern, as the risk of injury or fatality has been known to increase in specific locations that cyclists may regularly encounter, such as non-linear road segments (e.g. roundabouts and intersection); or with an increase in the length of the road taken [Meuleners et al. 2019]. Daniels et al. [2008] compared 91 intersections in Flanders, Belgium, before and after being converted to roundabouts and reported a 27% increase in the risk of injury in the latter, stressing that the number of crashes increased to 48% if the roundabouts are inside 'built-up' areas. The reason behind the increased risk of crashes at roundabouts is attributed to speed and visibility

field issues [Cumming, 2011]. This risk can be mitigated at a macro level (nation or city wide) by targeting more naturally levelled areas for selection of routes by planners [Meuleners et al., 2019], and on the meso or micro level (site-specific) by speed controlling treatments [Cumming, 2011].

Another journey-related aspect that may contribute to the limiting of cycling's increase is infrastructure connectivity. For cyclists to be able to rely on the bicycle for their commutes, it may be essential for cycling infrastructure to be connected with neighbourhood infrastructure, improved further with ease of access to services such as public transport and trip-end facilities such as bicycle parks or shared bicycle zones and docking stations (**Figure 1.2**). However, despite the presence and quality of cycling infrastructure, cycling uptake may still be limited by interactions with certain environmental attributes. Such interactions are detailed in the following subsection.

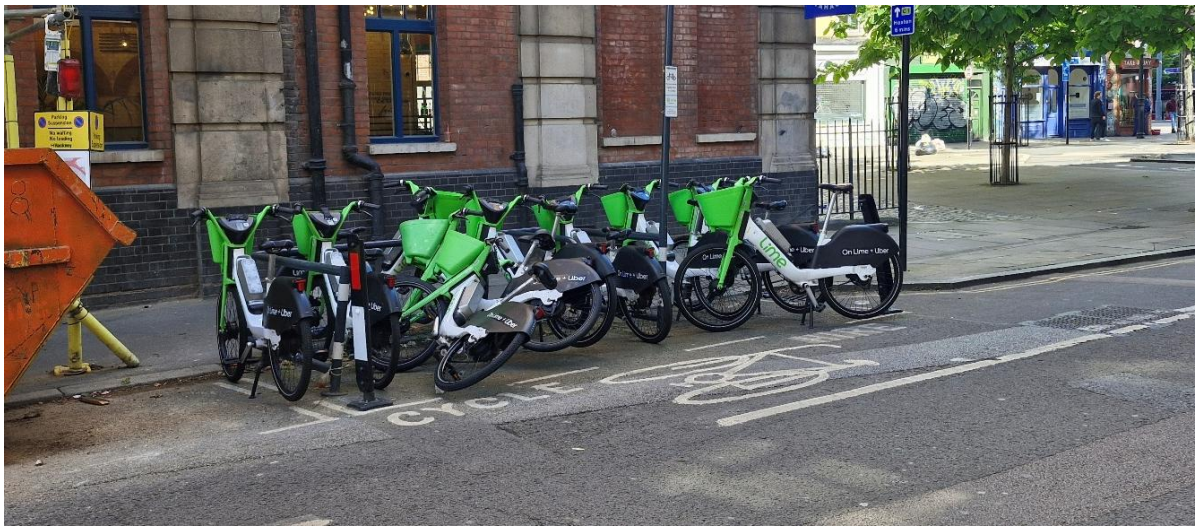


Figure 1.2 Example of a designated zone for hiring shared bicycles in Shoreditch, London, UK. (Photograph by author).

1.4.2.2. Environmental attributes

Three environmental attributes are consistently associated with a reduction in cycling in previous studies: i) Topography, ii) Weather, and iii) Darkness. Each of these attributes is explored below, with an outline of their influence on cycling uptake.

i) ***Topography:*** Cycling requires a certain level of physical effort, and it is reasonable to assume that challenging topography such as steep inclines or uneven terrain may make it more difficult for people to cycle. Research confirms that cycling rates are reduced in areas with steeper slopes [Parkin et al., 2008; Vandenbulcke et al., 2011] but argues that the level of experience in cycling may influence this interaction [Heinen et al., 2010]. The negative influence of steeper slopes is likely because cycling uphill requires additional expenditure of physical strength, as gravitational forces can consume up to 90% of a cyclist's power output when cycling uphill. This was reported in a study by Dahmen et al. [2011], which featured field and simulation tests with an 8.3% inclination.

Additionally, cycling downhill can introduce a different set of challenges relating to speed control and safety. Cycling downhill increases the speed of a bicycle and with it the risk of a crash [Harris et al., 2013]. Studies on cycling crashes have identified slopes as a significant factor, associating it with an increase in the risk of a crashes with and without the involvement of a motorist, compared to levelled roads [Meuleners et al., 2019]. However, other studies argued that average zonal slope was not positively associated with crashes [e.g. Chen et al., 2015], and suggested that the reason behind this is that there are generally less cyclists because of the slope, adding to the complexity of this relationship.

ii) ***Weather:*** Unlike motorists, cyclists lack the protective enclosure and climate control features (i.e. heating and air-conditioning) provided in a car. It is therefore understandable that seasonal variations may have a significant impact on cycling. Research on the impact of weather on cycling suggests that temperature may generally have a positive impact on cycling numbers [Böcker et al., 2019; Miranda-Moreno and Nosal, 2012; Tin Tin et al., 2012]. For example, the studies by Miranda-Moreno & Nosal and Tin Tin et al. analysed data from automated cycling counters in Montreal, CA, and Auckland, NZ, respectively, and reported an increase in cycling as temperatures rise – for Miranda-Moreno, this increase was up to 50% with rising temperatures up to 28°,

where the positive impact starts to reverse, especially with an increase of humidity above 60%. For Tin Tin et al., the reported increase was 3.2% for every 1° increase in temperature. However, all three studies also reported that rainfall had the opposite effect on cycling. Tin Tin et al. reported a decrease of 10.6% in cycling volumes with each 1mm of rainfall, and Miranda-Moreno & Nosal reported this decrease up to 21.8% within a period of up to 3 hours after precipitation, but only in morning and afternoon hours.

In a similar study, Bean et al. [2021] employed bike-sharing data to investigate the impact of weather on cycling in 40 cities (in 16 countries). Their findings confirm the same positive trend reported in Miranda-Moreno and Nosal [2012], in which temperatures influence cycling positively up to the 28° mark where it starts to reverse. Additionally, the findings reported that rainfall was one of two variables with the most impact on cycling, resulting in a direct reduction in cycling activity. The other variable was time-of-day, where the change in ambient light may have a significant influence on cycling.

iii) ***Darkness:*** While it may be expected that cycling naturally occurs less after dark, since this period often coincides with periods associated with rest following typical working hours, research suggests that the reduction in cycling when rest is not a factor might relate more to time-of-day routines than to ambient lighting conditions. For instance, the change in ambient lighting conditions across the year means that some hours of the day (e.g. 18:00-18:59) may be in daylight during summer and in darkness during winter, depending on the location. People cycling to or back from work in such hours may still choose to (or have on option but to) cycle, even when those hours are in darkness. Previous studies [Fotios et al., 2019; Fotios et al., 2023; Fotios & Robbins, 2021; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017; Wessel, 2022] have utilised these seasonal variations to compare cycling activity in daylight and darkness for the same time-of-day, confirming a reduction in cycling in those hours when they are in darkness compared to when they are in daylight.

Darkness, unlike other factors (e.g. infrastructure, rainfall, or slope) may be more difficult to quantify, especially because it is unclear to what extend street lighting

can mitigate this. This may explain the limited number of studies focusing on its impact on cycling. Darkness is also unique in its influence on cycling because, unlike other factors, it impacts all cyclists regardless of location, topography, weather, or infrastructure, making it a universal condition that requires more research.

Although previous studies recognise an increased risk and a reduction in cycling after dark, their findings only reflect the change in cycling in specific hours within a single city, leaving uncertainty as to whether similar patterns occur elsewhere or at other times of day. Moreover, it remains unclear how contextual factors, such as the type of cycling journey undertaken, interacts with the impact of darkness. A clearer understanding of how darkness influences cycling behaviour, to what extent, and how it may be influenced by other factors, is essential in mitigating any negative impact from it. This may help in improving cyclist safety and uptake, as it can inform lighting and design strategies and support the promotion of cycling as a sustainable mode of transportation. Exploring the effect of darkness on cycling is the focus of this thesis. Its chapters lay the theoretical and empirical foundation that inform the methodology followed to quantifying the impact of darkness on cycling and understand the extent of its influence across different locations, cycling cultures, and journey attributes.

1.4.3. Policy

Policy and legislation can contribute to the decline of cycling, especially when motor traffic is prioritised. When road design standards, funding allocations, and transport policies neglect the need for cyclist to feel safe, cycling uptake and route choice may directly be affected. Providing separate cycling infrastructure can reduce both actual and perceived risk associated with cycling [Ravensbergen et al., 2022]. While policy can have a large influence on the personal, interpersonal, and environmental factors, its detailed examination lies beyond the scope of this research.

This thesis focuses on the impact of darkness but considers the influence of some of the factors mentioned above, such as latitude and cycling culture. The overall aim of this

thesis and the structure it follows to meet it is defined in the remaining sections of this chapter.

1.5. Overall aim of the thesis

While darkness may be a barrier to cycling, the extent of its impact may not be generalizable. As such, the aim of this thesis is to explore and quantify this impact of darkness to understand how it affects cyclists and to what extent.

To achieve this, cycling data from 15 cities in 10 countries are analysed using a case-control method. This method quantifies the impact of darkness on cycling by comparing cyclist numbers under different ambient lighting conditions using an *odds ratio* (OR), which represents the change in cycling rates between those conditions. The results are then used to explore why the impact of darkness may vary across different cities, by analysing it against macroscale factors (e.g. latitude); and across different cycling sites within cities, by analysing the impact of darkness against microscale factors (e.g. the presence of street lighting).

Understanding how darkness impacts cycling can help inform how its influence is mitigated, ultimately benefiting efforts to promote cycling, particularly after dark.

1.6. Structure of the thesis

Chapter **1** discussed the importance of cycling and listed its environmental, economic, health, and social benefits. It briefly explored reasons behind cycling remaining marginal in many countries despite extensive promotional efforts by policy makers and communities. Darkness was identified as a key environmental barrier to cycling.

Chapter **2** explores why cyclists may find darkness discouraging and presents a review of literature on this effect. It identifies a methodological limitation in previous work and proposes extensions to its limited scope, which introduces seven research hypotheses.

Chapter **3** addresses the methodological limitation in previous work by introducing improvements to the case-control method and presenting the results of its application on cycling data from 15 cities to quantify the impact of darkness on their cyclists.

Chapter **4** explores the association between macroscale factors (such as latitude and cycling cultures) and the impact of darkness across the 15 cities. It describes the method and data collection process then presents the results.

Chapters **5** and **6** focus on exploring the association between microscale factors (such as the presence of street lighting and the type of journey undertaken) and the impact of darkness across individual cycling sites within 5 cities. The method and data collection process are described in chapter **5** and the results are presented in chapter **6**.

Chapter **7** discusses the results presented in the pervious chapters and how they address each of the 7 research hypotheses. It also describes the limitations and implications of the research.

Finally, the conclusion of this work is presented in Chapter **8**.

The structure of this thesis is illustrated in **Figure 1.3**.

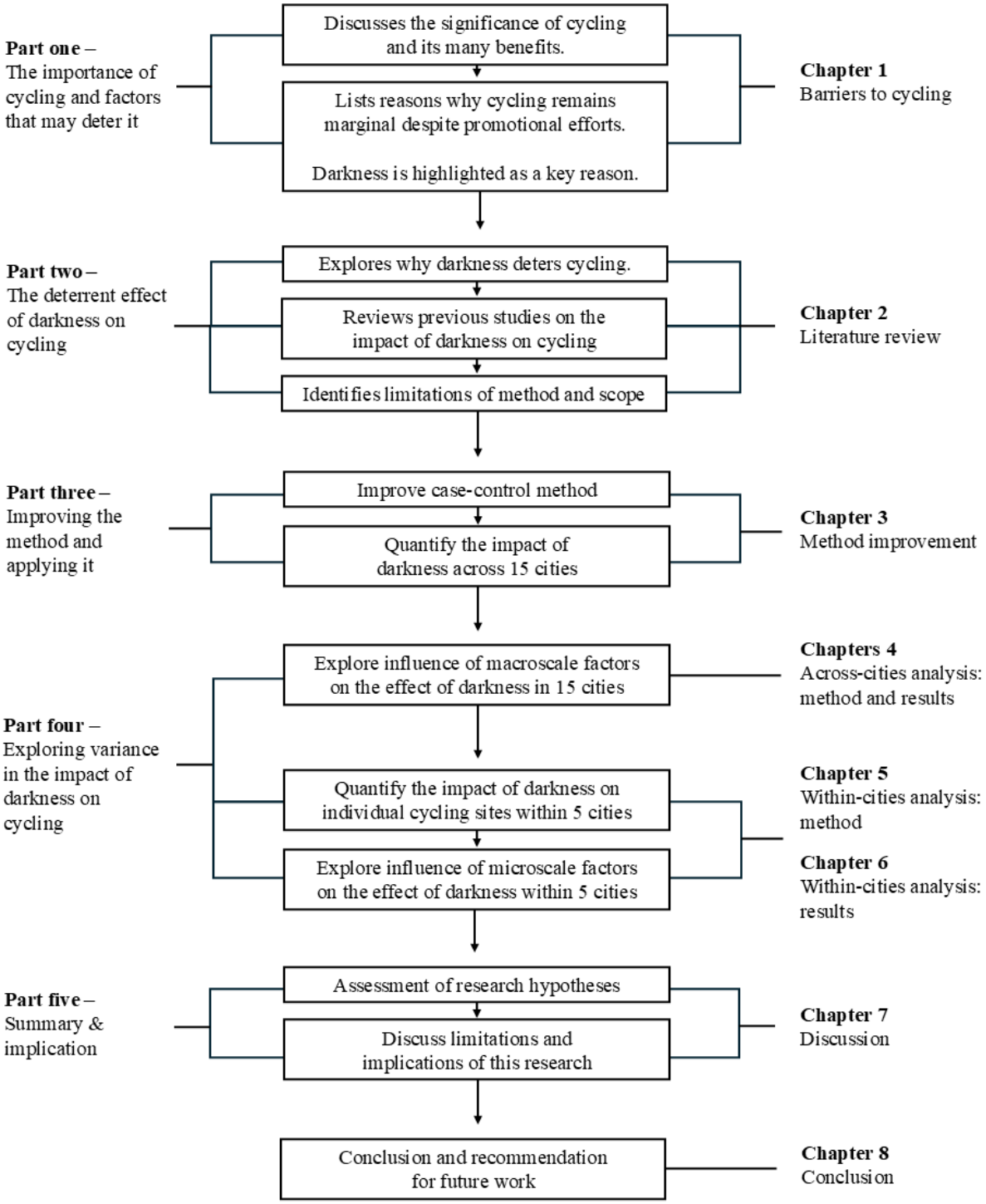


Figure 1.3 A summary of thesis structure with a brief description of subject areas discussed in its chapters.

Chapter 2. Literature review

2.1. Introduction

Chapter **1** described the benefits of cycling and discussed the impact that promotional efforts can have on cycling uptake in different countries, giving examples of how Germany, the Netherlands, and Denmark boosted cycling and made it attractive. Chapter **1** also discussed barriers to cycling, suggesting that darkness can significantly impact cycling. Chapter **2** explores why darkness may deter cyclists and reviews past studies that investigated the effects of darkness and street lighting on cycling. The structure of the chapter is detailed in **Figure 2.1**.

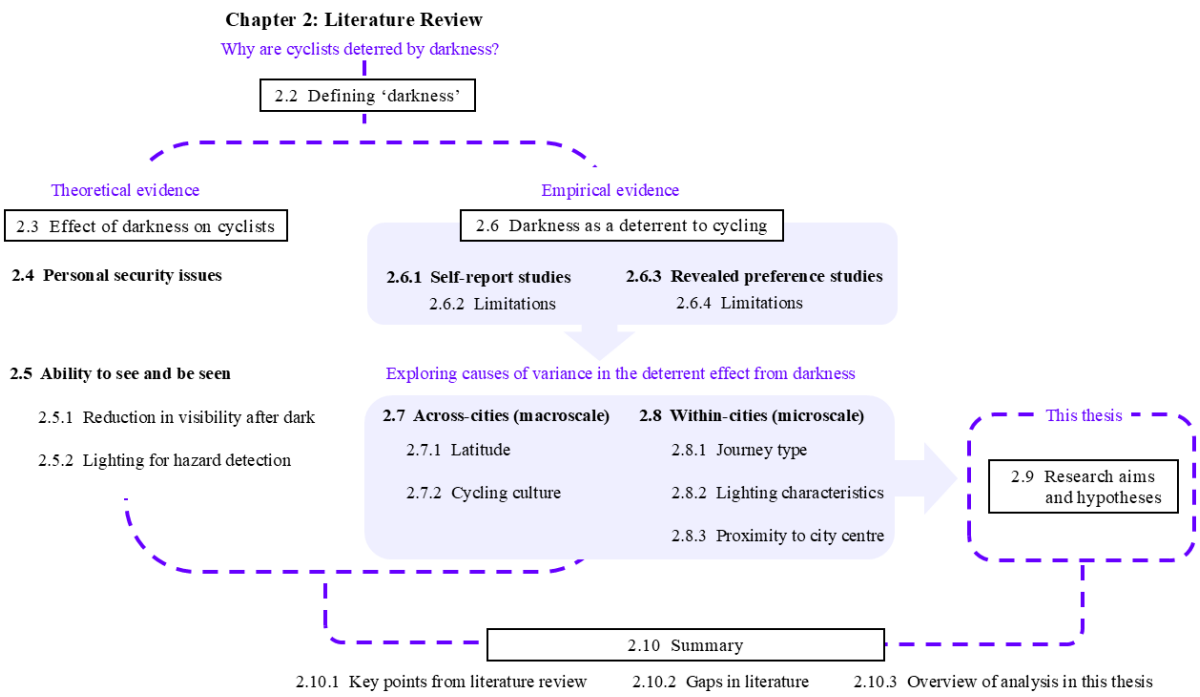


Figure 2.1 Structure for chapter 2. After defining darkness, theoretical and empirical evidence are reviewed to understand why darkness deters cycling. Observations and limitations from the latter inform the aims of this research and its hypotheses.

The impact of darkness on cycling has been investigated in previous studies using self-report and revealed preference methods. Self-report studies are those where participants record information about themselves through questionnaires, journals, or interviews [Castillo-Parades et al., 2022; Hesjevoll et al., 2021]. Revealed preference studies are

those where behaviours and preferences are observed or recorded, without the observed person being aware, for example by using traffic counters to record the number of road users [e.g. Fotios & Robbins, 2021; Wessel, 2022].

Findings from self-report studies [Castillo-Parades et al., 2022; Segadilha & Sanches, 2014; Lee & Moudon, 2008; Winters et al., 2011] suggest that cyclists are deterred by darkness. For example, Winters et al. [2011] asked 1,402 participants (cyclists and potential cyclists) how a route that's "not well-lit after dark" influences their journey and found it to result in considerable deterrence, particularly for potential cyclists. Self-report studies have also concluded that the presence of adequate lighting may encourage cycling by making it feel safer [Lee & Moudon, 2008; Sanders & Cooper, 2013]. However, self-report faces several challenges that could impact the reliability and accuracy of its findings, such as response bias (e.g. participants give answers that don't reflect actual behaviour due to question design or for self-enhancement) and confirmation bias (e.g. selective interpretation of findings). Furthermore, asking people to respond to a question containing statements such as "not well-lit after dark" may exaggerate their negative responses, which is a form of response bias [Schepers et al., 2014; Uttley et al., 2020].

The findings from traffic count studies show that cyclist numbers are reduced after dark, even after accounting for time-of-day and seasonal variations [Fotios & Robbins ,2021; Fotios et al., 2023; Uttley & Fotios, 2017; Fotios et al., 2019; Uttley et al., 2020; Uttley et al., 2023b]. However, there are several issues in the data and analyses presented in these studies, including inconsistent definitions of darkness and a fundamental methodological limitation. Chapter **2** starts by defining darkness and then proceeds to discuss why darkness is a deterrent to cycling.

2.2. Defining darkness

Investigating the degree to which darkness deters cycling requires that darkness is precisely and consistently defined. This is not the case in previous work (**Table 2.1**).

For example, Uttley and Fotios [2017] defined darkness as the period between sunset (marked by the descension of the sun's geometric centre below the horizon) and sunrise (marked by the ascension of the sun's geometric centre above the horizon), whereas other studies [e.g. Fotios & Robbins, 2021; Wessel, 2022] noted that the transition between daylight and darkness is gradual, defining (true) darkness as the period between civil dusk (when the sun drops to -6° below the horizon in the evening) and civil dawn (when the sun is rising and reaches -6° below the horizon in the morning).

Table 2.1 Darkness as defined in previous studies focusing on lighting and mobility.

Study	Focus	Definition of darkness
Uttley & Fotios [2017] Fotios et al. [2019b]	Impact of ambient light on pedestrians and cyclists	The period between sunset and sunrise
Uttley et al. [2023b]	Impact of ambient light on cyclists	The period between sunset and sunrise, but acknowledges that the change is gradual
Uttley et al. [2020]	Impact of ambient light on cyclists	The period after civil dusk. No mention of it ending with civil dawn, likely because data for that period was not used in the analysis
Fotios & Robbins [2021]	Impact of ambient light on pedestrians, cyclists, and motorists	
Uttley et al. [2023a]	Cyclist fatalities on unlit roads	The period between the end of civil dusk and sunrise
Fotios et al. [2021]	Impact of ambient light on road traffic collisions	The period between civil dusk and civil dawn
Wessel [2022]	Impact of Standard and Daylights Savings Time on cycling	

Periods within a typical day can be categorised by the ambient lighting conditions, whether daylight, darkness (the absence of daylight), or the intermediate twilight periods. Darkness refers to the period starting when the geometric centre of the sun is at an altitude of -6° (i.e. 6° below the horizon after sunset, also known as civil dusk) and ending when it returns to an altitude of -6° before sunrise the following day (also known as civil dawn) – see **Figure 2.2**. The period between solar altitudes of 0° (the horizon) and -6° is known as civil twilight. During civil twilight, the scattering of

sunlight means there is still sufficient light to allow for outdoor activities to continue without the need for additional lighting. Civil twilight is thus a confounding period for analysis of the effect of darkness or daylight on outdoor events, and should therefore be omitted from analyses of ambient light level [Fotios et al., 2021b; Raynham et al., 2020]. Illuminances in the two remaining periods of twilight, nautical (-6° to -12° solar altitude) and astronomical (-12° to -18°) are much lower, ranging from 2.33 lx to 0.001 lx (see **Table 2.2**) [Muneer, 1997], and thus present less of a confound.

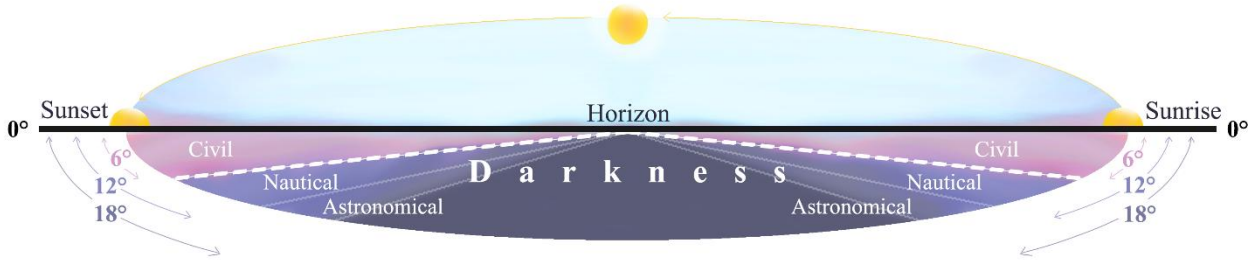


Figure 2.2 The transition in ambient light conditions across a 24-hour period. Illustration by the author using data from Muneer [1997].

Table 2.2 Definitions and visibility descriptions of ambient light conditions.

Ambient light condition	Solar altitude (θ_s)	Visibility conditions*	Descriptive illuminance (lx)*
Daylight	$\theta_s > 0°$	Illumination is very good	Horizontal surface under a cloudless sky: sun at horizon = 355 lx, sun at zenith = 103,000 lx,
Civil twilight	$0° > \theta_s > -6°$	Enough illuminance exists to enable outdoor activity to continue unhindered without resorting to the use of street lighting	End of civil twilight: 4.3 lx
Nautical twilight	$-6° > \theta_s > -12°$	The limit of the visibility of ships approaching a harbour	End of astronomical twilight: 0.001 lx
Astronomical twilight	$-12° > \theta_s > -18°$	The instance of the last stage of receipt of light emanating from the sun	-
Night	$-18° \geq \theta_s$	-	-

* As described by Muneer [1997].

The amount of ambient light available (daylight, darkness, or twilight) for a location varies with latitude and season [Schmal et al., 2020]. **Figure 2.3** shows an example of the distribution of ambient light throughout the year in Sheffield, UK (latitude 53.38°), with sky photographs of the different conditions taken on a street in Sheffield.

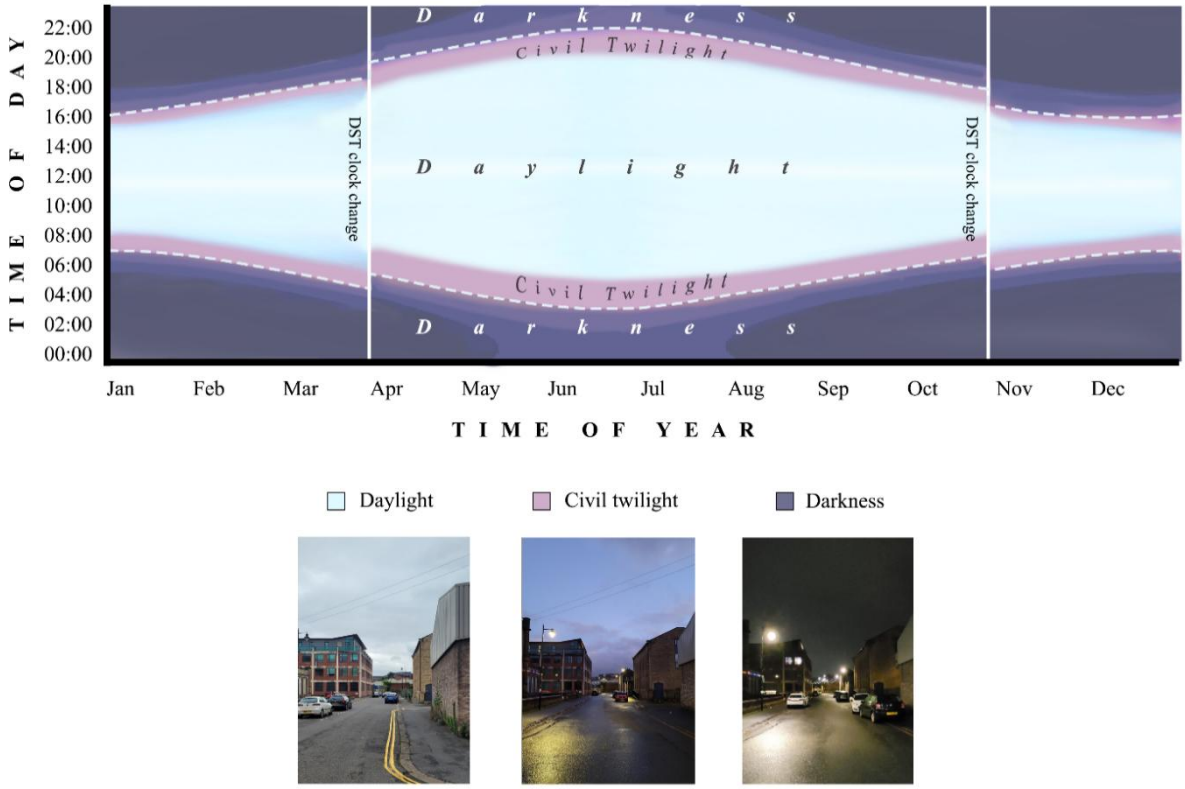


Figure 2.3 Top: Changes in ambient daylight for Sheffield, UK (latitude 53.38°). Based on data from Muneer, 1997 and timeanddate.com. Bottom: Photographs of typical daylight, civil twilight and dark conditions (photographs taken in Sheffield, UK.).

2.3. Effects of darkness on cyclists

After dark, low light levels bring a reduction in visual function. For example, the ability of the visual system to process information about low contrast objects is significantly reduced at low light levels, which increases our reaction time to these objects while in travel (**Figure 2.4**) [Plainis et al., 2006]. Furthermore, visual acuity (the ability to see small details) is significantly reduced with lower levels of lighting [Boyce, 2014, P. 96-70], further reducing our visual function after dark compared to daylight. This means that cyclists, like other road users, have a reduced ability to see their surroundings, see

others, and react to them after dark. Darkness can also bring increased apprehension about personal security (sometimes referred to as 'fear of crime' [Ferraro, 1995, p. 4]) by reducing visibility (the ability to perceive an object against a background, as determined by lighting conditions and capabilities of our visual system [Boyce, 2008. P. 4-6]), which is essential in aiding the appraisal of prospect (the ability to see ahead and visually scan for signs of danger and escape routes) and refuge (a safe place to shelter from potential danger) [Fisher & Nasar, 1992].

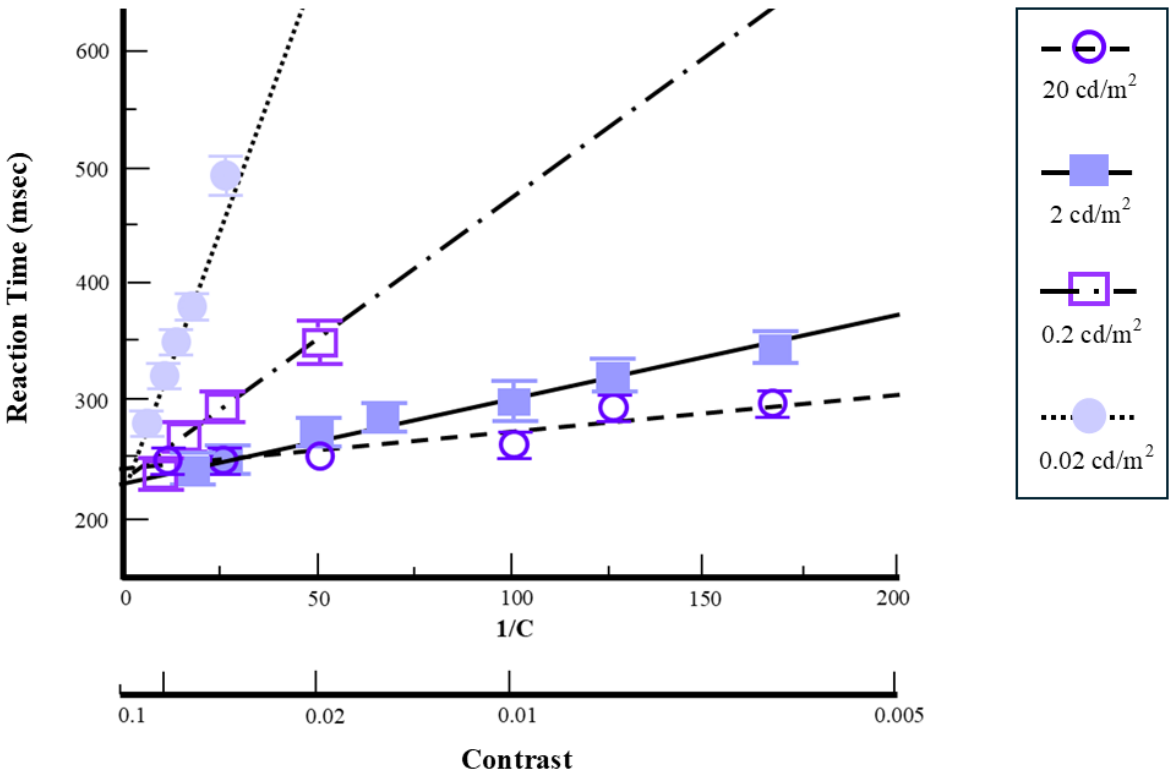


Figure 2.4 An example of results from experiments by Plainis and Murray [2002] showing an increase in reaction time (RT) with decreasing contrast (1/C) across different luminance levels. Each data point represents the mean of a minimum of 24 and maximum of 32 measurements and the error bars + S.E. The trendlines represent the least squares regression fits.

While the fear of crime and the ability to see and be seen generally affect all road users, they are likely to be more deterring for vulnerable road users such as cyclists [Woods & Masthoff, 2017]. Cyclists have less powerful lights than motorised vehicles, making it harder to see potential hazards in their path. Cyclists also have a smaller profile than motorised vehicles, meaning they can be harder for other road users to see. They are

also more physically vulnerable on the road than motorists, as they are not surrounded by a protective metal case. Cyclists are likely to feel a greater sense of vulnerability to being a victim of crime, compared with motorists, as they do not have the protective, lockable vehicle surrounding them, and they have less ability to escape from danger due to the slower speeds they can travel at. Observational evidence supports the idea that darkness may be a greater deterrent for cyclists than it is for motorists – for example, Fotios & Robbins [2021] assessed the impact of darkness on the numbers of cyclists and motorists at specific times of the day. They found that the number of motorists in a specific hour of the day remained constant, regardless of whether it was daylight or after dark. This was not the case for cyclists however, with significantly fewer people cycling in daylight compared with darkness, at the same time of day. Their findings (**Figure 2.5**) confirm that unlike pedestrians and cyclists, motorised vehicle flow is not significantly impacted by darkness. This is evident by their calculated odds ratio (OR), where ORs larger than 1.00 suggests that counts have decreased in darkness compared to daylight, and ORs equal to 1.00 suggests no impact.

The next two sections (section **2.4** and **2.5**) are further exploration of the two observed impacts from darkness on cyclists – reduced feelings of personal security and reduced visibility.

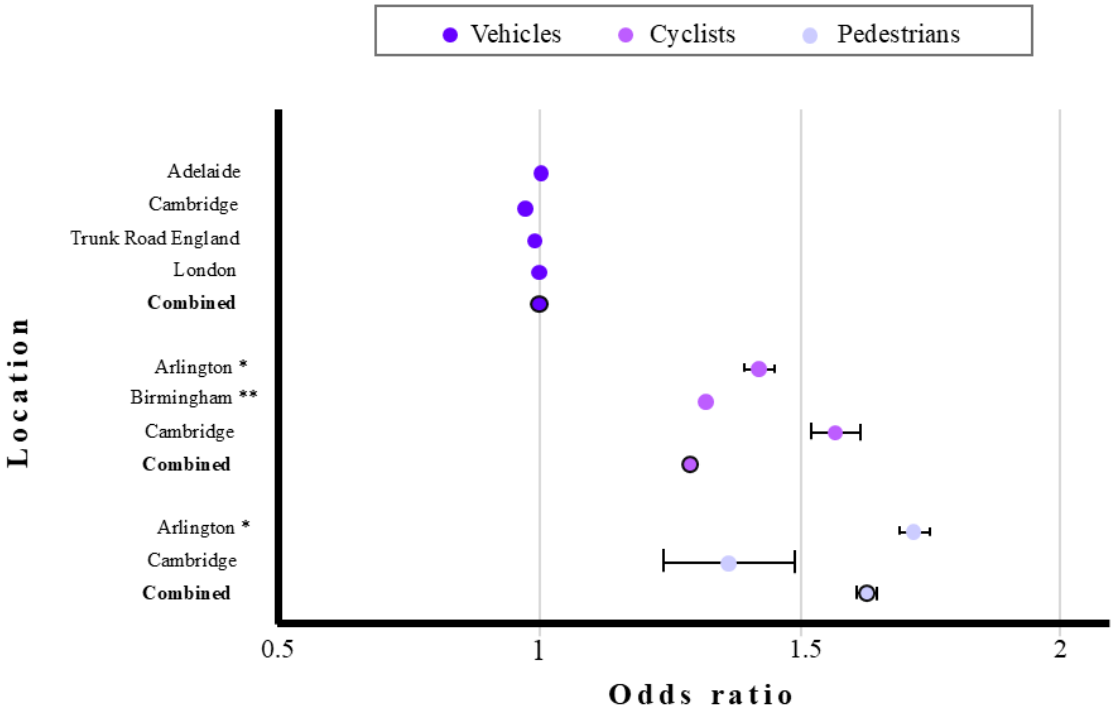


Figure 2.5 Fotios and Robbins [2021] compared their findings from new locations (Adelaide, Cambridge, London, and Trunk Roads in England) with work from previous studies (Arlington and Birmingham) to show differences in the impact of ambient light on different road user types. The chart shows ORs where an OR>1 suggests a significant reduction in traffic. Error bars show the 95% CI. Note that their analysis included data from previous studies [Uttley & Fotios, 2017; Fotios et al., 2019; Uttley et al., 2020]. The previous analysis for Birmingham [Uttley et al., 2020] did not include data for pedestrians.

2.4. Personal security issues

Cyclists, particularly those new to cycling or having less experience, can have concerns about their personal security, specifically being the target of physical harm or bicycle theft [Mosquera et al., 2012]. This is sometimes known as 'fear of crime' and may deter individuals from cycling.

The word 'crime' is used to describe any action in violation of regional law that warrants formal retribution [Thotakura, 2011; Michalowski, 2016]. 'Fear' is defined by Beckers et al. [2023] as "an adaptive emotion that mobilizes defensive resources upon confrontation". Fear of crime is therefore defined by Ferraro [1995, p. 4] as "an emotional response of dread to crime or symbols that a person associates with crime".

These definitions distinguish the subjective 'fear of crime' (e.g. I think I might be assaulted) from the objective action of crime (e.g. I have been assaulted). Both can exist independently with different dynamics and a different impact on the community [Struyf et al., 2019]. For example, the fear of crime can often mirror recorded crime, increasing where crime rates are higher, but the opposite is not true; crime rates are not necessarily higher in an area just because fear of crime is high [Deka et al., 2018]. Additionally, individuals previously victimized by crime express a higher fear of crime than individuals previously not victimized [Farrall et al., 2009]. This fear is also heightened in individuals indirectly affected by crime (knowing someone who's been victimized) [Doran & Burgess; 2012; Hale, 1996] and individuals with a perceived physical or social vulnerability [Franklin et al., 2008].

The effect of darkness and lighting on both crime and the fear of crime has been investigated. For crime, research found mixed results about its relationship with darkness and lighting, varying between a strong correlation [Welsh & Farrington, 2008; Ferrell & Mathur, 2012], a correlation only with specific types of crime (e.g. robbery) [Erturk et al., 2024;,Fotios et al., 2021a; Fotios et al., 2024a; Uttley et al., 2024], and no strong correlation [Castillo-Paredes et al., 2020]; for fear of crime, however, several studies suggest that darkness can increase this fear of being victimised by crime [e.g. Uttley et al., 2023a; Beckers et al., 2023].

It is worth noting that studies investigating the influence of darkness and lighting on reassurance and the fear of crime typically focused on pedestrians. It is reasonable to assume similar effects may also be found for cyclists, with people being deterred from cycling due to personal security issues and a lack of reassurance to travel after dark. Supporting evidence for this assumption can be found in a study on cycling in the U.S. by Duren et al. [2023], which identified 11 key factors that may influence perceived safety of cyclists, and conducted a survey where 6,735 participants were asked to rate the importance of these factors using a five-point scale. Using principal component analysis (PCA), Duren et al. found crime concerns to be among the five main factors influencing the perceived safety to cycle.

Reduced lighting reduces the visual information available to process and thus we might expect perceived safety to reduce with it. This has been shown in several studies [e.g.

Fisher & Nasar 1992; Gover at al., 2011]. For example, the study by Gover et al. [2011] used a questionnaire to investigate differences in perceptions of safety and crime in different ambient light conditions among staff at the University of Colorado Denver, USA. Their findings report that respondents felt an increase in feelings of fear and perceived risk after dark, and this was higher in female staff (**Table 2.3**). The study also suggested that increased lighting on campus might reduce these feelings of fear.

Table 2.3 Differences in perceptions of fear and perceived risk between males and females on campus [Gover et al., 2011]. In these 1-10 scale ratings, 1= not at all afraid; 10 = very afraid.

	Fear (day)		**Fear (night)**		**Perceived risk (day)**		**Perceived risk (night)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
M	1.73	2.44	2.42	4.06	2.02	2.08	2.82	4.40
SD	0.96	1.59	1.64	2.25	0.99	1.49	1.60	1.06
Significance of gender difference	*$p < 0.01$*		*$p < 0.01$*		*$p < 0.01$*		*$p < 0.01$*	

Respondents were asked the following questions:

Fear of crime: 1) 'During the day, while you were on campus, how afraid were you of being the victim of theft, robbery, assault, and rape?'; 2) 'At night, while you were on campus, how afraid were you of being the victim of theft, robbery, assault, and rape?'

Perceived risk of crime: 1) During the day, 'how likely do you think it is that you will be the victim of (1) theft, (2) robbery, (3) assault, (4) rape; 2) At night, 'how likely do you think it is that you will be the victim of (1) theft, (2) robbery, (3) assault, (4) rape.

Street lighting is understood to help decrease the fear of crime in multiple ways. For example, lighting increases visibility after dark, which increases community surveillance [Boyce, 2014, p. 485]. Increasing visibility can also help identify escape possibilities and limit concealment, thus, improving prospect and with it the chance of spotting and reacting to a predator in a timely manner [Nasar & Fisher, 1993]. Another example is that lighting improves feelings of safety after dark by facilitating assessment of perceived intentions from other pedestrians as inferred from visual cues (e.g. their facial expressions or visibility of their face and/or hands) [Boyce, 2014; Fotios & Yang, 2013; Hamoodh et al., 2023]. Lastly, lighting may also deter potential offenders due to the fear of being identified [Welsh & Farrington, 2008] or by the image it casts of competent and trustworthy governance which increases perceived safety [Perkins et al., 2015].

Reassurance, in the context of pedestrians, refers to the sense of confidence they may feel from factors such as street lighting, especially when walking alone after dark [CIE 236:2019; Fotios et al., 2015]. The positive effect of lighting on reassurance has been investigated further in several types of studies: the first is self-report studies. These studies had participants record their reassurance level after being exposed to different situations and conditions of ambient light in person and on site [Boyce et al., 2000; Fotios et al., 2019a]. For example, Fotios et al. [2019a] conducted a field study with 10 locations to investigate how pedestrian reassurance is impacted by changes in illuminance. Ratings of pedestrian reassurance were recorded before and after dark and plotted against lighting measurements to understand the impact of changes in lighting. The findings suggested that changes in lighting affected the level of reassurance, with increases in illuminance and uniformity improving levels of reassurance. The second type of studies investigating the positive impact of lighting on the fear of crime is traffic count studies, where a case-control method is used to analyse observed data [Fotios et al., 2024b; Uttley & Fotios 2017; Fotios & Robbins, 2021]. The assumption is that a reduction in the number of people travelling indicates lower levels of reassurance, all other things being equal. Findings from these different study designs suggest that while darkness can generally cause people to walk or cycle less, as evident by the reported reduction in active travel after dark compared to daylight periods in traffic count studies, lighting may improve reassurance, as evident by the improved levels of reassurance reported at higher illuminances in the self-report studies [Boyce et al., 2000; Fotios et al., 2019]. However, it is not a foregone conclusion that street lighting and increases in light levels can increase reassurance and address cycling deterrence caused by darkness. For example, fear of harassment and assault is increased due to being ‘on view’ to the public while cycling, a particular concern for women who feel vulnerably exposed to the male gaze [Horton, 2007, p. 134].

In summary, darkness promotes fear and therefore street lighting may help reduce fear by enhancing visibility. In turn, this could encourage more cycling.

2.5. Cyclists' ability to see and to be seen

2.5.1. The reduction in visibility after dark

Cyclists who feel safe from being involved in a crash are more likely to cycle. A survey by Sallis et al. [2013] asked participants (n = 1,780, aged 20 to 65 years, Seattle, WA) to estimate how improved feelings of safety from motorists would impact their cycling activity, using a 5-point scale ranging from *never* to *every day*. It was found that participants' cycling would increase if they felt safer (**Figure 2.6**). For example, cycling would increase at least once more per week for approximately 40% of bicycle owners (n = 488 from a baseline sample of 1,229).

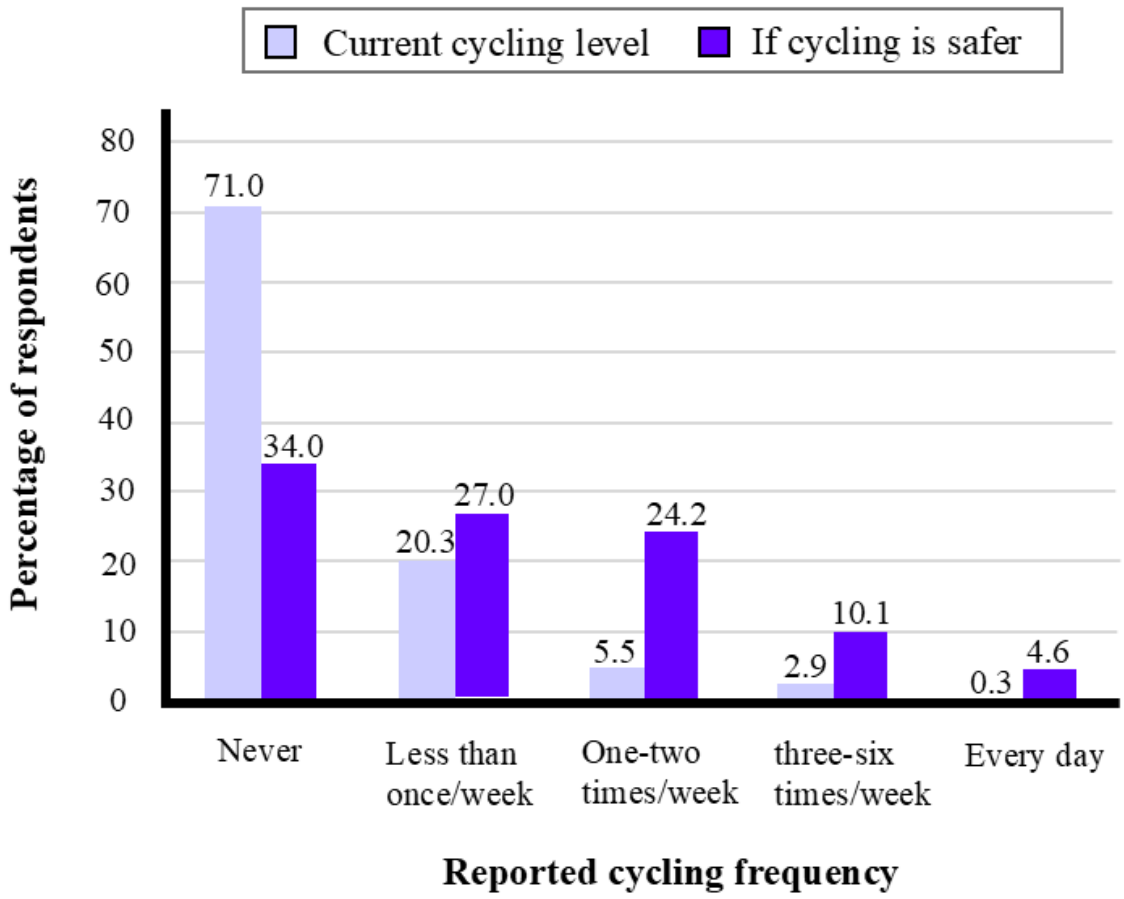


Figure 2.6 A comparison of cycling frequencies showing current cycling levels and projected cycling levels if the same sample felt safer in the Seattle, VA, and Baltimore, MD areas in 2002-2005 [Sallis et al., 2013].

The reduction in visibility after dark can impair our ability to see and avoid potential hazards while in travel. This is revealed as a lower probability of detecting a hazard, and/or an increase in the time from onset/first visible presence of the hazard to detection of the hazard (reaction time), particularly for low contrast low luminance objects [Plainis and Murray, 2002; Plainis et al, 2005]. This delayed reaction time in poor lighting conditions contributes to an increase in critical stopping distance (CSD), as Plainis [2006] observed when comparing differences in CSD for vehicles at different speeds (**figure 2.7**). Poor lighting conditions increase reaction times to detect a hazard, resulting in an increase in CSD of between 5.3 and 12.4 m, depending on vehicle speed.

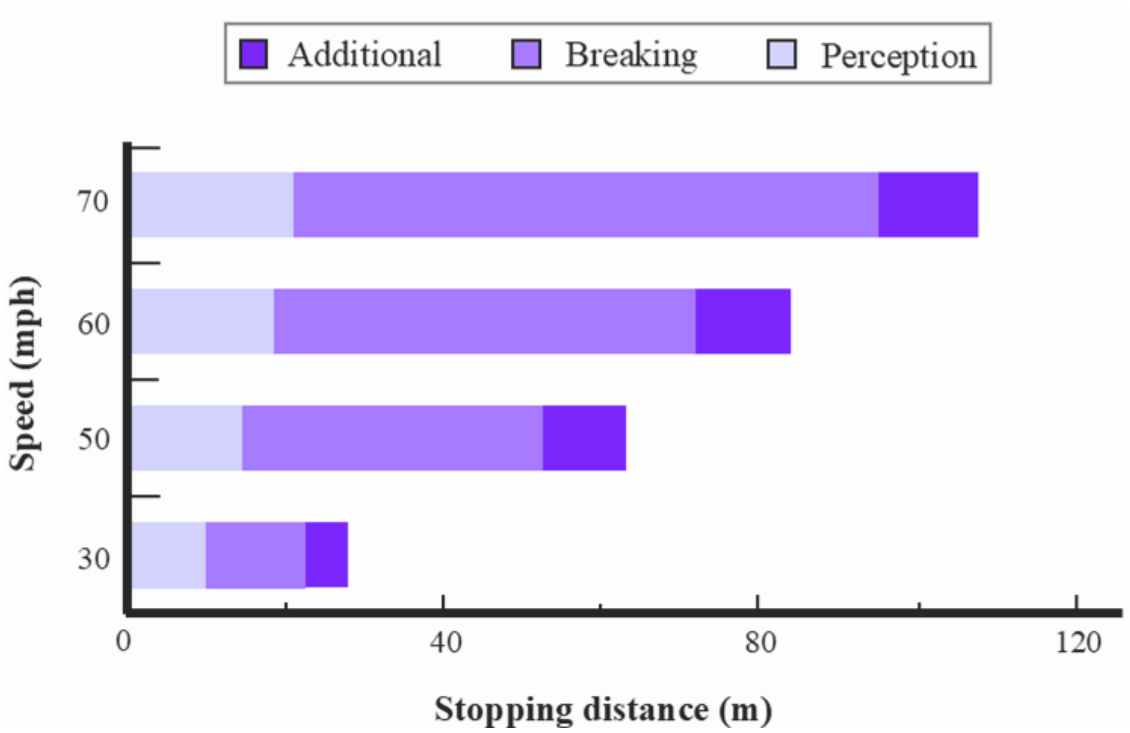


Figure 2.7 A comparison of critical stopping distances (CSDs) between different vehicle speeds [Plainis et al., 2006]. Three CSD components are shown: Breaking distance, perception distance (distance travelled during average reaction time), and additional distance (distance travelled during additional delay to reaction time caused by poor lighting conditions).

Delayed reactions caused by poor lighting conditions can also impact cyclists, making them more prone to collisions [Perkins et al., 2015]. This is because similarly to motorists (see **Figure 2.7**), the delayed reaction caused by the increased detection time can significantly increase the critical stopping distance needed to avoid collisions,

particularly at higher speeds. This might be more pronounced in older cyclists, as vision, muscle strength, and reaction time reduce with age [European Road Safety Observatory - Pedestrians and cyclists, 2018]. These concerns can heighten the feeling of danger for people cycling after dark and negatively influence the decision to cycle [Sustrans, 2018], particularly when compared to being able to make the same trip in daylight, which has been highlighted by research as a key motivator for people to cycle [Winters et al., 2011].

Reduced visibility after dark coupled with low conspicuity of cyclists (conspicuity refers to the ability of an object to effectively draw the attention of the observer against a background [Langham & Moberly, 2003]) can increase the rates of injury for them [Twisk & Reurings, 2013]. Such impairment in vision also impacts other road users like motorists, making motorist-cyclist collisions more prevalent after dark compared to daylight [Fotios et al., 2021b; Raynham et al., 2020], increasing with it the severity of resulting injury [Asgarzadeh et al., 2018; Twisk & Reurings, 2013; Yan et al., 2011]. Unlit roads particularly increase the odds of fatal collisions for cyclists after dark. Uttley et al. [2023a] calculated this increase as an odds ratio of 8.50, suggesting that the risk of fatality is increased by eight times after dark in unlit roads when compared to lit roads. **Figure 2.8** compares injury rates from cyclist-motorist collisions in different ambient light conditions, showing an increase in collisions in periods with reduced lighting (early morning and late evening) compared to periods of daylight.

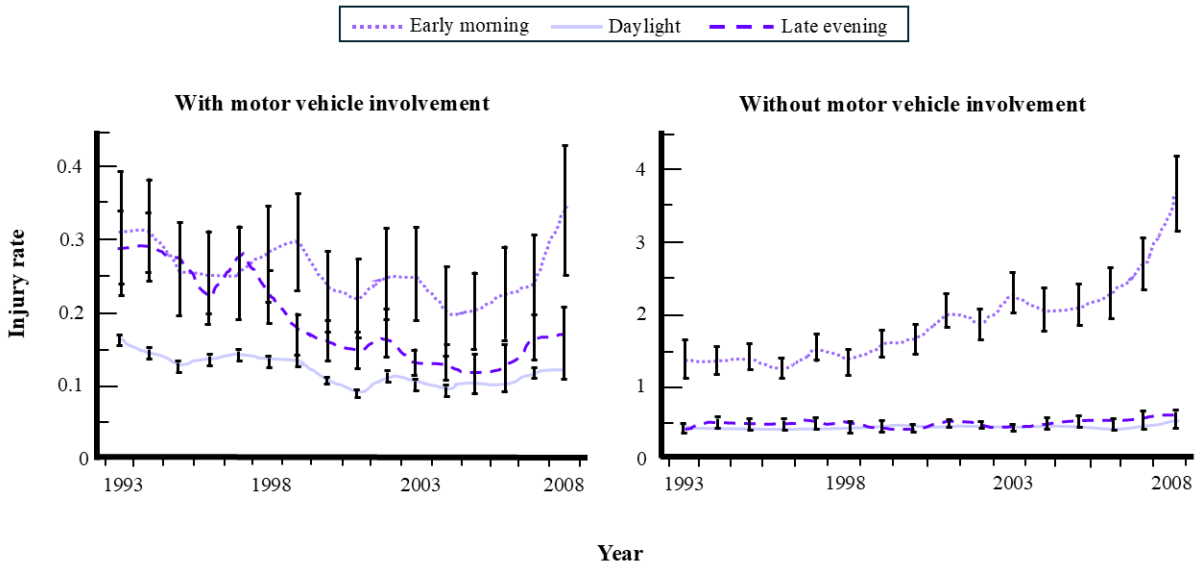


Figure 2.8 A comparison of cycling injury rates (per million kilometres travelled) in different ambient light conditions, with the involvement of motorists (left) and without it (right), for the period 1993-2008 [Twisk & Reurings, 2013].

Thus, enhancing visibility for cyclists and motorists who share the road with them is essential for safety. This is especially a necessity in countries where cycling infrastructure is not separated (where sharing the same road space by cyclists and vehicles is more common, and thus more visibility is needed) and in countries where limited cycling activity could mean that drivers do not expect cyclists on the road and are therefore less accustomed to interacting with them [Reynolds et al., 2009]. Within such settings, motorists are reported to be more likely to attempt lowering their own risk of collision with oncoming traffic at the expense of the well-being of cyclists who share the road with them [Rasch et al., 2022].

2.5.2. Lighting for hazard detection

One aim of street lighting is to enhance visibility after dark [BS 5489-1:2020, 2020]. In addition to addressing concerns about the fear of crime, lighting can aid cyclists in detecting obstacles and being visible to others, contributing to a reduction in the risk of injury and fatal traffic collisions [Chen & Shen, 2016, Uttley & Fotios, 2023]. A systematic review of 62 studies on lighting and collisions by Donnel et al. [2010] confirms this, with an estimation from more than half of the studies reviewed that

lighting intervention on unlit roads is expected to reduce collisions after dark by at least 30%, however, it should be noted that these studies did not specifically target cyclist-vehicle collisions.

Madsen et al. [2013] investigated the association between improved cycling safety and the use of permanent running cycle lights (lighting mounted on a bicycle that runs while the bicycle is in use despite time-of-day). This was done by monitoring two groups of cyclists: a 'treatment group' with permanent running lights installed (n = 1,845), and a 'control group' without permanent running lights (n = 2,000) for an entire year. Their findings reveal a reduction of 19% for cycling crashes with personal injury and 47% for cycling crashes involving other road users for the treatment group when compared to the control group. This suggests that lighting can enhance the safety of cyclists.

Further laboratory experiments have been used to investigate the effect of lighting on obstacle detection for both pedestrians and cyclists. For pedestrians, Uttley et al. [2017] conducted an experiment where 30 participants in two age groups (younger than 35 and older than 50 years old) recorded their detection of obstacles, focused particularly on peripheral vision which was achieved by providing a moving fixation target for participants to interact with while walking on a treadmill. This task was done under different combinations of five illuminances and three Scotopic/Photopic Luminance ratios (S/P ratios: a ratio used to characterise the effect of spectral power distribution (SPD) on visual performance at mesopic levels). Findings from this experiment suggests that increased illuminance improved obstacle detection performance, but this effect plateaued after illuminances greater than 2 lux. Additionally, age and S\P ratio of light source were found to impact detection at low illuminances, with obstacle detection performance being worse for older people compared with younger people and with light that had a lower rather than higher S/P ratio. A further study by Fotios et al. [2017] used a series of experiments to investigate peripheral obstacle detection for cyclists in different light variations (street lighting and cycle lighting), reporting that increases in illuminance were associated with better hazard detection performance in the path ahead of cyclists. Both studies [Fotios et al, 2017; Uttley et al., 2017] identified illuminance and spectrum as lighting attributes that enhance this obstacle detection. They also highlighted the importance of optimizing street lighting and fixed bicycle lights (already a legal requirement for cycling in many countries like the US and UK) for this detection. This adds to the evidence that lighting mitigates issues related to impairment of vision

for cyclists; after all, this is a key principle for lighting roads after dark: creating conditions that support safety for pedestrian and cycling journeys and to enhance general visibility [BS 5489-1:2020, 2020].

In summary, the literature suggests darkness may influence the decision to cycle or not to cycle, due to the reduction in perceived safety and security of cyclists, and through reduced visibility that can impact on the ability to see hazards and be seen by other road users. Enhanced street lighting may aid in mitigating this discouragement by improving feelings of reassurance; and by helping cyclists see better to avoid hazards and to be seen better to avoid collisions with motorists.

The next section explores further empirical studies that investigate the effect of darkness on reported and actual behaviour under conditions of darkness.

2.6. Darkness as a deterrent to cycling

The previous section described how there may be strong theoretical reasons why darkness could have an influence on cycling rates and why lighting can help offset such influence. Darkness may reduce feelings of personal security and impair visibility, impacting the ability of the cyclist to see potential hazards and the ability of other road users to see the cyclist (see section **2.4** and **2.5**). These factors could therefore deter people from cycling after dark. Lighting could mitigate this by improving visibility conditions which helps in the detection of hazards and can increase feelings of personal security.

This section discusses empirical evidence related to how darkness and lighting influence rates of cycling, exploring two types of studies: 1) Self-report studies about preferences and attitudes towards cycling, and 2) Observational studies on cycling behaviour.

2.6.1. Self-report studies

Self-report here refers to studies where participants record information about themselves through questionnaires, journals, or interviews. With regards to cycling, these studies typically gather information about attitudes and experiences to understand how behaviour is impacted (**Table 2.4**). Behaviours such as deciding to cycle to work or choosing one route over another have been linked to attitudes of cyclists or potential cyclists towards personal perceived safety [Castillo-Parades et al., 2022; Gatersleben & Appleton, 2007; Segadilha & Sanches, 2014]. A number of studies have shown that cyclists consider darkness a major deterrent. For example, Lee & Moudon [2008], Segadilha & Sanches [2014], and Gatersleben & Appleton [2007] found that inadequate lighting is a key concern for cyclists. This concern is echoed by "better lighting" being a strong demand for safe and comfortable cycling journeys [Lee & Moudon, 2008; Sanders & Cooper, 2013]. Winters et al. [2011] found and that being able to cycle during daylight hours was one of the top 10 motivators to cycle, and using a route that was not well lit was one of the top 10 deterrents to cycle, out of 73 factors asked about in a survey of 1,402 people. This study also found that cycling a route not well lit after dark was a bigger deterrent for novice cyclists than regular cyclists (see **Figure 2.9**).

Table 2.4 Previous studies using self-report methods to investigate the impact of attitudes and experiences on travel behaviour.

Method	Focus	Study	Key findings
Questionnaire	Impact of neighbourhood environment on active travel	Lee & Moudon [2008], Castillo-Parades et al. [2022]	Adequate lighting after dark among the top motivators for cyclists. Presence of lighting can influence active travel
	Motivators and deterrents of cycling	Winters et al. [2011]	Inadequate lighting is a deterrer for cyclists
	Road design preferences for cyclists, pedestrians, motorists, and public transit users.	Sanders & Cooper [2013]	adequate lighting can increase feelings of safety
	Cycling route choice	Segadilha & Sanches [2014]	Lighting among key influences for route choice
Feedback log after commute	Attitudes that affect the decision to cycle to work and how they change over time	Gatersleben & Appleton [2007]	Inadequate lighting is a deterrer for cycling uptake

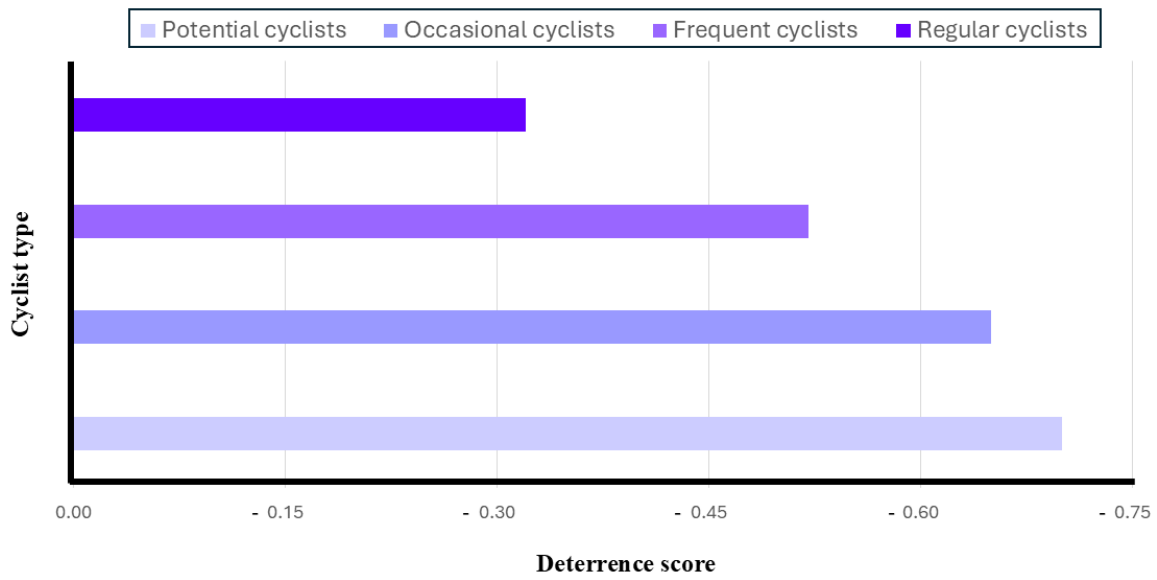


Figure 2.9 Reported deterrence from routes that are not 'well-lit after dark' on different cycling frequencies. Greater negative score indicates greater deterrence. Novice cyclists are the most impacted [Winters et al., 2011].

While studies in **Table 2.4** employed different variations of self-report and explored different aims, they confirmed that darkness is perceived as a deterrent to cycling, with one study finding that this effect is stronger in potential cyclists compared with regular cyclists [Winters et al. 2011]. Enhanced street lighting was named as a factor in mitigating the deterrence of darkness. However, criticism can be made against this self-report study and similar ones as they tend to include problems such as unintended subjectivity and stimulus range bias [Fotios et al., 2015; Fotios & Castleton, 2016]. These issues are discussed in the following section.

2.6.2. Limitations of self-reporting

Studies using self-report face several challenges that could lead to unreliable data. These challenges are typically centred around accuracy of reporting, with factors like self enhancement and relying on memory to recall past behaviour affecting its credibility [Paulhus & Vazire, 2007]. People's stated preferences or attitudes can often vary from their revealed preferences or actual behaviour. For example, stated attitudes towards sustainable transport are not always reflected in transport behaviour [Geng et

al., 2017]. This section discusses problems with self-report, with examples drawn from the studies in **Table 2.4** in the previous section.

1) ***Response bias/leading questions:*** When cyclists and potential cyclists are asked about the improvements that could make cycling more attractive to them, enhanced street lighting is consistently among the top recurring preferences. However, this stated preference might be directly influenced by experimental design. For example, adding "enhanced street lighting" in the list of factors a participant is being asked to evaluate might bring it to their attention and lead them to consider it, thus, following the experimenter's opinion about what might matter [Fotios et al., 2015; Fotios & Castleton, 2015]. This can be seen in two of the studies mentioned in **Table 2.4** for example, where participants were asked to evaluate how street lighting would influence their route choice [Segadilha and Sanches, 2014; Winters et al., 2011], bringing an issue to their mind that they may not have otherwise considered relevant. The choice of language might have also led participants to specific evaluations. Winters et al. asked participants how a route that's "not well-lit after dark" influence their route choice, possibly forcing a negative consideration of the issue on participants. Moreover, the question does not define what darkness is or what a well-lit route should mean. It also does not define the road type used nor the purpose of the trip. It does not factor in any other conditions, assuming it to be to be a single-factor issue.

2) ***Confirmation bias:*** To avoid leading questions, Sanders and Cooper [2013] used an open-ended question in an attempt not to influence participants about what they should consider. They asked participants to name all the street improvements that would increase traffic safety for them. Their results show that nearly 30% of participants answered this question with 'nothing'. The second largest percentage of participants (about 20%) answered this question with 14 different answers that the experimenter categorized into "other improvements". This might bring about confirmation bias criticism; where the level of approximation the experimenter did to fit answers into selected categories is unknown (no evidence of PCA found). For example, participants might have

appraised different aspects of street lighting (increase or reduction in brightness, colour, uniformity, use of smart lighting, etc.) but were grouped into one category titled "improved lighting". It should also be noted that participants in this survey were intercepted in the street while walking or cycling. Their answers might have significantly depended on appraisal of the location they were intercepted at. This interception might have not captured a representation of people already deterred from cycling in favour of other modes, although the researchers argue that intercepting people walking to bus stops and upon entering/existing local businesses might have accounted for this.

3) ***Self-enhancement:*** Previous studies have shown that active travel behaviours and patterns do not always align with self-reported behaviours and patterns. For example, when comparing daily cycling journals against wearable cycling camera data, Kelly et al. [2014] reported bias in self-reports about journey aspects such as duration and frequency. Participants tended to overreport their journey times by an average of 12% compared to camera data. Similarly, Geng et al. [2017] suggests that self-reported positive attitudes towards sustainability in travel are not consistently reflected on actual travel behaviour; these attitudes can be reconsidered or ignored when intersected with inconveniences such as distance, among other factors. One reason for the misalignment between self-reported behaviour and actual behaviour could be the perceived social desirability behind some self-reported answers. This can impact answers about perceived fear and safety across different communities and genders. Someone could say that they do not fear darkness just to improve impressions about them but can choose to take a route that is better-lit when given the option. The studies in **Table 2.4** focused on the improved feelings of safety gained from lighting after dark, leaving room for instances of self-enhancement.

Additional criticisms can be made for studies that focused on the influence of neighbourhood attributes on active travel [Castillo-Parades et al., 2022; Lee & Moudon, 2008], as perceived safety in one's own neighbourhood tend to be higher where social

interaction and road safety are relevant, and has been positively linked to more walking and cycling for adolescents [Carver et al., 2005].

It is therefore unclear from self-report studies whether darkness and street lighting truly influence behaviour or not. They also do not allow any conclusions to be drawn about how darkness is defined or about the characteristics of street lighting and how these may influence cyclist numbers. Knowing that a better-lit route may encourage more cycling than a worse-lit route is useful to some extent, but what constitutes better or worse is not well-defined. Understanding and quantifying the relationship between street lighting characteristics, such as illuminance, spatial distribution and spectrum, and rates of cycling after dark should be considered if we are to optimise street lighting to encourage cycling whilst avoiding energy waste and harmful ecological effects of excess light pollution. A method for evaluating and quantifying the effects of darkness and street lighting on cycling behaviour and preference is therefore needed, so that street lighting can be optimised to increase cycling propensity. Such efforts are discussed in the next section.

2.6.3. Revealed preference studies

Self-report studies suggest that cyclists feel deterred by darkness and that street lighting may mitigate this, but this type of study doesn't always reflect actual behaviour and tends to include limitations that reduce credibility in the conclusions that are drawn (see sections **2.6.1.** and **2.6.2.**). An alternative approach to investigating the impact of darkness on cycling is to observe actual cyclists' behaviour in response to it, revealing their preferences in the process. The studies in **Table 2.5** employ different methods to do this. These studies sought to eliminate the subjectivity and bias that pervade self-report by utilizing sensor data (GPS or traffic counters) to report on cycling behaviour. Such data can provide insight into the number of people cycling and their behaviour (route choice, speed, etc).

Table 2.5 Previous studies using different methods that employ sensor data to investigate the impact of environmental factors (including lighting) on cycling.

Method	Approach	Study
Regression modelling	Logistic regression performed on smartphone recorded GPS data with environmental variables	Chen et al. [2018]
	Linear regression performed on shared bicycle records with environmental variables	Zacharias & Meng [2021]
	Logistic and linear regression performed on automated counter data and weather records	Wessel [2022]
Case-control: clock change	*Analysis of cycling counts in short periods of daylight / darkness before and after DST clock change*	Uttley & Fotios [2017] Fotios & Robbins [2021] Fotios et al. [2023] Uttley et al. [2023b]
Case-control: whole year	*Analysis of cycling counts across a whole year, comparing periods of the year that are in darkness against periods of the year in daylight*	Uttley et al. [2023b] Fotios et al. [2019b] Uttley et al. [2020]

2.6.3.1 Regression modelling

Regression modelling is statistical analysis method used to determine the relationship between a response variable (known as a dependent variable) and explanatory variables (independent variables), facilitating the understanding of how changes in the latter affect the response variable [Ott and Longnecker, 2016]. Previous studies used this method to investigate how independent variables such as changes in weather and ambient light [Wessel, 2022] or built-environment attributes such as lighting [Chen et al., 2018; Zacharias & Meng, 2021] affect cycling.

For example, Chen et al. [2018] mapped cycling routes in Seattle, USA using GPS data collected through a smartphone app for cyclists and introduced alternative routes that might be taken instead. The study then pinpointed locations of built environment

attributes (e.g. land use, infrastructure, green spaces, and street lighting) to understand how these attributes influenced route choice. A logistic regression model revealed that cyclists tend to choose a route depending on multiple factors that influence their perceived safety, convenience, and comfort. One of the identified factors was the presence of street lighting, alongside other factors such as infrastructure, length of trip, traffic volume and speed, and slope.

Zacharias and Meng [2021] similarly identified built environment attributes in Beijing, China, but mapped it with records of dock-less shared bicycles (this variety can be picked up and dropped off anywhere without a docking station. e.g. Lime and Uber bicycles in the UK). A linear regression model then revealed that six factors significantly contribute to the use of dockless bicycles. These six factors are: separated infrastructure, street lighting, sidewalks, bicycle parking lots, density of POI (point of interest) per km^2, and road segment length. These factors were equally as important for uptake and depositing of bicycles. The researchers confirm that the findings also match that of previous work on fixed docks shared bicycles [Alcorn & Jiao, 2019; Mertens et al., 2017].

Wessel [2022] used basic and log-linear regression models to investigate how cycling numbers in Germany are impacted by changes in ambient lighting and weather conditions, extending the analysis further to understand how the extent of these changes is impacted by journey type and public holidays. The results suggest an increase in cycling when ambient lighting conditions are better (e.g. Daylight, or clear skies in the civil twilight period). However, the extent of this improvement is influenced by trip type (utilitarian, mixed, or leisure journeys) and time of day (the study assigned two periods for this: morning hours defined as 04:00 to 09:00 and evening hours as 15:00 to 22:00). Additionally, seasons and weather also limited the positive influence of daylight.

Beyond the three studies using regression modelling mentioned in **Table 2.5**, alternative forms of regression-based analyses were used, or could in principle be used, to investigate the effect of darkness on cyclist numbers. For example, Zhao [2016] employed a time-series analysis, specifically an Autoregressive Integrated Moving Average (ARIMA) model, to examine the effect of several factors including daylight duration on daily cycling volumes in Seattle, USA. The study found that daylight

duration contributed to seasonal variation in cycling, with lower cycling volumes in shorter winter days. This approach could, in theory, be adapted to incorporate ambient lighting conditions rather than daylight duration. Other types of time-series analyses, such as structural time-series models, may also be useful in exploring cycling trends associated with the change in ambient light; however, no study directly examining this effect on cycling was found. These Time-series approaches can be used but they might be more suited for modelling broader patterns rather than comparing changes in cycling rates across different ambient light conditions, which is central to this thesis.

Other forms such as regression discontinuity (RD) could also be used, particularly because they examine observations immediately before and after a boundary (e.g. the end of civil twilight). However, this would be more complex to apply here as the timing of civil twilight, if used as a threshold, changes continuously throughout the year. The use of spatial models or space-time models is also common in transport research and has been used in cycling-focused studies to investigate aspects like route choice under different conditions (including 'nightfall') [e.g. Hood et al., 2011]. However, these models may also not be well-suited for isolating and comparing the effect of darkness on cycling in specific hours of the day that alternate between daylight and darkness, nor do they readily accommodate analyses involving multiple such hours that change throughout the year.

Thus, for the aims of this thesis, regression-based approaches may not be suitable as the primary method of investigation. The second type of method identified in previous studies, the case-control method, may offer a better alternative, as it allows clearer isolation of ambient light conditions (i.e. examining the same hour in different conditions). Its findings may then be combined with regression-based analyses to explore any variation across different locations. This method is discussed in the next subsection.

2.6.3.2 The case-control method

The case-control method is named after the process of identifying a 'case' period, selected for its varying ambient light conditions; and a 'control' period, selected for having the same lighting condition at all times to represent a baseline for comparison.

This enables a ratio comparison between cyclist numbers in the case hour (when it's in daylight and when it's in darkness) against a control hour (for the same two periods as the case hour), resulting in an *odds ratio* (OR) [Szumilas, 2010]. This OR gives a measure of the effect of darkness on cycling, while also accounting for factors like weather changes in the process. When the OR increases significantly from 1.0, it suggests that cyclist numbers have decreased in darkness compared with daylight for the same time of day. The further the OR exceeds 1.00, the larger the effect of darkness. This method was originally used by Johansson et al. [2009] to assess the impact of darkness on the risk of a pedestrian being involved in a road traffic collision, and has been applied in recent studies to investigate multiple events such as crime [Fotios et al., 2021a; Fotios et al., 2024a; Uttley et al., 2024], cycling crashes [Mueleners et al., 2019], traffic flow [Fotios & Robbins, 2022], and the impact of darkness on cycling (see **Table 2.5**).

Studies employing the case-control method investigate the effect of darkness on cycling using two approaches: clock-change [Fotios & Robbins ,2021; Fotios et al., 2023; Uttley & Fotios, 2017; Uttley et al., 2023b] and whole year [Fotios et al., 2019b; Uttley et al., 2020; Uttley et al., 2023b]. These approaches differ only in the duration of the case and control period: clock change compares cycling activity in the same number of days before and after DST (daylights savings time) clock change, where the ambient light change is sudden at a given time of the day; while whole year compares it through the entire year, where ambient light changes are gradual (**Figure 2.10**).

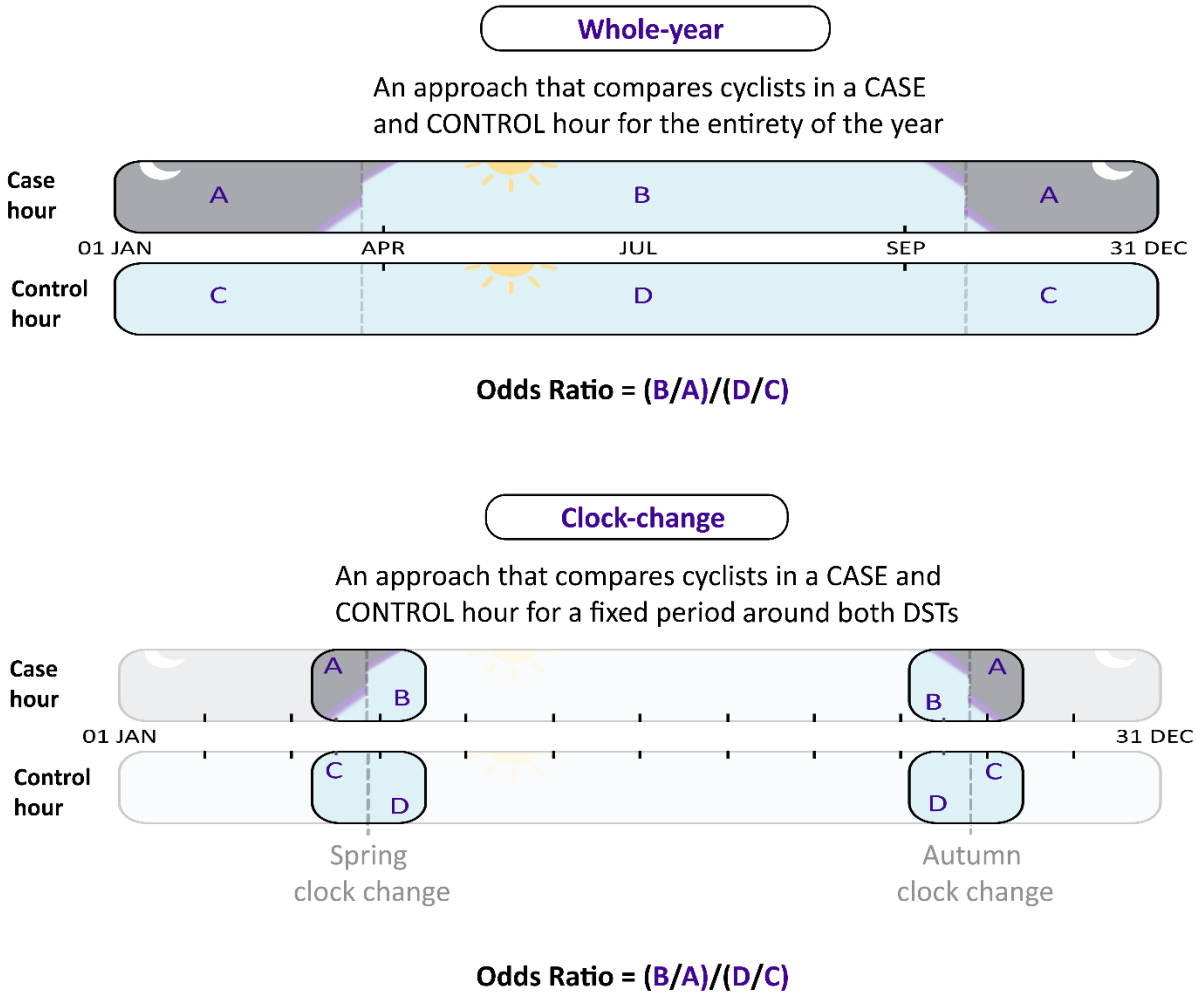


Figure 2.10 An illustration comparing the study periods of clock change and whole year.

Studies using the clock change method reported that darkness significantly reduced the number of cyclists. However, the use of clock change intervention to investigate activity changes has a few limitations that may challenge the validity of the conclusion drawn [Johansson et al., 2009], these are:

1) Limited sample sizes. The use of a single case hour reduces the number of events available for analysis in the limited number of days selected around DST. In addition, using only a short period (e.g. 7 or 14 days) either side of the DST clock change reduces the sample of events available for analysis. Smaller sample sizes lead to greater uncertainty in any calculated odds ratio.

2) Seasonal variations may introduce bias, particularly around the fall DST where conditions of road surfaces worsen closer to winter.

Fotios et al. [2019b] added a third limitation, in which they suggested that cycling rates can directly be impacted by any events taking place in the short periods of study (for example, a cycling event taking place in the week before the clock change), and proposed an alternative approach that uses data from the entire year instead. For this approach, they analysed data from the same database used in Uttley & Fotios [2017] to understand the differences between the two approaches. All three previous studies using the whole year approach [Fotios et al., 2019b; Uttley et al., 2020; Uttley et al., 2023b] confirm the general finding from studies using the clock change approach [Fotios & Robbins ,2021; Fotios et al., 2023; Uttley & Fotios, 2017; Uttley et al., 2023b], that darkness is associated with a reduction in the number of people cycling.

Similarly to Wessel [2022], most case-control studies utilized data from automated cycle counters (with the exception of Fotios et al. [2023], where manual count by human observers was used) to report on the number of people cycling in different phases of ambient lighting (daylight, twilight, and darkness). All studies reported a general decrease in cycling numbers after dark (**Table 2.6**).

Table 2.6 Previous studies using odds ratios to compare travel counts for cyclists in different ambient light levels.

Study	Data	Method of analysis			OR (95%CI) for effect of darkness on travel count*	Effect size**
	Location and period	Approach	Case hour	Control hours		
Uttley & Fotios [2017]	Arlington, Virginia, USA 2011-2016	Clock change	Spring: 18:00-18:59 Autumn: 17:00-17:59	Spring: 16:30-17:29; 19:30-20:29; 14:30-15:29; 21:30-22:29 Autumn: 15:30-16:29; 18:30-19:29; 13:30-14:29; 20:30-21:29	1.38 (1.37-1.39) p<0.001	Small
Fotios et al. [2019b]	Arlington, Virginia, USA 2012-2015	Whole year	18:00–18:59	15:00–15:59; 21:00–21:59	1.67 (1.66-1.68) p<0.001	Small
Uttley, Fotios & Lovelace [2020]	Birmingham, UK 2012-2015	Whole year	18:00–18:59	14:00–14:59; 22:00–22:59	1.32 (1.31–1.33) p<0.001	Small
Fotios & Robbins [2022]	Cambridge, UK 2019-2020	Clock change	Spring: 18:00-18:59 Autumn: 17:00-17:59	Spring: 14:00-14:59, 21:00-21:59 Autumn: 14:00-14:59, 21:00-21:59	1.57 (1.52-1.62) p<0.001	Small
Uttley, Fotios, Robbins, Moscoso [2023b]	Bergen, Lillestrøm, Oslo, Kristiansand and Trondheim, Norway, 2018-2020	Clock change	Spring: 19:00-19:59 Autumn: 17:00-17:59	Spring: 14:00-14:59, 21:00-21:59 Autumn: 14:00-14:59, 21:00-21:59	1.13 (1.10-1.16) p<0.001	Negligible
		Whole year	18:00-18:59	13:00-13:59, 22:00-22:59	1.05 (1.03-1.06) p<0.001	Negligible

*An OR>1.0 indicates a reduction in the numbers of cyclists after dark compared with the same period when in daylight

** Odds ratio effect size thresholds suggested by Olivier & Bell [2013]

While all studies in **Table 2.6** addressed the effect of darkness on cycling, some extended their focus to include walking [Fotios et al., 2019b; Fotios et al., 2023; Uttley & Fotios, 2017] and driving [Fotios & Robbins, 2020]. The findings report a reduction in pedestrians after dark but no significant impact on vehicles. Uttley et al. [2020] extended their focus to exploring the relationship between the calculated ORs and street lighting measurements. They compared ORs from 48 locations in Brimingham, UK, with: 1) Records of lantern density, and 2) street brightness measurements estimated from aerial images, following a method by Keuchly et al., [2012]. The comparison suggests that street lighting has a positive influence on cyclists, increasing the number of people cycling after dark even with a small increase in brightness. Further increases in brightness or density of street lighting did not yield additional benefit.

In summary, all nine revealed-preferences studies reviewed for this thesis [Chen et al., 2018; Fotios et al., 2019; Fotios et al., 2023; Fotios & Robbins, 2021; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017; Wessel, 2022; Zacharias & Meng, 2021] confirm a general deterrence of cycling associated with darkness and low light levels. The extent of this deterrence was shown to vary across locations compared in **Table 2.6**.

2.6.4. Limitation of previous studies: selective case and control hours

One limitation of previous work using the case-control method to investigate the effect of darkness on cycling [Fotios et al., 2019b; Fotios et al., 2023; Fotios & Robbins, 2021; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017] is the limited choice of case and control hours. For example, Uttley et al. [2020] used one case hour (18:00-18:59) and two control hours (14:00-14:59 and 22:00-22:59) in their analysis. However, based on the definitions of daylight and darkness applied in their study, there are five other case hours and nine other control hours, meaning that a number of alternative combinations could have been used instead (**Table 2.7**). This limitation of using only a selective number of case or control hours applies to all previous studies using the case-control method, where several alternative combinations of case and control hours could have been possible for the locations used in each study (**Table 2.8**).

Table 2.7 The alternative case and control hours that could have been used by Uttley et al. [2020] for their analysis of cycling in Birmingham, UK.

Case hour		Control hour	
Used	**Additional possible**	**Used**	**Alternative possible**
18:00–18:59	17:00-17:59; 19:00-19:59; 20:00-20:59; 06:00-06:59; 07:00-07:59	14:00–14:59; 22:00–22:59	09:00-09:59; 10:00-10:59; 11:00-11:59; 12:00-12:59; 13:00-13:59; 23:00-23:59; 00:00-00:59; 01:00-01:59; 02:00-02:59

Table 2.8 A comparison between the number of case and control hour combinations used in previous studies and the total number of possible case and control hour combinations that could be used, based on the definitions of daylight and darkness used in those studies.

Study	Location and period	Approach	Number of combinations used	Total number of possible combinations
Uttley & Fotios [2017]	Arlington, Virginia, USA 2011-2016	Clock change	8	42
Fotios et al. [2019b]	Arlington, Virginia, USA 2012-2015	Whole year	2	90
Uttley, Fotios & Lovelace [2020]	Birmingham, UK 2012-2015	Whole year	2	66
Fotios & Robbins [2021]	Cambridge, UK 2019-2020	Clock change	4	40
Uttley et al. [2023b]	Bergen, Lillestrøm, Oslo, Kristiansand, and Trondheim, Norway 2019-2020	Clock change	4	36*
		Whole year	2	80*

* This number is an approximation generated using typical case and control hours shared between the five cities in the study (i.e. *control hour* is any hour between 10:00 to 14:59 and 22:00 to 02:59; and for the whole year method *case hour* is any hour between 05:00 to 07:59 and 17:00 to 21:59).

It is possible that the use of alternative case and control hours could lead to different results, potentially even different conclusions about the effect of darkness on cycling. An example of how results can vary with different choice of hours is the analysis of cyclist and pedestrian flows in Arlington by Uttley and Fotios [2017]. This work used four control hours, two in daylight and two in darkness, these beginning either 1.5 hours or 3.5 hours away from the start of the case hour. The ORs determined for cyclists for each control hour varied from 1.36 to 1.43, and from 1.17 to 1.75 for pedestrians: one

apparent trend is that the OR was closer to 1.0 for the control hours closer to the case hour (dark control and day control rather than late dark and early day: see **Figure 2.11**). This difference in OR contributes to the apparent difference in ORs reported by studies using different choices of control hours.

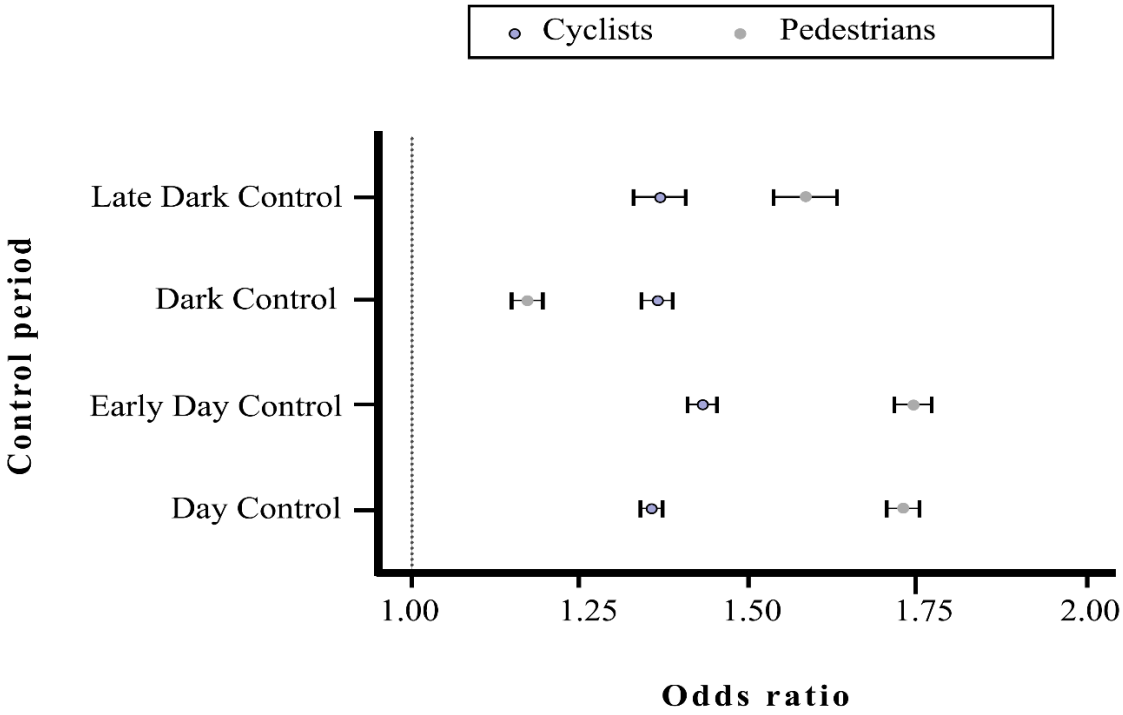


Figure 2.11 Odds ratios increase in cyclists and pedestrian frequencies during daylight compared with dark, relative to control periods. Error bars show 95% confidence intervals. [Uttley & Fotios, 2017].

Uttley and Fotios [2017] used the clock change method in their analysis. When analysing count data for the same location but using instead the whole year method with two control hours, Fotios et al [2019b] found ORs of 1.75 and 1.22 for the control hours starting at 15:00 (daylight) and 21:00 (dark) respectively, revealing a much larger effect of control hour choice when compared to Uttley and Fotios [2017].

One reason why the choice of case and control hours may influence the OR is because the numbers and/or the type of traveller (or purpose for travelling) may change significantly between certain hours of the day. For example, choosing a case hour that's in peak commuting time may show a different effect of darkness than an hour that's off-peak. The choice of which case and control hours to use represents one of many

researcher degrees of freedom; if different choices are made, different conclusions may be reached [Simmons et al., 2011; Wicherts et al, 2016]. Further work is required to determine the extent to which the choice of case and control hour affects the OR calculated from those data.

2.7. Exploring causes of variance in the deterrent effect of darkness: across-cities

It can be seen in **Table 2.6** in the previous section that the OR is not the same in each city. This may suggest that something other than darkness influences the tendency to cycle after dark. Section **2.7** explores causes of that variance at a macro scale, i.e. the differences across cities. Other causes may also impact darkness on at a micro scale, i.e. across different sites within the same city, as the results from Uttley et al. [2020] show when comparing sites within Birmingham, UK. These causes of variance at the micro scale are explored in section **2.8**.

Previous studies investigating the effect of darkness on cyclists explored locations in the UK [Fotios & Robbins, 2021; Uttley et al., 2020], USA [Fotios et al., 2019b; Uttley & Fotios, 2017], Germany [Wessel, 2022], and Norway [Uttley et al., 2023b]. Their findings showed that the impact of darkness is not uniform across these analysed cities. For example, cities in Norway were shown to be the least impacted by darkness, with an OR of 1.05, whereas Arlington in the USA was the most impacted, with an OR of 1.67.

Two causes of variance are explored here – latitude and cycling culture.

2.7.1. Latitude

Previous studies have analysed cyclist flows at latitudes ranging from Arlington at 38.88° [Uttley & Fotios, 2017] to Trondheim at 63.43° [Uttley et al., 2023b]. Change in latitude might affect cycling decisions because latitude, the position of a location on a north-south scale based on distance from the equator, contributes towards a location's climate and the amount of daylight it receives during a year (including the seasonal change in the amount of daylight across a year) [Schmal et al., 2020]. Both climate and the amount of daylight can significantly influence cycling (see section **2.6.3.**).

Table 2.9 shows the OR and latitude for cities analysed in previous work using the case-control method. Latitudes were determined using the *Latitude and Longitude Finder* website (www.latlong.net). **Figure 2.12** shows OR plotted against latitude of cities in previous work. These tentative findings indicate that ORs may tend to decrease with higher latitudes.

Table 2.9 ORs and latitudes of cities analysed in previous studies.

Study	Location	Latitude	OR
Fotios et al. [2019b]	Arlington, Virginia, USA	38.9°	1.67
Uttley, Fotios & Lovelace [2020]	Birmingham, UK	52.5°	1.32
Fotios & Robbins [2021]	Cambridge, UK	52.2°	1.57
Uttley et al. [2023b]	Bergen, Lillestrøm, Oslo, Kristiansand, & Trondheim, Norway	60.4° *	1.05

*Mean average latitude of the five Norwegian cities analysed.

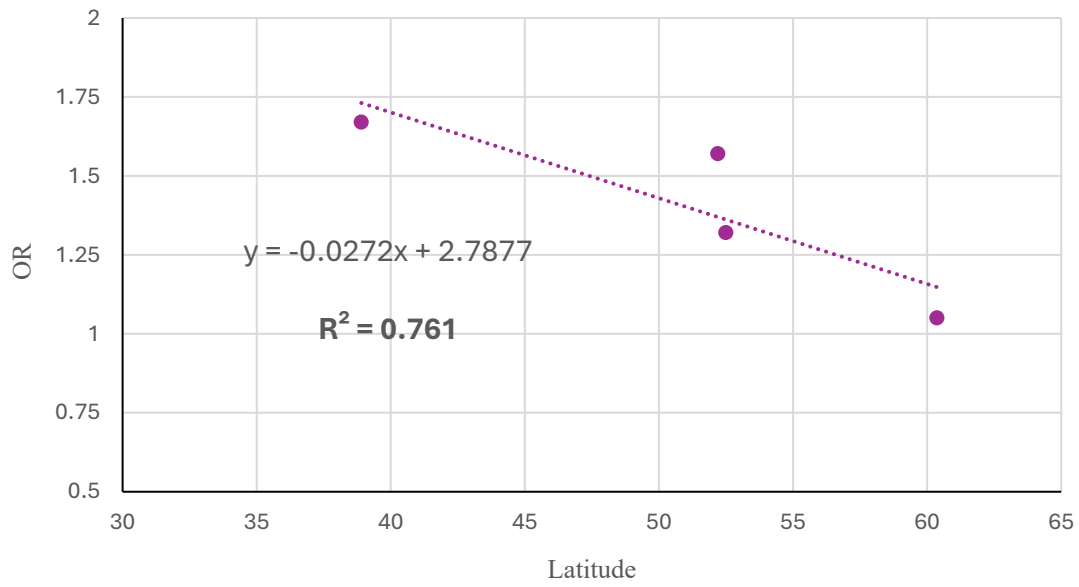


Figure 2.12 The relationship between latitudes and ORs established in the previous studies listed in Table 2.9.

Uttley et al. [2023b] suggested that the high latitude of Norway means dark periods are longer and the weather more adverse when compared to previously studied locations, and this may make cyclists more resilient to suboptimal cycling conditions like adverse weather or darkness.

There is also support for this theory from revealed-preference studies exploring the impact of exposure to adverse weather conditions on cycling. For example, Goldmann and Wessel [2021] compared 30 German cities using cycle counts and weather data and reported varying degrees of adaptation and resilience to adverse weather across these cities. While the study did not identify latitude as a contributor to this variation, several factors were identified, including cycling culture and infrastructure connectivity. This resilience to adverse weather, commonly referred to as "weather elasticity", is also reported by Nosal and Miranda-Moreno [2012] and Bean et al. [2021] when comparing the impact of weather on cycling in multiple cities. The latter study also identified similar contributing factors to those reported in Goldmann and Wessel [2021], including cycling culture, which may contribute to the variation in cycling rates across different countries. Cycling culture is discussed in the following subsection.

2.7.2. Cycling culture

Cycling culture refers to the collective values and attitudes shared among cyclists of a location, which impact how cycling is perceived and practiced. Studies using the case-control method [Fotios et al., 2019b; Fotios et al., 2023; Fotios & Robbins, 2021; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017] applied it on locations with varying levels of cycling activity. Uttley et al. [2023b] compared the propensity to cycle in cities analysed in previous work using cycling modal shares (**Table 2.10)** and suggested that cycling culture may be one reason why cycling modal shares vary between those cities. There is support for this suggestion from Haustein et al. [2020] who reported cycling culture as a reason behind differences in cycling rates between Stockholm, Sweden, and Copenhagen, Denmark.

Table 2.10 Uttley et al. [2023b]'s comparison of locations where cyclists count data has been captured and analysed to assess the impact of ambient light on cycling rates.

Study	Location	Available cycle counters	Year range	Modal share for cycling*
Fotios et al. [2019b]	Arlington, USA	33	2011-2016	2%
Uttley et al. [2020]	Birmingham, UK	48	2012-2015	1%
Fotios & Robbins [2021]	Cambridge, UK	14	2019-2020	18%
Uttley et al. [2023b]	Norway**	14	2019-2020	4%

* Modal share for cycling is estimated from different sources. See Original paper for details.

** Counts from five cities in Norway were included: Bergen, Lillestrøm, Oslo, Kristiansand, and Trondheim.

Figure 2.13 shows ORs plotted against modal shares of cities analysed in previous work. The limited association between the two variables may partially be explained by the small range of modal shares shown, as most cities range between 1% and 4%, with Cambridge standing out at 18%. This may have limited Uttley's exploration. It may therefore be beneficial to include cities with a wider range of cycling modal shares in order to understand how it relates to the deterrent effect of darkness.

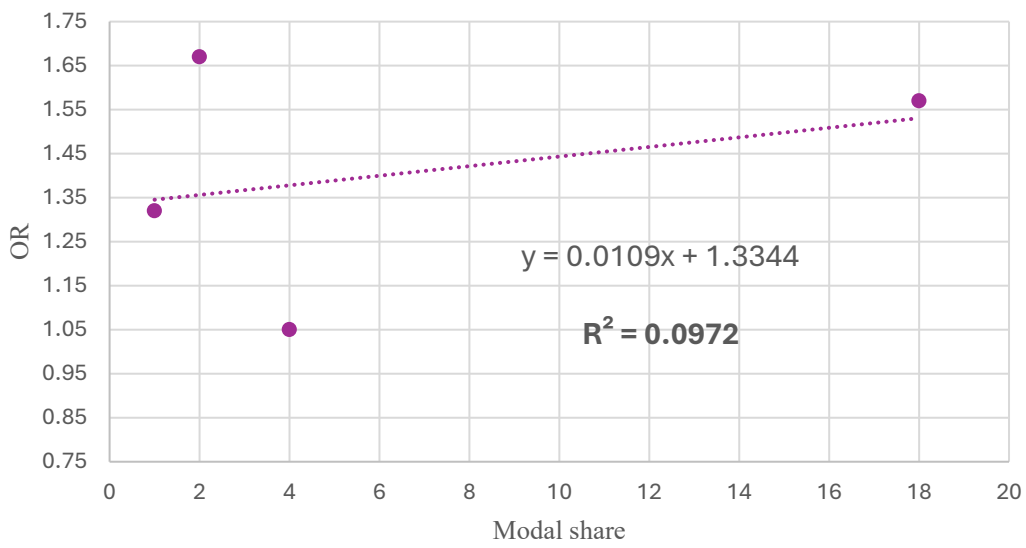


Figure 2.13 The relationship between modal shares and ORs established in the previous studies listed in Table 2.10.

In summary, research indicates that geographical variance can impact cycling numbers through the variation in the amount of available daylight, climate differences, or cycling culture. Multiple studies addressed the impact of weather on cycling, but the need to understand the regional impact on cycling has been identified as one of the main gaps in current literature [Vidal-Tortosa & Lovelace, 2024], stressing the need to examine countries that vary in their latitude and cycling culture. This is an issue that has long not been addressed, being identified as a gap in cycling research by Heinen et al. in [2010], in their review of literature, stating that *"in order to gain better insights into the transferability of knowledge, bicycle research should be conducted across a wider range of countries"*.

2.8. Exploring causes of variance in the deterrent effect of darkness: within-cities

2.8.1. Journey type

The impact of darkness on cyclists may vary depending on the purpose of their journey. For example, Utilitarian cyclists (e.g. commuters cycling to and from work) may be more persistent against darkness or low light levels in their journeys compared to those cycling for leisure, because they may cycle more regularly and have less choice about the times they travel. Utilitarian cyclists are reported to be generally less affected by factors that deter other types of cyclist and non-cyclists [Duren et el., 2023]. Duren et al. hypothesize that the greater the experience in cycling, the less affected cyclists are by safety concerns (these concerns being a key reason why darkness may deter cyclists). This is likely due to an elevated sense of 'self-efficacy'; a confidence in one's own ability and acquired skills to overcome obstacles or challenges.

While previous research has investigated and confirmed a reduced influence from factors like weather on commuters regularly cycling to and from work [Ahmed et al., 2017; Heinen et al. 2011], the impact of darkness on journey type has largely been overlooked. One limitation that hindered such investigation is that previous work studying the impact of darkness on cyclists [Fotios et al., 2019b; Fotios & Robbins, 2021; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017] uses data recorded by automated cycle counters in its analysis, and these counters are not able to record the purpose of cycling journeys. Thus, a classification method for journey type is needed in order to understand how journey type affects the impact darkness has on the decision to cycle.

Wessel [2020] proposed a classification method that can be applied to cycling counts in individual counter locations to enable an estimation of the main use for each route, ranging between 'utilitarian', 'recreational', or 'mixed' cycling. This classification method (summarized in **Figure 2.14**) works by comparing patterns in cycling counts in peak and off-peak periods. It takes influence from a study by Nosal and Miranda Moreno [2012] which classified journey types to understand how they are impacted by weather. Wessel [2022] updated this classification method and used it to confirm that the negative impact of weather on cycling is increased on leisure journeys. Additionally, Wessel's results confirmed that better lighting conditions (e.g. daylight or a clear sky

civil twilight, compared with darkness) lead to an increase in cycling, but the extent of this increase depends on journey type and time of day. However, the classification proposed by Wessel categorises a location into one of three possible options, creating a strict measure of the dominant journey type in the location. This approach may lack the flexibility that could better represent the nature journey types in these locations, a flexibility that could be gained from a continuous measure such as a scale or a ratio. Additionally, Wessel's analysis focuses only on German cities, and this limits the exploration of how different journey type interact with different climates, ambient light patterns, and cycling infrastructures.

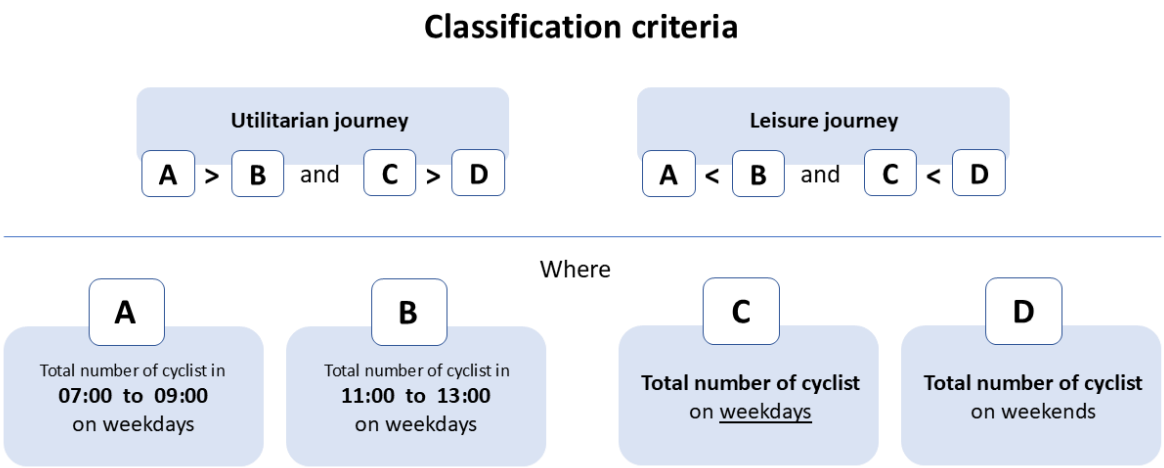


Figure 2.14 Illustration of Wessel's [2022] cycling route classification method. These criteria suggested that a route is dominated either by utilitarian or leisure cycling. If neither sets of criteria are met for utilitarian or leisure journeys, then a route is classified as "mixed".

2.8.2. Lighting characteristics

Locations where street lighting is present may show less of a deterrence for cycling after dark. This is because lighting can enhance visibility for cyclists which may increase reassurance (see sections **2.4)** and hazard detection (see sections **2.5)** after dark. When comparing cycling in lit and unlit routes, research reports a reduction in cycling flow in unlit routes. For example, Fotios et al., [2019b] used on odds ratio to compare active travel in locations with installed street lighting (n = 11) and without street lighting (n = 7), recording an OR of 1.61 and 1.95 respectively. This suggests that the deterrence coming from darkness is less significant in locations that are lit when compared to unlit locations. Alternatively, Uttley et al. [2020] used lantern density to

classify the presence of lighting in counting locations, between a lantern density of none (no lanterns present), low (<2.7 lanterns/100 m), or high (>2.7 lanterns/100 m), and recorded ORs of 2.17, 1.31, and 1.20 respectively. This suggests that the deterrence coming from darkness is less significant in locations with any lantern density when compared to unlit locations.

While findings from both studies suggest that cyclists have a clear preference for lit routes, a few limitations can be observed. First, it is it unclear if this preference is shared in locations with different latitudes (where weather, longer daylight periods, and cycling culture could play a role). Second, it is unclear if journey type plays a role; would utilitarian cyclists be less deterred by a location that is unlit?. Third, while Fotios et al. [2019b] observed that on-road cycling locations are typically lit, whereas a large portion (39%) of off-road locations are unlit, the extent that infrastructure plays a role in making a location cyclable even if it's unlit remains unclear. For example, if a location is buffered from traffic, would cyclists feel safe to cycle while relying only on their mounted lights?

2.8.3. Proximity to city centre

A third mediating factor that may contribute to a reduction in the impact of darkness on cycling is proximity to the city centre. This may be because cyclists and pedestrians feel safer in zones where traffic is controlled or restricted, and such areas are often centralized within the city, particularly in larger cities [Pucher & Dijkstra, 2000]. Additionally, city centres are where a large portion of services are typically located. Services here refers to urban amenities: whether commercial (such as retail), public (such as governmental buildings or public transport); or infrastructural (designated cycling areas). The following is further exploration of reasons why proximity to city centre may influence the effect of darkness:

1) ***Integration with public transport:*** Main public transportation hubs (i.e. railway stations and bus terminals) in cities are typically located in central areas. Proximity to public transport and connectivity with cycling infrastructure has been associated with an increase in utilitarian cycling [Heesch et al., 2015]. This might be due to the availability of cycling parks and infrastructure or because

cyclists can integrate public transportation for a portion of their journey. Although the study by Heesch et al. was conducted on adults over 40 years old in Brisbane, Australia, its findings are echoed by other studies such as Titze et al. [2010] which suggested that utilitarian cycling is influenced by meso (larger than micro, smaller than macro) attributes like access to infrastructure, neighbourhood connectivity, greenery, and traffic-controlled streets. Proximity to public transport has also been mentioned in the study by Zacharias and Meng [2021], reporting that the frequency of dockless hire bicycle use in Beijing, China, increased with proximity to public transport, and while this study did not classify the purpose of the journey, a study by Chen et al. [2020], found that the use of Dockless hire bicycles for utilitarian travel is four times higher compared to other types of journeys. For Leisure cycling, research suggests that it is influenced by journey length, cycling network, and low vehicle zones [Sun et al., 2017]. Another meso attribute considered by multiple studies is bicycle parking. For example, utilitarian journeys are reportedly increased with the provision of 'trip-end facilities', like bicycle parking and showers at the place of work [Buehler, 2013]. The availability of cycling facilities and the integration with public transportation might help cyclists feel less deterred by darkness.

2) ***Car-free zones in city centres***: A car-free central zone is a concept that's been implemented in multiple major cities around the world including Copenhagen, Milan, Madrid, and many more. There are several aims behind it such as improvements in air quality, reducing congestion, and promoting physical activity. Hass-Klau [1997] gives an example of how such efforts can benefit cyclists, reporting that cycling in Lüneburg, Germany increased 59% and the number of injuries decreased 13.5% in one year following the implementation of car-free zones in the city centre in 1993. Separate cycling infrastructure is a key factor in making cyclists feel safer [Lee & Moudon, 2008; Sanders & Cooper, 2013; Segadilha & Sanches, 2014], thus, the reassurance coming from car-free zones in city centres may help cyclists feel less deterred by cycling in the dark.

3) ***Environmental zones and lighting design:*** Lighting design guidelines vary between different zones of the city. For example, lighting design guidance suggests higher illuminances for areas of a higher environmental zone, which may lead to a reduced impact from darkness on cyclists in the city centre when compared to zones further from it. **Table 2.11** shows the classification for Environmental Zones E2 to E4, these being the zones associated with inhabited areas [ILP, 2021]. For subsidiary roads in England and Wales, BS5489-1:2020 [BSI, 2020] recommends a higher lighting class (P3: average illuminance = 7.5 lx) for zones E3 and E4 than it does for zones E1 and E2 (P4: 5.0 lx) (see Table A.5 of BS5489-1:2020[BSI, 2020]). According to a lighting designer's interpretation of the environmental zones, the classifications shown in **Table 2.11** might lead them to select a lower light level in peripheral areas than in central areas of a town or city. This would affect the impact of darkness on cycling rates if lower light levels are associated with a greater deterrent effect of darkness [Uttley et al, 2020].

Table 2.11 Environmental zones and lighting environments [ILP, 2021].

Zone	Surrounding	Lighting environment	Examples
E2	Rural	Low district brightness	Sparsely inhabited rural areas, village, or relatively dark outer suburban location
E3	Suburban	Medium district brightness	Well inhabited rural and urban settlements, small town centres of suburban locations
E4	Urban	High district brightness	Town/city centres with high levels of night-time activity

2.9. Research Aims and Hypotheses

The overall purpose of this thesis is to understand how darkness affects cycling rates. This is divided into three focused aims based on the literature reviewed in chapter **2**. The three aims are addressed through seven research hypotheses (**Figure 2.15**) as described below.

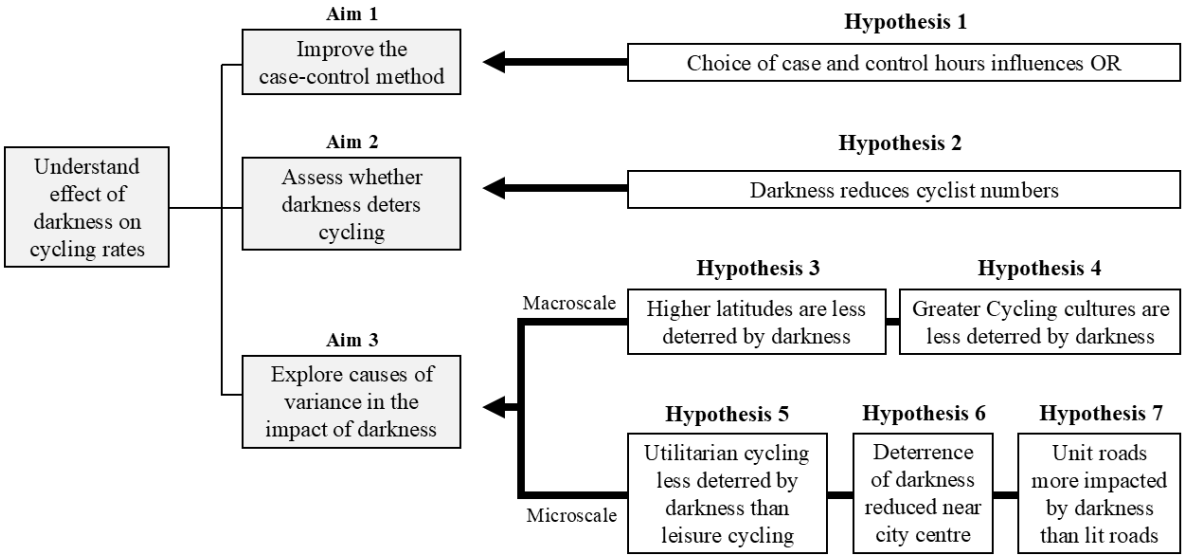


Figure 2.15 Summary of research aims and hypotheses that address them.

Research aim 1: Improve the method of analysis for quantifying the impact of darkness on cycling. The varying results that can be obtained from different case and control hour choices are addressed through the following hypothesis.

Hypothesis 1: The choice of case and control hour has a significant influence on the odds ratio produced.

Research aim 2: Assess whether darkness deters cycling. The effect of darkness on cycling is addressed through the following hypotheses.

Hypothesis 2: Darkness reduces the number of cyclists after dark.

Research aim 3: Explore causes of variance in the impact of darkness on cycling. This exploration is addressed on two levels: first, macroscale factors that may influence the effect of darkness (i.e. latitude and cycling culture) are addressed through the following hypotheses.

Hypothesis 3: Locations at higher latitudes will show less of a deterrent effect of darkness on cycling.

Hypothesis 4: Locations with a greater cycling culture will show less of a deterrent effect of darkness on cycling.

Next, microscale factors that may influence the effect of darkness (i.e. journey type, distance to city centre, and presence of lighting) are addressed through the following hypotheses.

Hypothesis 5: Locations that have a higher proportion of utilitarian cyclist journeys will show a smaller deterrent effect of darkness.

Hypothesis 6: Locations that are further from the city centre will show a larger deterrent effect of darkness than locations closer to it.

Hypothesis 7: Locations where street lighting is present will show a smaller deterrent effect of darkness than locations where no lighting is present.

2.10. Summary

2.10.1. Key points from literature review

As the main aim of this thesis is to investigate the effect of darkness on cyclist numbers, the literature review begins by defining what *darkness* means. This is particularly useful because definitions varied in the reviewed studies, especially around the inclusion or exclusion of twilight in periods of darkness. Therefore, in this thesis, darkness is defined as the period starting when the sun's altitude is -6° below the horizon at sunset and ending when the sun's altitude is -6° below the horizon at sunrise. This definition excludes civil twilight but includes nautical and astronomical twilight periods in darkness, ensuring a clear distinction between the periods of ambient light being defined as daylight and darkness.

After dark, low light levels bring a reduction in visual function. This can affect cyclists in two ways. First, it reduces their ability to see their surroundings and be seen by others, making them more vulnerable to hazards and collisions; and second, it increases their fear of crime by hindering the visibility that helps them appraise prospect and refuge. These factors could deter people from cycling after dark.

In a review of empirical studies investigating the influence of darkness and lighting on cycling, a total of 15 studies were identified for this thesis. These studies were grouped into two types:

1. **Self-reporting studies (n = 6).**

This refers to studies in which participants report information about their preferences and behaviours. Findings from six reviewed studies can be summarised in four key points: 1) Darkness and inadequate lighting are considered a deterrent for cycling. 2) Potential cyclists are more deterred by darkness than regular cyclists. 3) Better lighting conditions are consistently a top demand for safe and comfortable cycling journeys. 4) Cycling during daylight hours is preferred to cycling after dark.

However, self-reported studies face the criticism that they tend to include several issues like leading questions and confirmation bias, and self-reported attitudes and behaviour often do not correlate well with actual behaviour. Additionally, the studies did not allow for a consistent conclusion to be drawn about characteristics of street lighting or the definition of darkness used. It could therefore be argued that self-report studies may not reflect the true influence of darkness on cycling behaviour. Thus, an alternative type of study that observes actual cyclist behaviour in relation to darkness is considered.

2. **Revealed-preference studies (n = 9).**

Nine revealed-preference studies were reviewed. These studies analysed sensor-recorded cycling data against secondary data such as time-of-day to investigate the influence of light on cycling activity and route choice. These studies used either regression analysis or a case-control method to reveal that darkness and low light levels can indeed deter cycling. Street lighting can reportedly mitigate this even with a small increase in brightness. However, several gaps that impact the scope and generalizability of these studies were observed.

2.10.2. Gaps in literature

Three gaps are identified in the reviewed literature, the first concerns the case-control method used in previous studies, and the second and third concern the scope of those previous studies. These gaps influenced the division of the main research aim into three focused aims described in section **2.9**.

1) ***Methodological issues:*** Findings from previous case-control studies are limited by their choice of case and control hours. When different choices are made, different results are reached. Additionally, several revisions such as a concise definition of darkness can be made to enhance study design.

2) ***Lack of geographic and cycling culture variety:*** More research is needed to confirm if darkness deters cycling and whether this effect varies between countries with different latitudes (resulting in different seasonal changes and ambient light patterns) and cycling cultures.

3) ***Unaddressed mediating factors:*** More research is needed into the impact of location-specific factors on the extent of the deterrence caused by darkness on cycling. These factors include journey type (leisure vs. utilitarian), the presence or absence of street lighting, and proximity to the city centre.

2.11. Analysis overview

The following plan provides a general outline for the methodology of this thesis. **Figure 2.16** illustrates this plan, dividing it by chapter and highlighting the hypotheses relevant to each stage of analysis.

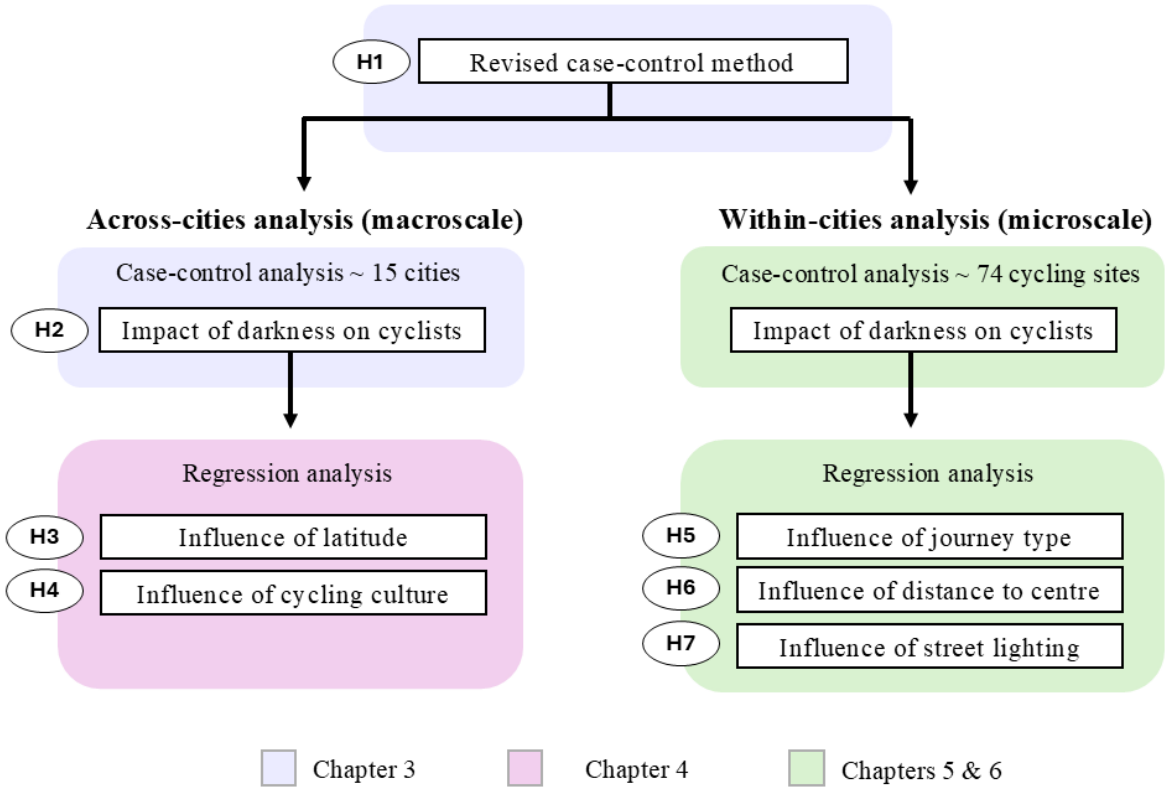


Figure 2.16 Outline of the methodology in this thesis, highlighting the relevant hypothesis (H1-H7) addressed by the results from each stage of the analysis.

Chapter **3** assesses the impact of different choices of case and control hours on the effect of darkness. This aims to address H1, which states that the choice of case and control hours influences the ORs produced. An improved case-control method that combines all case and control hours is introduced as the foundation for two scales of analysis:

<u>Across-cities analysis of the impact of darkness:</u> The impact of darkness on 15 cities is assessed using the improved case-control method, which establishes ORs that are presented in chapter **3**. This aims to address H2, which states that darkness reduces

cyclist numbers. To explore the influence of macroscale factors (i.e. latitude and cycling culture), the established ORs are analysed against records of latitudes and estimates of cycling cultures using linear regression. This is presented in chapter **4** and aims to address H3 and H4, which state that locations in higher latitudes and with greater cycling cultures are less deterred by darkness.

Within-cities analysis of the impact of darkness: The impact of darkness on 74 cycling sites within five cities is assessed using the improved case-control method, which establishes ORs that quantify the impact of darkness at individual sites rather than at the city level. To explore the influence of microscale factors (i.e. journey type, distance to city centre, and the presence of street lighting), the established ORs are analysed against estimates of these four factors using linear and stepwise regression analyses. This is presented in chapters **5** and **6**, and aims to address H5-H7, which state that darkness is less of a deterrent for utilitarian journeys and locations closer to the city centre, and more of a deterrent for unlit locations after dark.

Chapter 3. Improving the method of analysis

3.1. Introduction

In previous work, ORs for the effect of darkness on cyclist flows were determined using typically only one case hour and one or two control hours. There are other possible choices, and some initial evidence [Fotios et al., 2019b; Uttley & Fotios, 2017] suggests different choices of case and control hours lead to different ORs. As Identified in the literature review (Chapter **2**), the limited choice of case and control hours used in previous studies is a key methodological limitation of research investigating the effect of darkness on cyclist numbers. Chapter **3** addresses this limitation, describing the process of refining the case-control method and introducing additional considerations to improve study design.

3.2. The case-control method

The case-control method compares cyclist numbers in two defined periods, a case hour and a control hour. The current work considers the effect of change in ambient lighting conditions and therefore a case hour is one that is in daylight for part of the year and in darkness for another part: a control hour (necessary to provide a 'normal conditions' baseline for comparison) is one that remains in daylight (or darkness) across the whole year. For example, in Leeds, UK, one possible case hour is 18:00 to 18:59, because that hour is in darkness during winter but in daylight during summer, while 11:00 to 11:59 remains in daylight for the whole year and is thus a possible control hour.

Comparing the frequencies of events occurring within specific parts of the case and control hours using an OR [Szumilas, 2010] shows the size of the deterrent effect of darkness. **Equation 1** shows how the OR is calculated, and **Equation 2** shows the 95% confidence interval (95%CI) for the OR [Johansson et al., 2009]. When the OR increases significantly from 1.0, it suggests that cyclist numbers have decreased in darkness compared with daylight for the same time of day.

The case-control method can be applied in two approaches: clock-change and whole year (see section **2.6.3.2.**). This thesis follows the whole year approach. Using cyclist counts from the entire year rather than the limited number of days in the clock-change approach increases the data sample and includes counts across seasonal changes that may affect cycling patterns.

$$R_{\text{odds}} = \frac{(A\ /\ B)}{(C\ /\ D)} \tag{1}$$

$$95\%\ CI = \exp\left(Ln\ (R_{\text{odds}}) \pm 1.96\ \text{x} \sqrt{\frac{1}{A} + \frac{1}{B} + \frac{1}{C} + \frac{1}{D}}\right) \tag{2}$$

Where:

R_{odds} is the odds ratio for the effect of darkness on cyclist numbers.

A is the number of cyclists when the case hour is in daylight.

B is the number of cyclists when the case hour is in darkness.

C is the number of cyclists in the control hour when the case hour is in daylight.

D is the number of cyclists in the control hour when the case hour is in darkness.

To establish the values of A, B, C, and D, two types of data are required to allow for cyclists counts to be allocated to specific ambient light conditions. These are:

1) Hourly counts of cyclists.

2) The daily times of sunset, sunrise, and the start and finish of civil twilight.

Cyclist count data for the current and previous studies [Fotios et al., 2019b; Fotios et al., 2023; Fotios & Robbins, 2021; Goldmann & Wessel, 2021; Miranda-Moreno and Nosal, 2011; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017; Wessel, 2022] are gained using automated counters. These counters are installed by local authorities for their own needs, and here the data is available to the public. The count sensors employ various technologies (e.g. piezoelectric cables, inductive loops, etc.).

On-street counting by observers is also possible [e.g. Buhler et al., 2021] but that greatly restricts the count data.

The daily times of sunset, sunrise, and the start and finish of civil twilight can be obtained from multiple sources, such as online platforms (e.g. https://www.timeanddate.com) or from built-in datasets and packages available in statistical analysis software such as Microsoft Excel and R (a free open-source data analysis software).

Sections **3.3** and **3.4** introduce the two datasets collected for this study, outlining revisions made to each of them to improve the overall study design compared to that of previous work.

3.3. Hourly counts of cyclists

Previous studies using automated cycle counter data in their analyses [Fotios et al., 2019b; Fotios et al., 2023; Uttley et al., 2020; Uttley & Fotios, 2017] tended to consider only a single city. A few studies [Fotios & Robbins, 2021; Uttley et al., 2023b; Wessel, 2022] extended their scope to include multiple cities, though they faced limitations in sample size. For example, Wessel [2022] incorporated 23 cities in his analysis, but several of them had a very low number of counting sites, including six cities with data from a single cycling counter. This does not meet the recommended threshold of 4 counters (per clusters of locations with similar cycling patterns, e.g. leisure cycling) recommended by Nordback et al. [2019] to improve data reliability. Furthermore, both Wessel [2022] and Uttley et al. [2023b] restricted their analysis to cities within a single country (Germany and Norway, respectively), reducing geographic diversity.

To improve representation, the current work used cycling data from 15 cities across 10 countries. These cities were chosen using the following set of criteria applied in sequence.

1) Data availability: cities were first screened based on the availability of cycle count data to the public and in a suitable format (e.g. hourly counts as a CSV

file), with an effort to locate data from a range of countries and continents where available.

2) Data threshold: cycle count data from the step above were examined for two requirements: a minimum of four counting locations per city, meeting the threshold recommended by Nordback et al. [2019], and a minimum of one complete calendar year of hourly counts. These requirements ensure that cycling activity is represented across varying locations and seasons within each city. Cities meeting both requirements were retained.

3) Bicycle-friendliness: cities remaining from the previous step were cross-checked against Luko's *Global Bicycle Cities Index* [Luko, 2022], and were retained only if they appeared on the 90-city list. This step ensured that only cities with an adequate baseline of cycling activity were included in the analysis, thereby minimising any potential confound from low cycling volumes. Luko's index was selected here as it was the most detailed and comprehensive index identified during this research (see section **4.2.2.3**). Its use also aligns with later analyses in this thesis, focusing on cycling culture.

An initial list of 12 cities were identified using the criteria above. To those, a further three cities that were either examined in previous studies (Arlington, VA, USA, and Birmingham, UK) or were being examined in a parallel study (Leeds, UK) were added, given that publicly accessible sources were provided in the original study [Fotios et al., 2019b; Uttley et al., 2020; Yesiltepe et al., under review]. These cities were added to enable comparability with previous work.

Table 3.1 lists all 15 cities collected for analysis in this research. In total, the dataset includes 277 counter sites across the 15 cities. This is a larger sample than that used in previous studies (e.g. a total of 146 counters in Wessel [2022]; see **Table 2.10** for other examples).

Table 3.1 The 15 cities included in the city-scale analysis of the deterrent effect of darkness on cycling The table shows the range for which data were available and the maximum number of counters in each city.

Location	Max No. of counters	Date range	Data source
Antwerp, Belgium	30	2012-2019	Projektgruppe Bicycle Data [retrieved May 2023] https://bicycle-data.de/bicycles-data/
Arlington, VA, USA	25	2012-2015	BikeArlington [retrieved January 2023] https://counters.bikearlington.com/data-for-developers/
Auckland, New Zealand	37	2012-2019	Auckland Transport – NZ Government [retrieved March 2023] https://at.govt.nz/cycling-walking/research-monitoring/monthly-cycle-monitoring/#archive
Berlin, Germany	26	2016-2019	Berlin Senate Department for Urban Mobility, Transport, Climate Action, and the Environment [retrieved October 2022] https://www.berlin.de/sen/uvk/mobilitaet-und-verkehr/verkehrsplanung/radverkehr/weitere-radinfrastruktur/zaehlstellen-und-fahrradbarometer/
Birmingham, UK	48	2012-2015	Birmingham City Council [retrieved December 2022] https://data.birmingham.gov.uk/dataset/cycling-sensors *
Dublin, Ireland	5	2019	Dublin City Council [retrieved June 2022] https://data.gov.ie/dataset/dublin-city-centre-cycle-counts?package_type=dataset
Edinburgh, Scotland	7	2019	Edinburgh Council [June 2023] Provided by Rachel Bonds, Cycling Scotland, via email contact
Helsinki, Finland	19	2014-2019	Finland Open Data [retrieved November 2021] https://www.opendata.fi/data/en_GB/dataset/helsingin-pyorailijamaarat
Leeds, UK	27	2010-2019	Leeds City Council [retrieved February 2023] https://datamillnorth.org/dataset/leeds-annual-cycle-growth-
Münster, Germany	8	2019	OpenNRW – NRW Government [retrieved October 2021] https://open.nrw/dataset/verkehrszaehlung-fahrradverkehr-tagesaktuelle-daten-ms *
Montreal, Canada	40	2019	Government of Canada open data [retrieved May 2022] https://open.canada.ca/data/en/dataset/f170fecc-18db-44bc-b4fe-5b0b6d2c7297
New York, USA	5	2012-2019	NYC Open Data [retrieved July 2022] https://data.cityofnewyork.us/Transportation/Bicycle-Counts/uczf-rk3c/about_data

Location	Max No. of counters	Date range	Data source
Oslo, Norway	12	2018-2019	Norwegian Public Roads Administration [retrieved May 2023] https://www.vegvesen.no/trafikkdata/ *
Paris, France	55	2018-2019	French Public Data Platform [retrieved May 2023] https://www.data.gouv.fr/fr/datasets/comptage-velo-historique-donnees-compteurs-et-sites-de-comptage/
Seattle, USA	10	2014-2019	Seattle Department of Transportation [retrieved April 2023] https://www.seattle.gov/transportation/projects-and-programs/programs/bike-program/bike-counters

* Database no longer accessible through the listed page. A previously downloaded version is used for the analysis.

The data presented in **Table 3.1** were first cleaned to ensure consistent inclusions. This resulted in the removal of the following:

1) Data from counters missing more than half a year of cycling counts. This means that, for any given counter, incomplete years were removed while whole years were retained.

2) Data for the years 2020 and 2021. While this data was available at the time of collection, a decision was made to omit them from analysis to avoid any confounds from the Covid-19 period, which saw an overall cycling boom. Cycling counter data showed that cycling averages in Europe increased by up to 8% and in the USA by up to 16% [Buehler & Pucher, 2021], this was facilitated by an unprecedented increase in bicycle sales [Combs & Pardo, 2021] and a rising phenomenon of 'Covid Cycle Lanes' created in cities after the first lockdown [Rérat et al., 2022]. This resulted in data from four locations (Dublin, Edinburgh, Montreal, and Münster) to be reduced to a single year of counts.

3) For locations included in previous research (Arlington, USA and Birmingham, UK), data for years that were not included in those previous studies were omitted. This means that for both these locations, data beyond 2015 were excluded despite their availability. This omission targets consistency and comparability with previous work.

4) Missing or negative values, indicating a fault in the operation of the counter, were checked and removed. The numbers for the corresponding control or case hour were also removed to ensure an accurate comparison between the two periods. For example, if a cycle count was missing for the proposed case hour 18:00-18:59 on January 1st 2012 in a counting location, the cycle count for any control hour paired with it for the same date and location was removed from the analysis.

While the aim of the data cleaning process was to improve consistency and comparability across different cities, it should be noted that the sensor technology used in automated cycle counters can differ across and even within cities. Each sensor type carries specific limitations that may influence count accuracy. **Table 3.2** lists known sensor types for each city and highlights their potential limitations. For most sensors, these limitations are not expected to introduce systematic bias in the results related to the effect of darkness on cyclist numbers. One exception to this might be the camera-based sensor, which has the potential to underestimate counts during hours of darkness as accuracy may depend on image quality, which is likely to deteriorate under lower light levels. However, given that the camera-based sensors are only known to be used in one city (Antwerp), and only in a limited number of locations within it, any possible bias introduced by these sensors is likely to have little influence on the overall results of the study. Therefore, with inductive loop sensors used in the majority of counting sites, the associated limitations can be expected to largely be consistent and comparable across the majority of cities.

Table 3.2 Sensor types used in automated cycle counters in the 15 cities (as specified in the source material or relevant webpages) and their potential limitations. Cities in bold use more than one type.

City	Sensor type	Sensor limitations
Antwerp Arlington Berlin Dublin Montreal * New York ***Oslo*** Paris * Seattle	Inductive loops	May be prone to undercounting when: - Faced with installation, calibration, or maintenance issues [Nordback & Janson, 2010]. - Used in complex road segments such as roundabouts [Kothuri et al., 2017]. - Cyclists do not pass directly on the detection zone [Ozan et al., 2021]. - Bicycles are made of non-ferromagnetic materials (i.e. carbon fibre) [Mašinda, 2025].
Edinburgh ***Oslo***	Piezoelectric sensors	Harder to install, due to its intrusive nature, and more sensitive to weather conditions (e.g. temperature fluctuations or rain) [Ozan et al., 2021]
Antwerp limited locations	Camera-based	Count accuracy may be reduced in low-light or glare conditions, particularly with non-LiDAR technology [Guan et al., 2023; Ozan et al., 2021]
Auckland Brimingham Helsinki Leeds Munster	Unspecified	-

*Not clearly specified in source material but its description may suggest the use of inductive loops.

3.4. Daily times of ambient lighting conditions

Within a typical day, ambient lighting conditions change between daylight, darkness, and the intermediate phases of twilight. The definitions of darkness used in previous case-control studies, compared in Section **2.2**, are inconsistent, particularly in how events occurring during civil twilight periods were categorized. For example, Uttley and Fotios [2017] defined darkness as the period between sunset and sunrise (0° solar altitude), which means that cyclist counts captured during civil twilight were included in the period labelled as darkness. Analysis of road traffic crashes suggests that such an assumption can cause the difference between daylight and darkness to be underestimated [Fotios et al., 2021b], which may be because civil twilight remains daylit to some extent due to the scattering of sunlight. Other studies such as Wessel [2022] and Uttley et al. [2020] recognized this and conducted separate analyses for civil twilight periods, with the latter study showing that conditions of twilight produced lower odds ratios than conditions of darkness, when compared with daylight. This

suggests the inclusion of civil twilight in the definition of darkness is likely to dilute the estimated effect of darkness on cycling.

Some studies chose to completely exclude counts in civil twilight from their analysis [e.g. Uttley et al., 2024] to provide a clearer separation between counts occurring in darkness and in daylight. The counts removed may present a confound when added to either the daylight or darkness periods, as previous work [Uttley et al. 2020] reported that people cycle less in civil twilight periods compared to daylight, but that this effect isn't as strong as the deterrence from darkness periods.

The current work therefore defines darkness as the period starting when solar altitude is -6° (i.e. the sun is below the horizon) after sunset one evening, and ending before the next sunrise when solar altitude is -6° below the horizon. Daylight is the period when solar altitude is above 0°. This definition ensures that periods of civil twilight (solar altitudes of 0° to -6°) are omitted from the analyses to give a stronger contrast between daylight and darkness. For each location, all possible darkness and daylight periods for each of the 15 cities were defined according to data collected from the Time and Date website (https://www.timeanddate.com). This data provides times of daily sunrise and sunset (solar altitude 0°) and the transition between civil and nautical twilight (solar altitude -6°).

3.5. Choice of case and control hours

In Chapter **2,** it was suggested that a limitation of previous studies is their limited choice of case and control hours. These studies tended to use only one case hour and up to two control hours, despite the availability of several other case and control hours to choose from (see **Tables 2.7** and **2.8**). This was done with the assumption that the choice of case and control hours would not significantly matter. However, comparing ORs reported in previous studies using different control hours at the same location [Fotios et al., 2019b; Uttley & Fotios, 2017] suggests that hour selection may impact the estimated effect of darkness (see section **2.6.4.1**).

To investigate whether the choice of case and control hour matters, cyclist count data were collated for all possible case and control hours, and ORs were calculated for all possible combinations of case and control hours. Case and control hours were defined

for each city according to solar altitude data. Case hours containing periods of daylight or darkness for less than two months per year were excluded. If a control hour contained any amount of civil twilight at any point in the year, it was not used. **Figure 3.1** shows the case and control hours for each of the 15 cities included in this thesis.

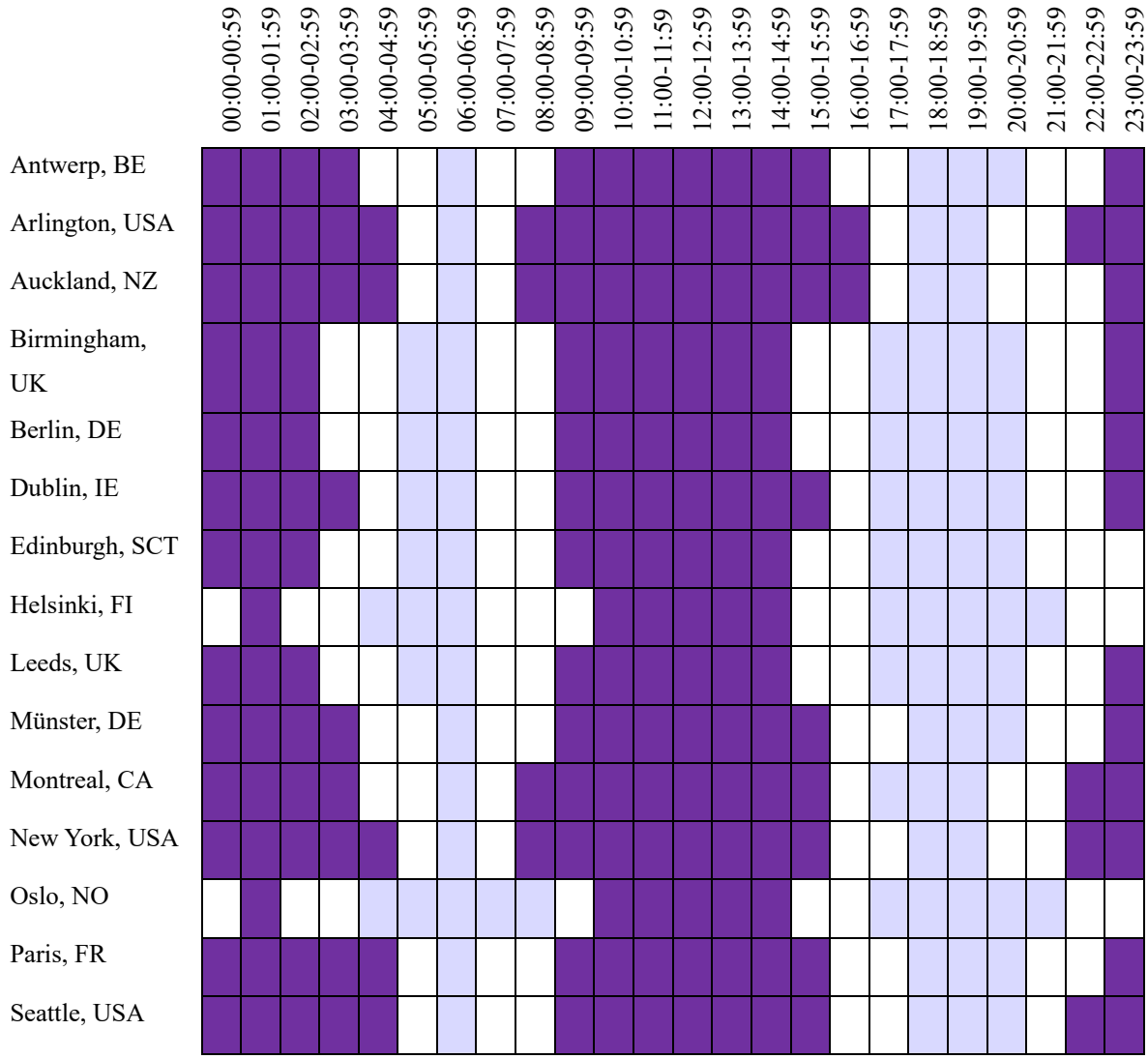


Figure 3.1 Case (light shaded) and control (dark shaded) hours included in the current analysis. Unshaded cells are hours that are excluded from calculation as they included some period of civil twilight at some point during the year.

An OR was calculated for each combination of case and control hour. In Antwerp, for example, there are four case hours and twelve control hours, resulting in 48 (4 x 12)

combinations of case and control hours and thus 48 calculated ORs. **Table 3.3** shows the number of combinations for each city.

Table 3.3 Number of ORs for each city as determined by the number of possible combinations of case and control hours.

City	Total number of ORs per city
New York, USA	45
Antwerp, Belgium Arlington, VA, USA Auckland, New Zealand Münster, Germany	48
Paris, France	52
Edinburgh, Scotland, UK Helsinki, Finland	54
Montreal, Canada Seattle, USA	56
Birmingham, UK Leeds, UK Berlin, Germany Oslo, Norway	60
Dublin, Ireland	72

A weighted mean was used to report the OR across a range of case and control hour combinations, similar to meta-analyses methods where a weighted OR is used to measure the overall effect across multiple studies [Deeks et al., 2019]. The weighting for a specific OR is the total numbers of cyclists in the relevant case and control hours. This was determined following the Mantel-Haenszel method for calculating weighted odds ratios, developed originally for assessing factors associated with disease [Mantel and Haenszel, 1959; Silcocks, 2005] as shown in **Equation 3**. The 95% Confidence Intervals for the weighted ORs are calculated using the method proposed by Robins, Breslow, and Greenland (V) as outlined in **Equations 4** and **5** [Silcocks, 2005].

$$MH_{\text{w-odds}} = \frac{\sum_i \frac{A_i\ D_i}{N_i}}{\sum_i \frac{B_i\ C_i}{N_i}} \quad (3)$$

Where:

$MH_{\text{w-odds}}$ is the Mantel-Haenszel weighted odds ratio

i indexes each combination of case and control hours

A_i is the number of cyclists when the case hour is in daylight.

B_i is the number of cyclists when the case hour is in darkness.

C_i is the number of cyclists when the control hour is in daylight.

D_i is the number of cyclists when the control hour is in darkness.

N_i is the total number of cyclists in the i-th combination ($A_i + B_i + C_i + D_i$)

$$95\%\ CI = exp\left(ln(MHw - odds)\ \pm 1.96\ x\ \sqrt{V}\right) \quad (4)$$

$$V = \frac{\sum R_i\, P_i}{2R^2} + \frac{\sum(P_i\, S_i + Q_i\, R_i)}{2RS} + \frac{\sum S_i\, Q_i}{2S^2} \quad (5)$$

here,

P_i is calculated as $((A_i + D_i) / N_i)$

Q_i is calculated as $((B_i + C_i) / N_i)$

R_i is calculated as $((A_i D_i) / N_i)$

S_i is calculated as $((B_i C_i) / N_i)$

N_i is the total number of cyclists in the i-th combination ($A_i + B_i + C_i + D_i$)

i indexes each combination of case and control hours

A weighted mean OR was used because the arithmetic mean OR may not be suitable. For example, consider Fotios et al [2019b] who used the case hour 18:00-18:59 paired with the control hours 15:00-15:59 and 21:00-21:59 in Arlington, VA, USA. They found an ORs of 1.75 and 1.22 for those two control hours. Calculating the arithmetic mean

gives an OR of 1.49. Calculating instead the Mantel-Haenszel weighted OR using the combined data for the two control hours instead gives an OR of 1.67. Such instances can particularly arise where cyclist numbers are significantly different at different hours, which may have a larger influence on ORs calculated using combined data from these hours compared to arithmetic ORs calculated from individually calculated ORs.

The Mantel–Haenszel weighting approach is widely used to combine odds ratios across strata with different sample sizes. It assigns greater influence to strata (in this case, specific case and control hour combinations) with more observations and therefore lower sampling variance. This minimises random noise without introducing systematic bias, provided that the strata represent comparable instances of the same underlying effect: here, the impact of light conditions on cycling.

It could be argued that some case and control hour combinations may be less comparable due to systematic variations in cycling activity across the day (e.g. commuting peaks). Likewise, case and control hours closer in time might appear more directly comparable. However, because each odds ratio measures the relative change between the same seasonal periods, the Mantel–Haenszel method captures the common directional effect of darkness rather than absolute hourly differences. Moreover, treating all case/control combinations symmetrically avoids subjective bias that could arise from manually selecting “close” or “distant” pairs, while the weighted pooling provides an objective aggregate estimate across all possible pairings.

3.6. Results

3.6.1. Odds ratio arrays

The ORs determined for each combination of case and control hour are presented in this section as an array, one per city, to enable trends to be observed, if any. A summary table is first shown to describe the range of ORs observed (**Table 3.4**), before the detailed arrays are presented in subsections **3.6.2** to **3.6.16**.

From a total of 821 established ORs, 74% were greater than 1.0, with a strong concentration of ORs between slightly larger than one (e.g. 1.01) and 1.3.

Table 3.4 Total number of odds ratios for each city and their range.

City	Number of ORs	OR range		
		Min OR	Median OR	Max OR
Antwerp	48	0.88	1.05	1.27
Arlington	48	0.94	1.45	2.65
Auckland	48	1.01	1.34	1.92
Berlin	60	0.74	1.04	1.41
Birmingham	60	1.00	1.54	2.62
Dublin	72	0.84	1.07	1.60
Edinburgh	54	0.72	1.21	4.21
Helsinki	54	0.60	0.98	1.45
Leeds	60	0.98	1.23	1.52
Munster	48	0.96	1.09	1.24
Montreal	56	0.76	1.03	1.77
New York	45	0.69	1.21	1.44
Oslo	60	0.53	0.78	1.59
Paris	52	0.77	1.06	1.19
Seattle	56	0.78	1.57	4.33

Tables 3.5 to **3.19** and **Figures 3.2** to **3.16** present the ORs for each combination of case and control hour in each city. The tables highlight which of these ORs are significantly below 1.0 (shaded dark purple) or significantly above 1.0 (shaded light purple) ($p<0.05$), and the minimum and maximum OR for the city.

Table 3.5 and **Figure 3.2** show the ORs for Antwerp, BE. ORs are greater than 1.0 in the majority of cases (n = 37 of 48); the remaining are ten ORs below 1.0 and a single OR equal to 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.5 ORs for **Antwerp**, BE, calculated for each combination of case and control hours.

Control hours		Case hours			
		Morning	Evening		
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59	20:00 - 20:59
In darkness	23:00 - 23:59	0.89	1.01	1.01	1.03
	00:00 - 00:59	0.88 min.	0.98	0.98	1.01
	01:00 - 01:59	0.92	1.02	1.02	1.06
	02:00 - 02:59	0.99	1.09	1.09	1.13
	03:00 - 03:59	1.08	1.11	1.13	1.23
In daylight	09:00 -09:59	1.07	1.10	1.16	1.27 max.
	10:00 -10:59	0.99	1.05	1.09	1.18
	11:00 - 11:59	0.94	1.00	1.04	1.11
	12:00 - 12:59	1.04	1.06	1.12	1.23
	13:00 - 13:59	1.01	1.03	1.08	1.18
	14:00 - 14:59	0.94	0.97	1.02	1.10
	15:00 - 15:59	1.02	1.01	1.08	1.19

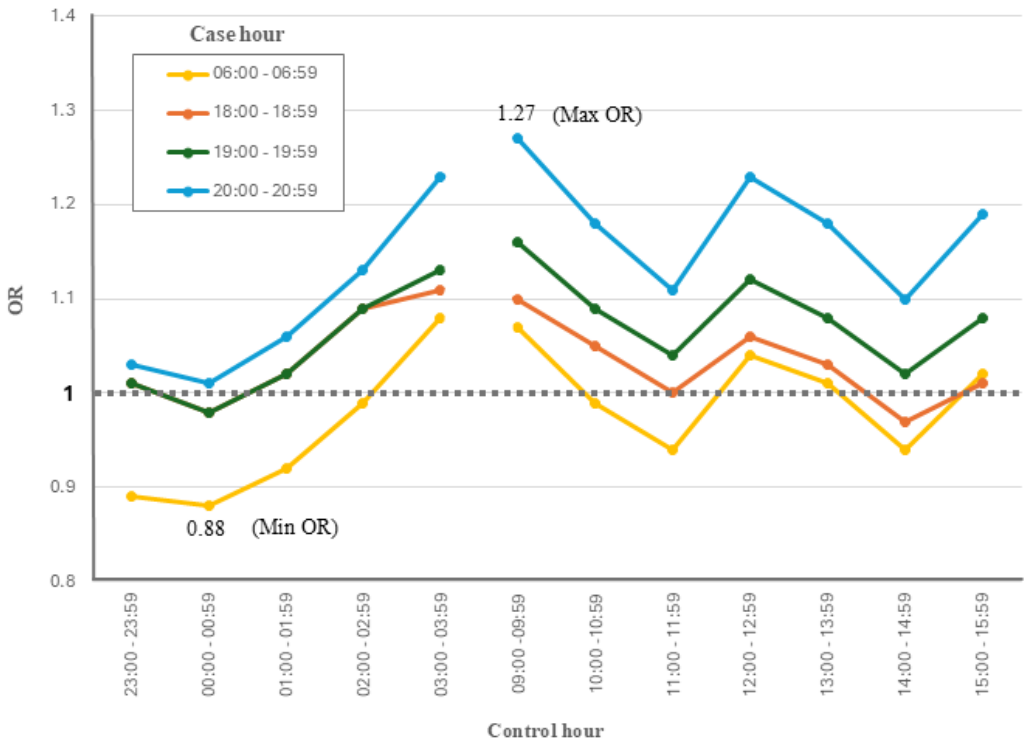


Figure 3.2 ORs for **Antwerp**, Belgium (n = 48). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.6 and **Figure 3.3** show the ORs for Arlington, VA, USA, calculated for each possible combination of case and control hours. ORs are greater than 1.0 in all but two

ORs (n = 46 of 48). Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.6 ORs for **Arlington**, VA, USA, calculated for each combination of case and control hours.

Control hours		Case hours		
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59
In Darkness	22:00 - 22:59	0.96	1.37	1.62
	23:00 - 23:59	1.05	1.45	1.70
	00:00 - 00:59	1.08	1.51	1.73
	01:00 - 01:59	1.15	1.20	1.38
	02:00 - 02:59	1.19	0.94 **min.**	1.09
	03:00 - 03:59	1.23	1.18	1.29
	04:00 - 04:59	1.24	1.64	1.87
In Daylight	08:00 - 08:59	1.22	1.58	2.00
	09:00 -09:59	1.13	1.39	1.73
	10:00 -10:59	1.08	1.21	1.47
	11:00 - 11:59	1.18	1.33	1.62
	12:00 - 12:59	1.27	1.55	1.93
	13:00 - 13:59	1.38	1.80	2.26
	14:00 - 14:59	1.45	1.96	2.52
	15:00 - 15:59	1.52	2.02	2.65 **max.**
	16:00 - 16:59	1.49	1.80	2.44

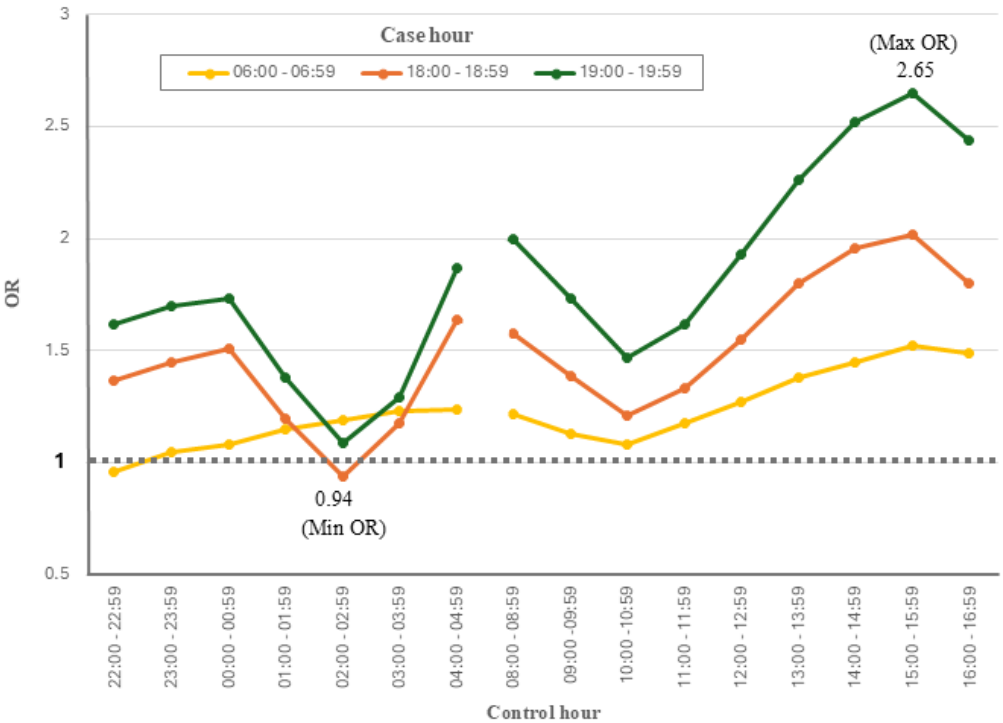


Figure 3.3 ORs for **Arlington**, VA, USA (n = 48). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.7 and **Figure 3.4** show the ORs for Auckland, New Zealand, calculated for each possible combination of case and control hours. All ORs are greater than 1.0 (n = 48). Shaded cells indicate statistical significance ($p < 0.05$).

Table 3.7 ORs for **Auckland**, NZ, calculated for each combination of case and control hours.

Control hours		Case hours		
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59
In Darkness	22:00 - 22:59	1.04	1.17	1.52
	23:00 - 23:59	1.01 **min.**	1.14	1.46
	00:00 - 00:59	1.21	1.01	1.54
	01:00 - 01:59	1.05	1.23	1.47
	02:00 - 02:59	1.15	1.26	1.49
	03:00 - 03:59	1.38	1.30	1.70
	04:00 - 04:59	1.35	1.39	1.85
In Daylight	08:00 - 08:59	1.16	1.31	1.80
	09:00 -09:59	1.17	1.25	1.70
	10:00 -10:59	1.25	1.23	1.65
	11:00 - 11:59	1.33	1.26	1.69
	12:00 - 12:59	1.35	1.29	1.72
	13:00 - 13:59	1.38	1.34	1.79
	14:00 - 14:59	1.35	1.36	1.84
	15:00 - 15:59	1.33	1.38	1.92 **max.**
	16:00 - 16:59	1.21	1.33	1.81

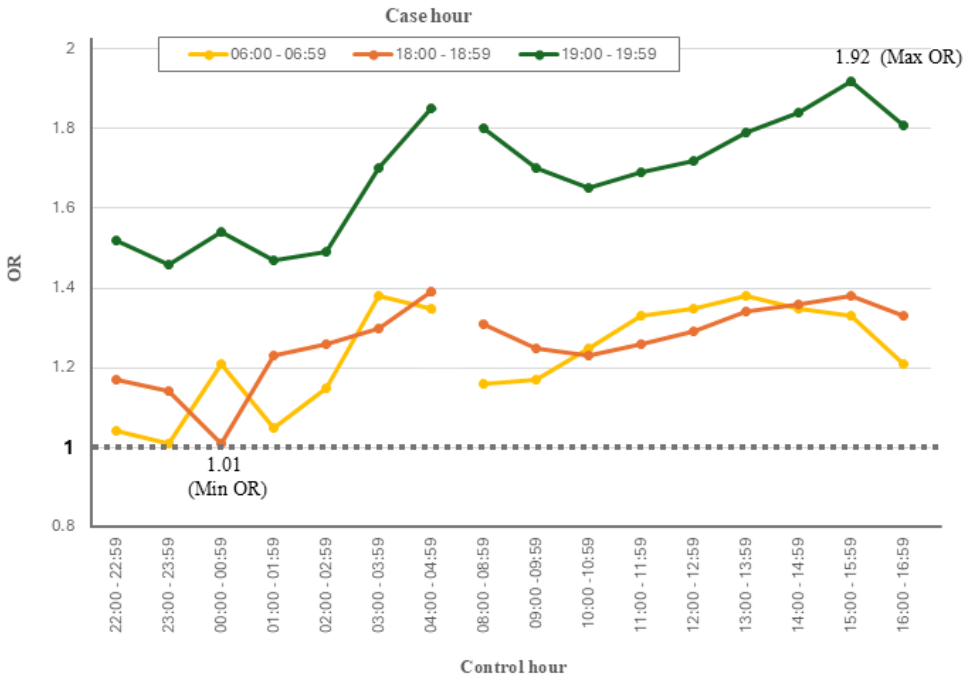


Figure 3.4 ORs for **Auckland**, New Zealand (n = 48). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.8 and **Figure 3.5** show the ORs for Berlin, Germany, calculated for each possible combination of case and control hours (n = 60). 55% of all ORs are greater than 1.0, while 10% are equal to 1.0 (indicated by underlined lettering), and 35% are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.8 ORs for **Berlin**, DE, calculated for each combination of case and control hours.

Control hours		Case hours					
		05:00-05:59	06:00-06:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59
In darkness	23:00 - 23:59	0.75	0.77	0.95	0.93	0.93	0.98
	00:00 - 00:59	0.74 **min.**	0.76	0.97	0.93	0.91	0.96
	01:00 - 01:59	0.79	0.78	*1.00*	0.94	0.93	*1.00*
	02:00 - 02:59	0.83	0.83	1.07	1.03	0.99	1.06
In daylight	09:00 - 09:59	1.04	1.07	1.22	1.25	1.30	1.41 **max.**
	10:00 - 10:59	*1.00*	*1.00*	1.18	1.18	1.21	1.33
	11:00 - 11:59	*1.00*	0.98	1.14	1.15	1.18	1.32
	12:00 - 12:59	1.02	0.98	1.14	1.15	1.19	1.33
	13:00 - 13:59	1.04	*1.00*	1.16	1.17	1.21	1.36
	14:00 - 14:59	1.07	1.01	1.17	1.18	1.24	1.40

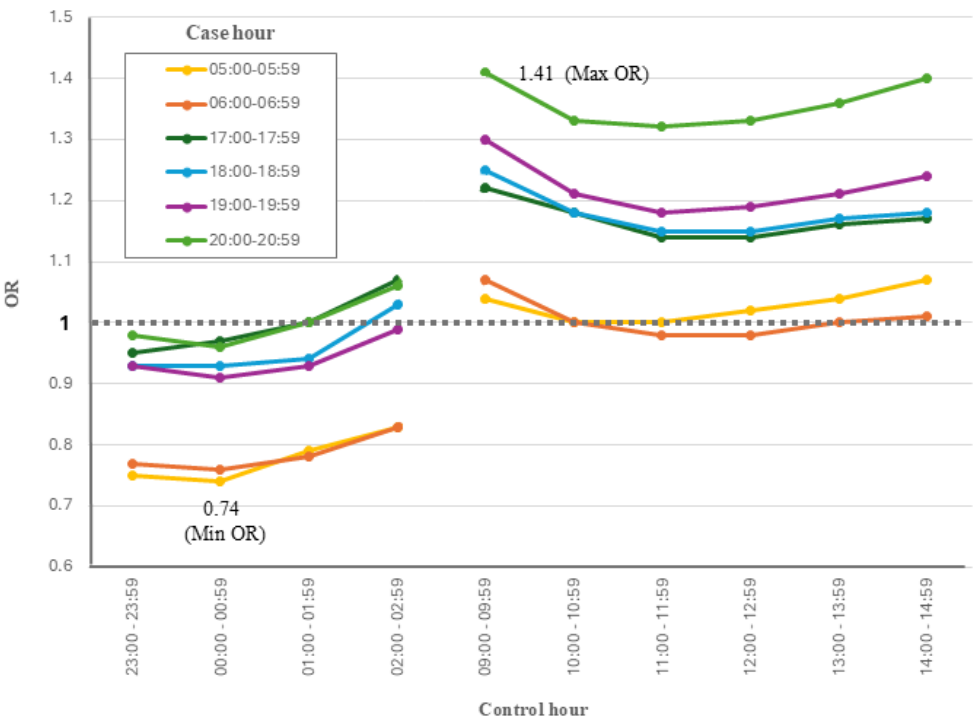


Figure 3.5 ORs for **Berlin**, DE (n = 60). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.9 and **Figure 3.6** show the ORs for Birmingham, UK, calculated for each possible combination of case and control hours (n = 60). ORs are greater than 1.0 in all but one combination (n = 59), where the OR is equal to 1.0 (indicated by underlined lettering). Shaded cells indicate statistical significance ($p < 0.05$).

Table 3.9 ORs for **Birmingham**, UK, calculated for each combination of case and control.

Control hours		Case hours					
		05:00-05:59	06:00-06:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59
In darkness	23:00 - 23:59	1.11	1.39	1.59	1.61	1.97	2.16
	00:00 - 00:59	1.21	1.50	1.61	1.66	2.07	2.33
	01:00 - 01:59	1.29	1.65	1.84	1.85	2.23	2.45
	02:00 - 02:59	1.35	1.80	1.86	1.92	2.35	2.62 **max.**
In daylight	09:00 - 09:59	1.07	1.25	1.37	1.44	1.87	2.11
	10:00 - 10:59	1.05	1.22	1.33	1.38	1.77	2.08
	11:00 - 11:59	1.03	1.21	1.32	1.36	1.73	2.03
	12:00 - 12:59	1.02	1.20	1.29	1.34	1.72	2.01
	13:00 - 13:59	1.03	1.20	1.31	1.35	1.73	2.01
	14:00 - 14:59	*1.00* **min.**	1.18	1.27	1.31	1.70	1.97

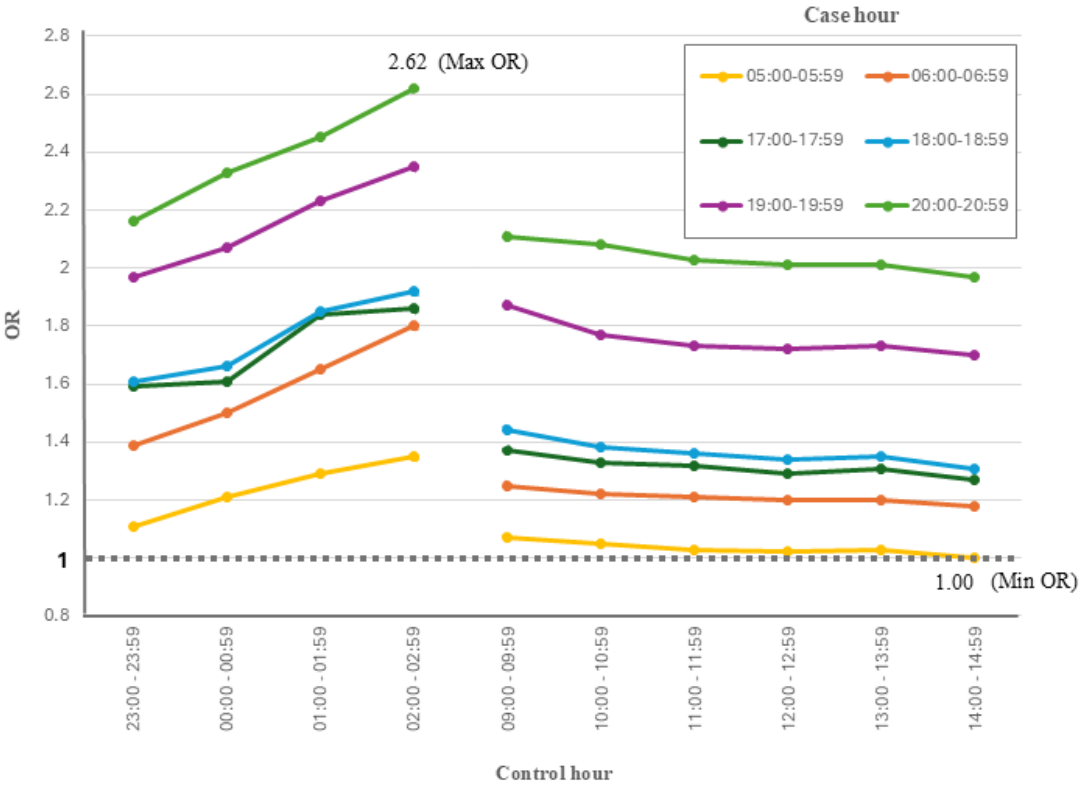


Figure 3.6 ORs for **Birmingham**, UK (n = 60). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.10 and **Figure 3.7** show the ORs for Dublin, Ireland, calculated for each possible combination of case and control hours (n = 72). The majority of ORs (approx. 76.4%) are greater than 1.0, only three ORs (4.2%) are equal to 1.0 (indicated by underlined lettering), and fourteen ORs (19.4%) are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.10 ORs for **Dublin**, IE, calculated for each combination of case and control hours.

Control hours		Case hours					
		05:00-05:59	06:00-06:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59
In darkness	23:00 - 23:59	0.89	0.84 min.	1.04	0.88	0.92	0.98
	00:00 - 00:59	0.93	0.90	1.21	0.94	0.97	*1.00*
	01:00 - 01:59	0.96	0.95	1.46	1.06	1.04	1.05
	02:00 - 02:59	1.14	1.04	1.60 max.	1.09	1.07	1.12
	03:00 - 03:59	1.01	0.96	1.37	1.03	1.03	1.08
In daylight	09:00 - 09:59	1.21	1.10	1.15	1.12	1.17	1.27
	10:00 - 10:59	1.09	*1.00*	1.11	1.04	1.08	1.16
	11:00 - 11:59	1.11	*1.00*	1.17	1.05	1.09	1.17
	12:00 - 12:59	1.11	0.99	1.16	1.03	1.07	1.14
	13:00 - 13:59	1.12	1.02	1.20	1.05	1.09	1.17
	14:00 - 14:59	1.09	0.99	1.17	1.03	1.07	1.13
	15:00 - 15:59	1.11	1.02	1.20	1.06	1.10	1.16

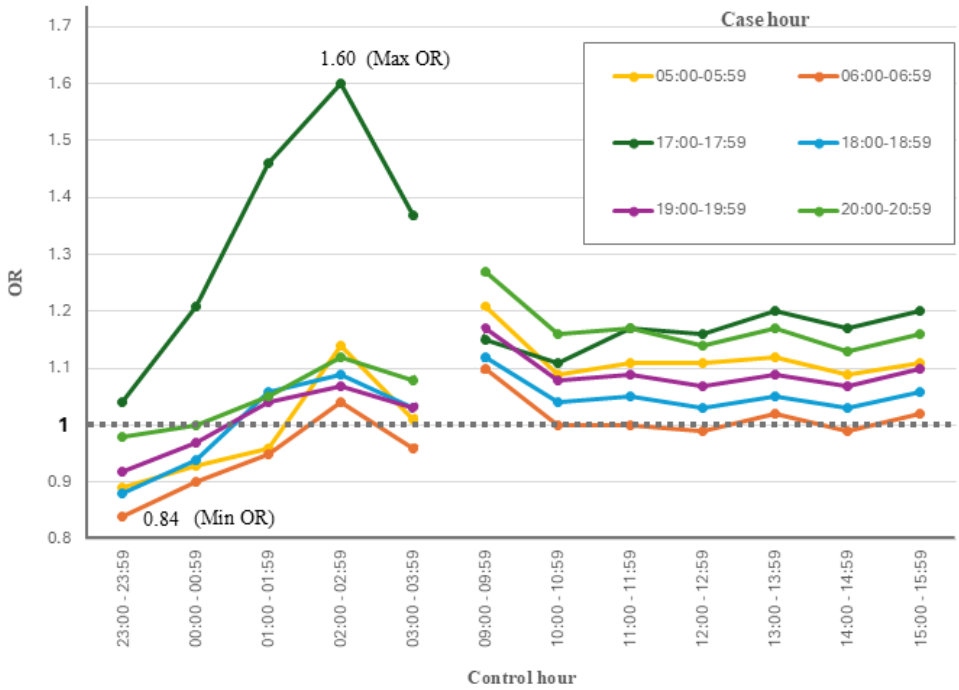


Figure 3.7 ORs for **Dublin**, Ireland (n = 72). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.11 and **Figure 3.8** show the ORs for Edinburgh, Scotland, UK, calculated for each possible combination of case and control hours (n = 54). The majority of ORs (72.2%) are greater than 1.0, fourteen ORs (27.8%) are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.11 ORs for **Edinburgh**, SCT, calculated for each combination of case and control hours.

Control hours		Case hours					
		05:00-05:59	06:00-06:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59
In darkness	00:00 - 00:59	3.17	2.82	1.44	1.07	1.07	1.21
	01:00 - 01:59	3.36	2.87	1.27	0.98	1.11	1.19
	02:00 - 02:59	3.15	2.91	1.20	0.94	1.13	1.21
In daylight	09:00 - 09:59	4.21 max.	3.90	1.69	1.36	1.44	1.69
	10:00 - 10:59	3.08	2.88	1.34	0.97	1.01	1.20
	11:00 - 11:59	2.56	2.42	1.21	0.76	0.78	0.96
	12:00 - 12:59	2.50	2.40	1.19	0.72 min.	0.75	0.93
	13:00 - 13:59	2.61	2.47	1.20	0.74	0.78	0.96
	14:00 - 14:59	2.56	2.41	1.18	0.74	0.77	0.94

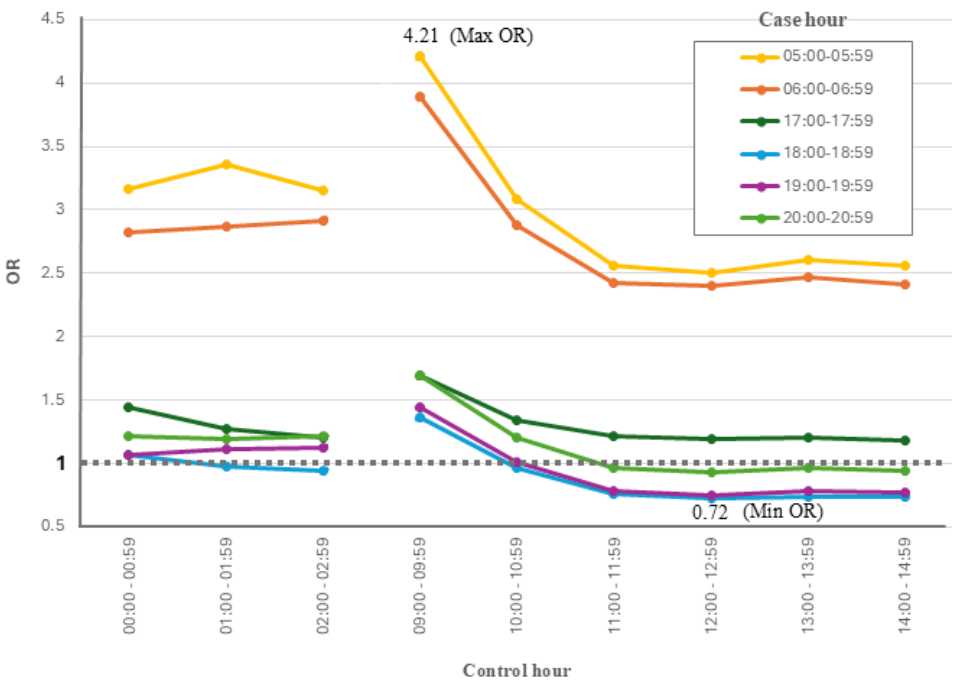


Figure 3.8 ORs for **Edinburgh**, SCT, UK (n = 54). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.12 and **Figure 3.9** show the ORs for Helsinki, Finland, calculated for each possible combination of case and control hours (n = 54). Nearly half of all ORs are greater than 1.0, as twenty-eight ORs (approx. 51.8%) are below 1.0. All values significantly depart from 1.0 ($p < 0.05$). Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0.

Table 3.12 ORs for **Helsinki**, FI, calculated for each combination of case and control hours.

Control hours		Case hours								
		04:00-04:59	05:00-05:59	06:00-06:59	07:00-07:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59	21:00-21:59
In darkness	01:00-01:59	0.78	0.60	0.60	0.68	0.77	0.80	0.88	0.86	0.85
In daylight	10:00-10:59	1.26	0.95	0.93	0.92	1.07	1.16	1.33	1.41	1.45
	11:00-11:59	1.20	0.87	0.84	0.85	0.98	1.04	1.21	1.30	1.34
	12:00-12:59	1.18	0.85	0.82	0.82	0.95	1.01	1.17	1.26	1.30
	13:00-13:59	1.16	0.84	0.81	0.84	0.95	1.01	1.16	1.24	1.28
	14:00-14:59	1.17	0.87	0.84	0.87	0.99	1.04	1.20	1.28	1.32

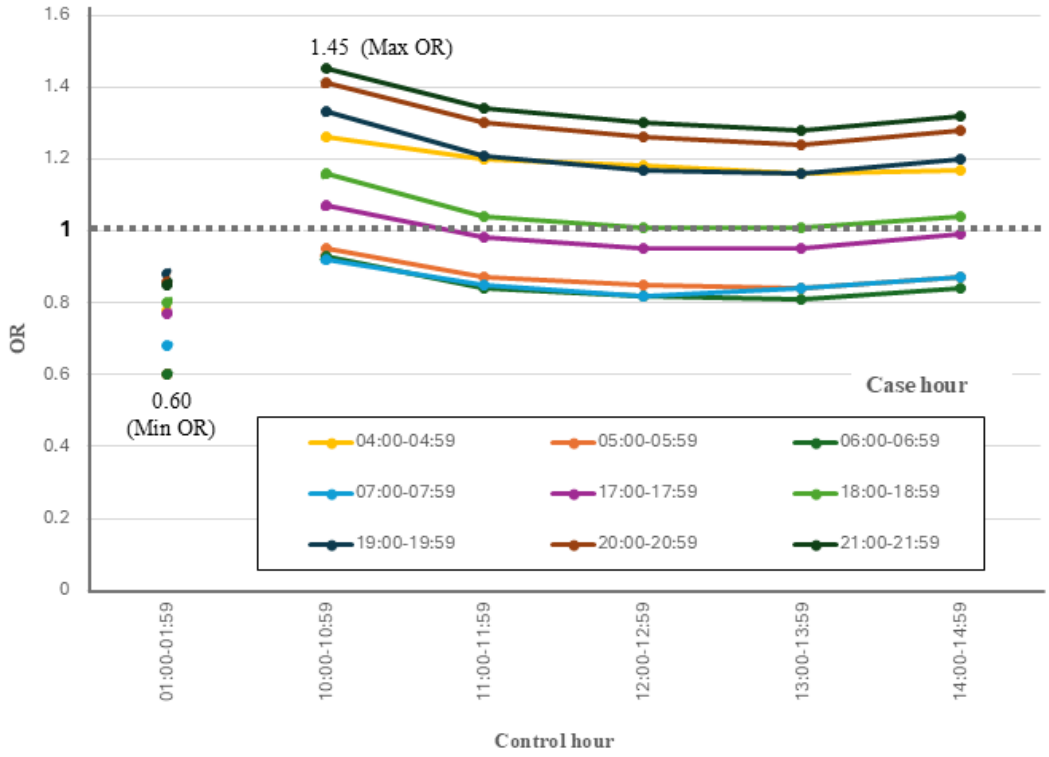


Figure 3.9 ORs for **Helsinki**, Finland (n = 54). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.13 and **Figure 3.10** show the ORs for Leeds, UK, calculated for each possible combination of case and control hours (n = 60). All but two of the ORs are greater than 1.0, out of the two one is equal to 1.0 (indicated by underlined lettering) and one is below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.13 ORs for **Leeds**, UK, calculated for each combination of case and control hours.

Control hours		Case hours					
		05:00-05:59	06:00-06:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59
In darkness	23:00 - 23:59	1.01	1.25	1.28	1.31	1.38	1.35
	00:00 - 00:59	1.14	1.36	1.38	1.43	1.51	1.52 **max.**
	01:00 - 01:59	1.05	1.27	1.30	1.35	1.44	1.41
	02:00 - 02:59	1.05	1.30	1.37	1.36	1.45	1.43
In daylight	09:00 - 09:59	1.07	1.19	1.16	1.24	1.36	1.41
	10:00 - 10:59	1.02	1.12	1.10	1.16	1.27	1.33
	11:00 - 11:59	0.98 **min.**	1.07	1.06	1.11	1.20	1.27
	12:00 - 12:59	*1.00*	1.09	1.07	1.12	1.21	1.29
	13:00 - 13:59	1.02	1.10	1.08	1.13	1.23	1.30
	14:00 - 14:59	1.01	1.10	1.09	1.12	1.23	1.31

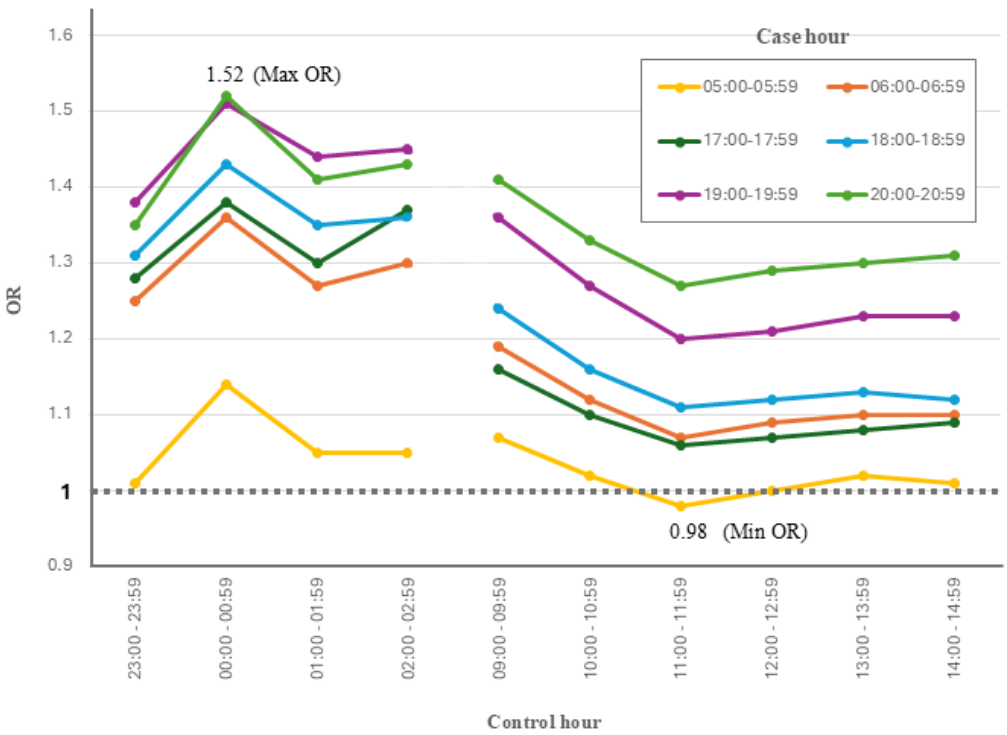


Figure 3.10 ORs for **Leeds**, UK (n = 60). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.14 and **Figure 3.11** show the ORs for Münster, Germany, calculated for each possible combination of case and control hours (n = 48). All but six ORs are greater than 1.0, out of the six one is equal to 1.0 (indicated by underlined lettering) and five are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.14 ORs for **Münster**, DE, calculated for each combination of case and control hours.

Control hours		Case hours			
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59	20:00 - 20:59
In darkness	23:00 - 23:59	0.96 **min.**	0.97	0.98	1.02
	00:00 - 00:59	*1.00*	0.96	0.97	1.03
	01:00 - 01:59	1.07	1.05	1.05	1.11
	02:00 - 02:59	1.17	1.12	1.13	1.20
	03:00 - 03:59	1.20	1.11	1.10	1.24 **max.**
In daylight	09:00 - 09:59	1.08	1.08	1.10	1.16
	10:00 -10:59	1.05	1.08	1.08	1.11
	11:00 - 11:59	1.06	1.05	1.06	1.12
	12:00 - 12:59	1.08	1.07	1.10	1.16
	13:00 - 13:59	1.09	1.06	1.10	1.18
	14:00 - 14:59	1.09	1.07	1.11	1.18
	15:00 - 15:59	1.09	1.07	1.11	1.18

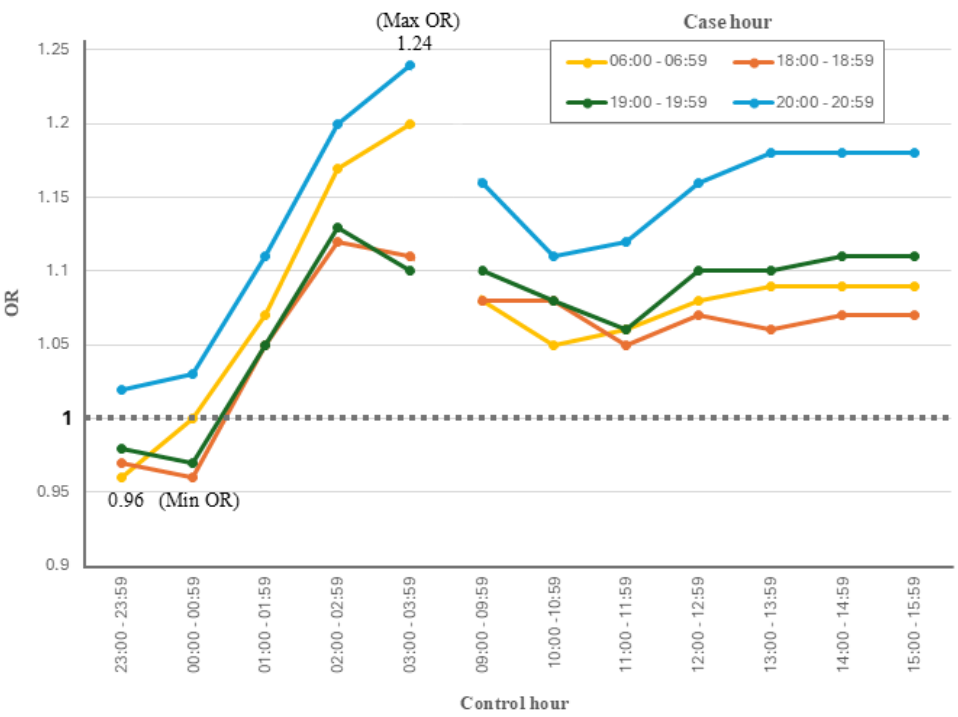


Figure 3.11 ORs for **Münster**, Germany (n = 48). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.15 and **Figure 3.12** show the ORs for Montreal, Canada, calculated for each combination of case and control hours (n = 56). The majority of ORs (55.4%) are greater than 1.0 , three ORs are equal to 1.0 (indicated by underlined lettering) and twenty-two are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.15 ORs for **Montreal**, CA, calculated for each combination of case and control hours.

Control hours		Case hours			
		06:00 - 06:59	17:00 - 17:59	18:00 - 18:59	19:00 - 19:59
In Darkness	22:00 - 22:59	0.96	0.93	0.92	*1.00*
	23:00 - 23:59	0.98	0.79	0.76 **min.**	0.83
	00:00 - 00:59	1.17	0.84	0.81	0.91
	01:00 - 01:59	1.44	1.01	0.99	1.07
	02:00 - 02:59	1.77 **max.**	1.01	0.98	1.10
	03:00 - 03:59	1.74	1.02	1.04	1.12
In Daylight	08:00 - 08:59	1.14	1.15	1.25	1.47
	09:00 - 09:59	1.30	1.16	1.23	1.42
	10:00 -10:59	1.21	*1.00*	*1.00*	1.21
	11:00 - 11:59	1.26	0.95	0.96	1.23
	12:00 - 12:59	1.29	0.95	0.96	1.25
	13:00 - 13:59	1.32	0.96	0.97	1.25
	14:00 - 14:59	1.23	0.91	0.91	1.21
	15:00 - 15:59	1.25	0.98	0.98	1.29

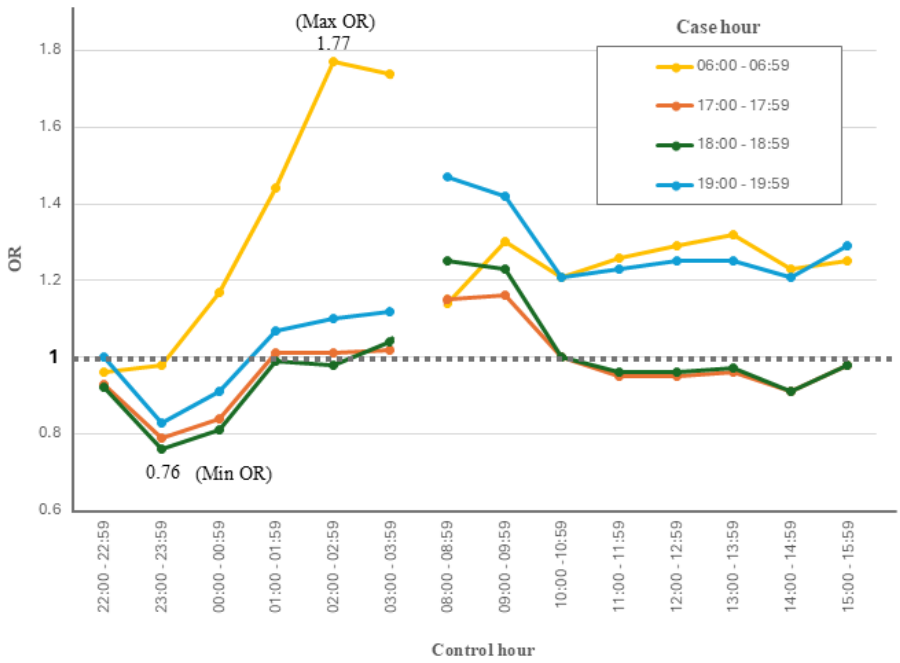


Figure 3.12 ORs for **Montreal**, Canada (n = 56). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.16 and **Figure 3.13** show the ORs for New York, NY, USA, calculated for each combination of case and control hours (n = 45). ORs for the evening case hours 18:00-18:59 and 19:00:19:59 are greater than 1.0, while ORs for the morning case hour 6:00-6:59 are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.16 ORs for **New York**, NY, USA, calculated for each combination of case and control hours.

Control hours		Case hours		
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59
In Darkness	22:00 - 22:59	0.85	1.30	1.30
	23:00 - 23:59	0.92	1.25	1.26
	00:00 - 00:59	0.95	1.19	1.21
	01:00 - 01:59	0.84	1.22	1.22
	02:00 - 02:59	0.69 **min.**	1.21	1.23
	03:00 - 03:59	0.72	1.23	1.27
	04:00 - 04:59	0.77	1.42	1.44 **max.**
In Daylight	08:00 - 08:59	0.76	1.18	1.24
	09:00 -09:59	0.77	1.18	1.22
	10:00 -10:59	0.85	1.30	1.31
	11:00 - 11:59	0.87	1.26	1.28
	12:00 - 12:59	0.89	1.17	1.20
	13:00 - 13:59	0.86	1.16	1.21
	14:00 - 14:59	0.92	1.22	1.27
	15:00 - 15:59	0.93	1.22	1.28

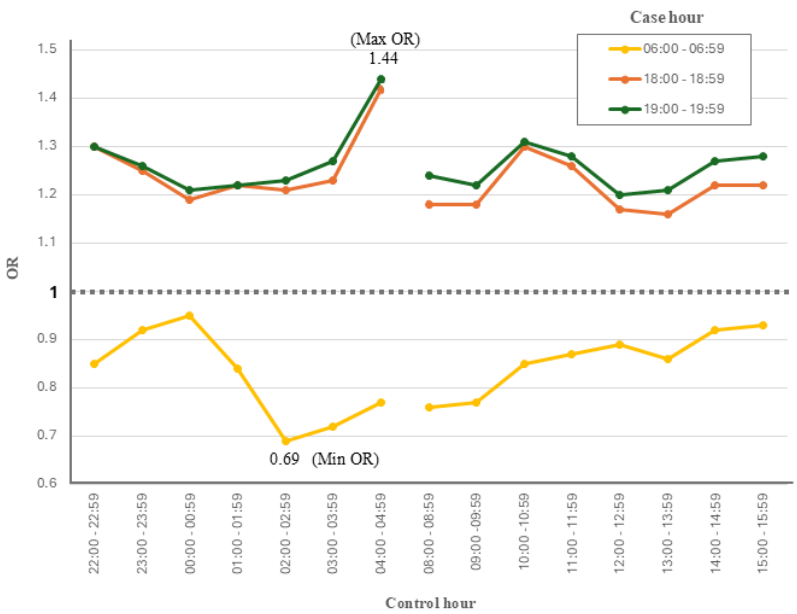


Figure 3.13 ORs for **New York**, NY, USA (n = 45). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.17 and **Figure 3.14** show the ORs for Oslo, Norway, calculated for each combination of case and control hours (n = 60). The majority of ORs are below 1.0. All ORs for the evening case hours 19:00-19:59, 20:00:20:59, and 21:00-21:59 are greater than 1.0. OR for the case hours 18:00-18:59 is greater than 1.0 when combined with a control period in darkness. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.17 ORs for **Oslo**, NO, calculated for each combination of case and control hours.

Control hours		Case hours									
		04:00-04:59	05:00-05:59	06:00-06:59	07:00-07:59	08:00-08:59	17:00-17:59	18:00-18:59	19:00-19:59	20:00-20:59	21:00-21:59
In darkness	01:00-01:59	0.65	0.66	0.73	0.90	0.65	0.90	1.13	1.48	1.48	1.35
In daylight	10:00-10:59	0.94	0.70	0.66	0.66	0.79	0.73	0.95	1.30	1.51	1.59
	11:00-11:59	0.89	0.62	0.56	0.55	0.66	0.60	0.79	1.11	1.35	1.44
	12:00-12:59	0.89	0.60	0.53	0.56	0.57	0.58	0.76	1.06	1.33	1.45
	13:00-13:59	0.92	0.62	0.54	0.55	0.56	0.58	0.77	1.06	1.33	1.45
	14:00-14:59	0.97	0.66	0.60	0.65	0.65	0.67	0.87	1.19	1.43	1.53

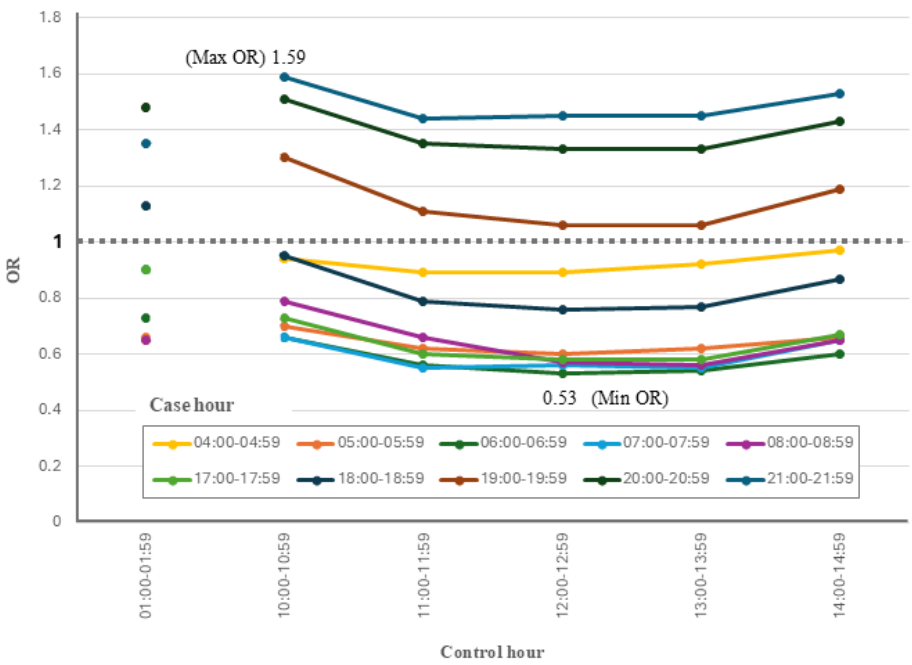


Figure 3.14 ORs for **Oslo**, Norway (n = 60). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.18 and **Figure 3.15** show the ORs for Paris, France, calculated for each combination of case and control hours (n = 52). The majority of ORs (approx. 67%) are greater than 1.0, one OR is equal to 1.0 (indicated by underlined lettering), and sixteen total ORs (approx. 30.8%) are below 1.0. Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0. Unshaded cells indicate non-significant values.

Table 3.18 ORs for **Paris**, FR, calculated for each combination of case and control hours.

Control hours		Case hours			
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59	20:00 - 20:59
In darkness	23:00 - 23:59	0.82	0.94	0.91	0.92
	00:00 - 00:59	0.77 **min.**	0.92	0.87	0.86
	01:00 - 01:59	0.80	0.95	0.90	0.88
	02:00 - 02:59	0.89	1.02	*1.00*	0.96
	03:00 - 03:59	0.94	1.09	1.04	1.01
	04:00 - 04:59	1.01	1.15	1.11	1.07
In daylight	09:00 - 09:59	1.03	1.09	1.11	1.17
	10:00 -10:59	1.02	1.13	1.11	1.14
	11:00 - 11:59	0.98	1.06	1.06	1.10
	12:00 - 12:59	1.03	1.07	1.09	1.15
	13:00 - 13:59	1.06	1.12	1.13	1.19 **max.**
	14:00 - 14:59	1.07	1.12	1.13	1.19
	15:00 - 15:59	1.07	1.13	1.13	1.19

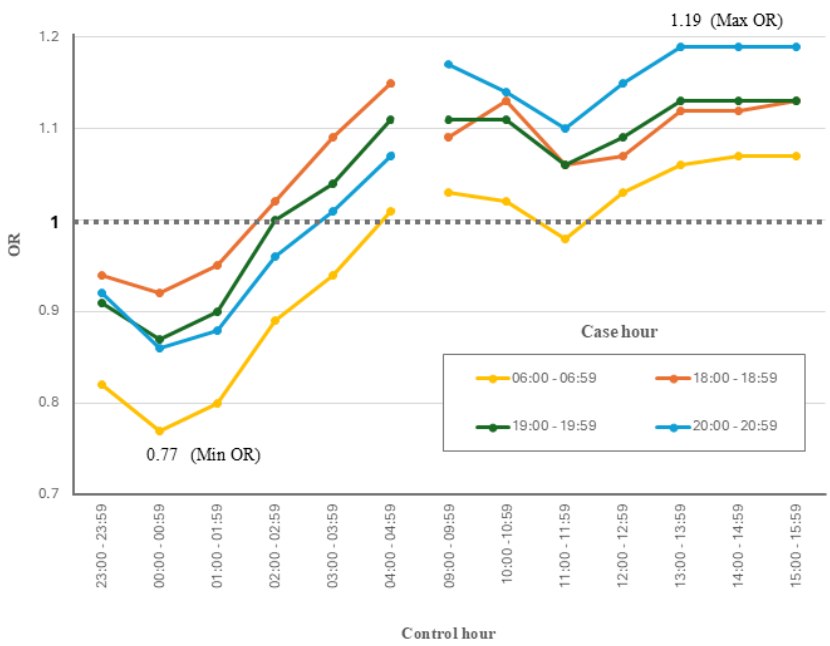


Figure 3.15 ORs for **Paris**, France (n = 52). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

Table 3.19 and **Figure 3.16** show the ORs for Seattle, WA, USA, calculated for each possible combination of case and control hours (n = 56). The majority of ORs (approx. 83.9%) are greater than 1.0, Nine ORs in the dark control period are below 1.0. All values significantly depart from 1.0 ($p < 0.05$). Statistical significance ($p < 0.05$) is indicated with light shading if above 1.0 and dark shading if below 1.0.

Table 3.19 ORs for **Seattle**, WA, USA, calculated for each combination of case and control.

Control hours		Case hours			
		06:00 - 06:59	18:00 - 18:59	19:00 - 19:59	20:00 - 20:59
In darkness	22:00 - 22:59	0.82	1.08	1.43	1.60
	23:00 - 23:59	0.89	1.09	1.53	1.84
	00:00 - 00:59	0.90	1.07	1.55	2.36
	01:00 - 01:59	0.91	1.06	1.56	2.57
	02:00 - 02:59	0.81	0.84	1.31	2.75
	03:00 - 03:59	0.92	1.17	1.33	4.33 **max.**
	04:00 - 04:59	0.78 **min.**	0.93	1.28	3.05
In daylight	09:00 -09:59	1.31	1.69	2.28	2.54
	10:00 -10:59	1.21	1.58	2.08	2.32
	11:00 - 11:59	1.22	1.58	2.06	2.35
	12:00 - 12:59	1.26	1.64	2.15	2.50
	13:00 - 13:59	1.27	1.63	2.15	2.54
	14:00 - 14:59	1.30	1.64	2.18	2.63
	15:00 - 15:59	1.31	1.64	2.20	2.62

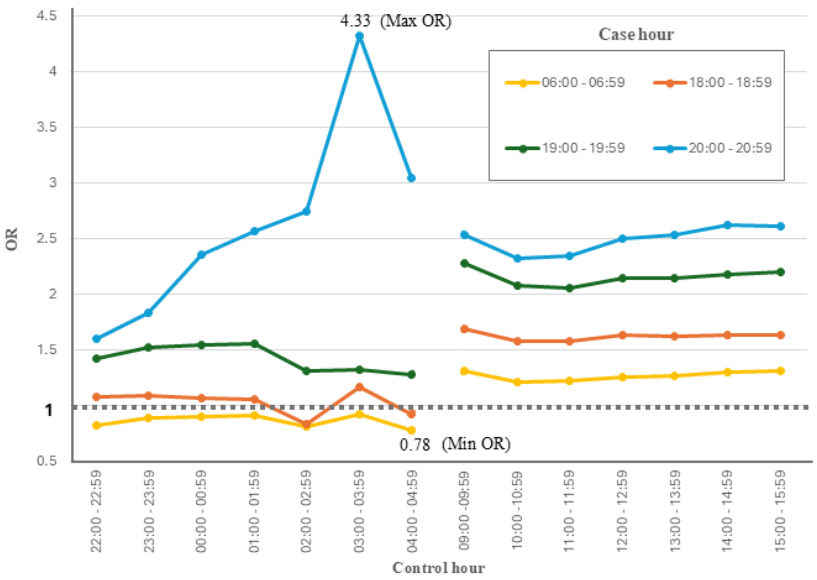


Figure 3.16 ORs for **Seattle**, WA, USA (n = 56). An OR greater than 1.0 tentatively suggests a reduction in the number of cyclists after dark.

The figures for the 15 cities (**Figure 3.2-2.16)** indicate that ORs vary depending on case and control hour combinations. Different case hours generally mirror the rise-and-fall pattern set by the control hour across the day, although the strength of the effect of darkness varied. In some cities, the large spread between different case hours indicates that the exact hour matters, whereas in others, closely clustered case hours suggest a more uniform effect. ORs typically peak in the first hour of the daylight control period, then decreased until midday before increasing again towards evening. These patterns suggest that case and control hour choices may therefore influence the ORs produced.

3.6.2. Weighted odds ratios

Table 3.20 shows the weighted mean OR for each city, determined in accordance with **Equations 3-5** (see section **3.5**). With the exception of Oslo, weighted ORs are larger than 1.0 in all cities. Departure from 1.0 appears statistically significant for all ORs ($P<0.05$). P-values were derived using the Wald Z-test, based on the natural logarithm of the weighted OR and its standard error. The threshold for a small effect size is exceeded in five cities (New York, Auckland, Birmingham, Seattle, and Arlington) but is negligible for the remaining ten.

Table 3.20 Weighted ORs and their 95% confidence intervals for each of the 15 cities, arranged ascendingly. All ORs significantly depart from 1.0 ($p<0.05$).

City	Weighted OR	95% CI	z statistic	P-values	Effect size
Oslo, NO	0.87	0.871 – 0.874	-109.10	P < 0.0001	Negligible
Antwerp, BE	1.06	1.063 – 1.065	144.73	P < 0.0001	
Paris, FR	1.08	1.077 – 1.079	169.76	P < 0.0001	
Dublin, IE	1.08	1.078 – 1.084	59.76	P < 0.0001	
Helsinki, FI	1.08	1.081 – 1.083	202.16	P < 0.0001	
Münster, DE	1.09	1.089 – 1.092	167.92	P < 0.0001	
Montreal, CA	1.11	1.107 – 1.112	99.47	P < 0.0001	
Berlin, DE	1.14	1.143 – 1.144	521.19	P < 0.0001	
Edinburgh, SCT, UK	1.15	1.144 – 1.153	71.09	P < 0.0001	
Leeds, UK	1.18	1.180 – 1.185	187.84	P < 0.0001	
New York, NY, USA	1.23	1.230 – 1.236	187.04	P < 0.0001	Small
Auckland, NZ	1.44	1.441 – 1.444	573.02	P < 0.0001	
Birmingham, UK	1.51	1.506 – 1.512	469.98	P < 0.0001	
Seattle, WA, USA	1.74	1.736 – 1.740	1064.87	P < 0.0001	
Arlington, VA, USA	1.76	1.757 – 1.762	676.24	P < 0.0001	

3.7. Summary

This chapter described the case-control method for investigating the deterrent effect of darkness on cycling. It highlighted study design improvements such as introducing a more precise definition of darkness and addressed a key limitation in previous studies, which is the limited choice of case and control hours.

The OR arrays established for each city showed variance in the impact of darkness across different case and control hour combinations, which could change the outcome of the analysis should one combination be chosen over another. Therefore, a weighted mean OR was proposed.

The aspects introduced in this chapter address the first two hypothesis made in this research, concerning the significance of the choice of case and control hours and the general impact of darkness. The next three chapters describe how the revised case-control method, established in this chapter, is applied to address the remainder of the research hypotheses, which focus on factors that influence the impact of darkness on cyclists across cities (Chapter **4**) and within cities (Chapters **5** and **6**).

Chapter 4. Across-cities analysis of the impact of darkness

4.1. Introduction

In the literature review (chapter **2**), it was concluded that the deterrent effect of darkness varies between locations. The possible explanations for this variance are categorised into factors that influence the impact of darkness on two scales: macroscale factors (across-cities) and a microscale factors (within-cities). Chapter **4** presents the method and results for the investigation of macroscale factors – latitude and cycling culture. This analysis is carried out for the 15 cities using the weighted mean OR reported in chapter **3**. The analysis aims to address hypotheses H3 and H4, which state that locations at higher latitudes and with a greater cycling culture will show less of a deterrent effect of darkness on cycling.

4.2. Exploring causes of variance in ORs

Two causes for the variance in ORs across the 15 cities are proposed: latitude and cycling culture. Their monotonic association with ORs was assessed and their ability to explain any variance in ORs was explored using linear regression.

4.2.1. Latitude

Latitudes for the 15 cities (arranged north to south) and their corresponding weighted odds ratios are presented in **Table 4.1**.

While latitudes could be established from a geographic source (e.g. the *Latitude and Longitude Finder* website: www.latlong.net), this would only represent the latitude of the counters if those counters were uniformly distributed around the city centre. To address this, the latitude for a city was also determined by calculating the arithmetic mean latitude of the individual counting sites within that city. Coordinates for counting sites were often available with the publicly accessible counter data. In instances where coordinates were not included in the data package, efforts were made to estimate them using any information available in the source material (i.e. guide map). The difference between the arithmetic mean latitude and the latitude established from a geographic

source was 0.01 to 0.03 for seven locations; for the remaining eight locations, there was no difference (see **Table 4.1**).

Table 4.1 Latitudes for the fifteen cities included in my research arranged from north to south, and their corresponding ORs as established in chapter 3.

City	Odds Ratio	Estimated latitude	
		City*	Mean of counter locations**
Helsinki, Finland	1.08	60.19° N	60.19° N
Oslo, Norway	0.87	59.91° N	59.92° N
Edinburgh, Scotland	1.15	55.95° N	55.95° N
Leeds, UK	1.18	53.80° N	53.81° N
Dublin, Ireland	1.08	53.35° N	53.35° N
Berlin, Germany	1.14	52.52° N	52.51° N
Birmingham, UK	1.51	52.48° N	52.48° N
Münster, Germany	1.09	51.96° N	51.96° N
Antwerp, Belgium	1.06	51.22° N	51.22° N
Paris, France	1.08	48.86° N	48.86° N
Seattle, USA	1.74	47.61° N	47.62° N
Montreal, Canada	1.11	45.50° N	45.53° N
New York, USA	1.23	40.73° N	40.71° N
Arlington, VA, USA	1.76	38.88° N	38.88° N
Auckland, New Zealand	1.44	36.85° S	36.87° S

* Established using the Latitude and Longitude Finder website [www.latlong.net].

Calculated as the arithmetic mean of individual counters within the city. All individual counter latitudes are available in **Appendix A.

Next, the distribution of the ORs was assessed for normality using a graphical representation, measure of dispersion (skewness and kurtosis), and a statistical test (Shapiro-Wilk). It was determined that the data was not normally distributed, and since ORs are the primary variable, assessing normality for other variables (e.g. latitude) will not change the outcome. Thus, it is reasonable to bypass further normality tests and use a Spearman Rank Correlation (instead of a Pearson correlation) as the primary investigation of the monotonic association between ORs and other variables (latitude

and cycling culture proxies) in the next subsections. A Spearman rank correlation coefficient (r_s) is calculated on Microsoft Excel using the command =RANK.AV, followed by =CORREL. The resulting coefficient r_s = -0.534 (p=0.040) indicates a statistically significant negative association with moderate strength [Dancey and Reidy, 2020, P. 183] – as latitude increases, the odds ratio decreases.

Figure 4.1 shows latitude plotted against the ORs for each city. The scatterplot suggests a negative association between ORs and latitude – ORs tend to decrease with an increase in latitude. The variance in these data shows that latitude is only a partial explanation for the variance in ORs (36.7%), but this is suggested to be a significant relationship (p=0.017).

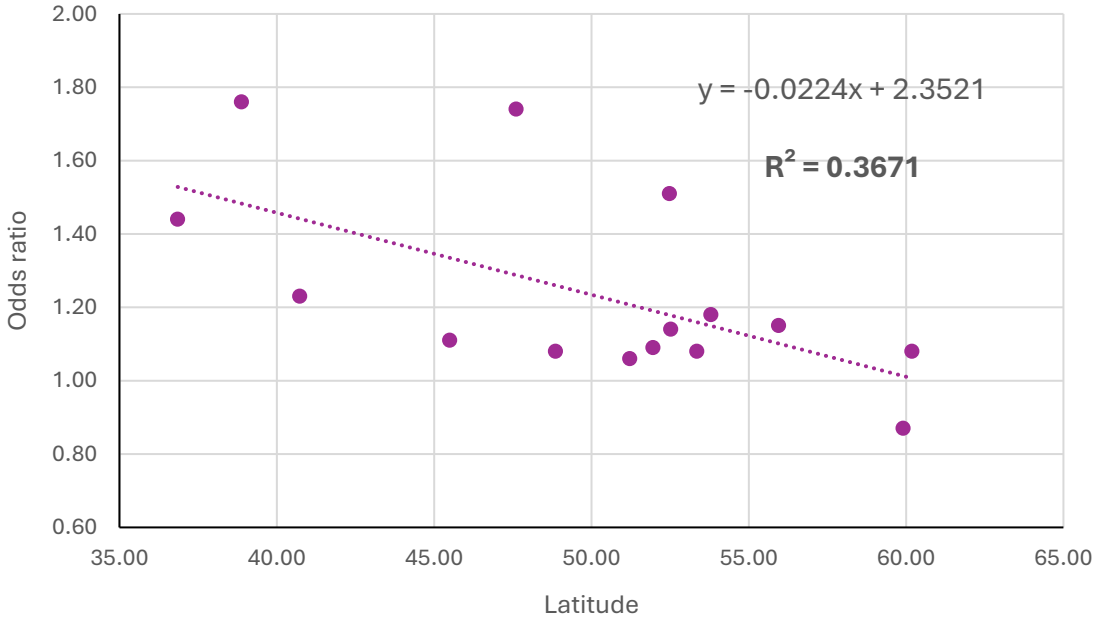


Figure 4.1 The relationship between Odds ratios and latitude for the 15 cities.

4.2.2. Cycling culture

The second factor suggested to influence the variance in ORs for the impact of darkness on cyclists is cycling culture. Cycling culture refers to the collective values and attitudes shared among cyclists of a location, which impact how cycling is perceived and practiced in a location. This may be a factor contributing to cyclists being resilient to adversities such as weather or darkness [Bean et al., 2021; Goldmann and Wessel, 2021; Uttley et al., 2023b], however, cycling culture isn't something tangible, thus three proxies were used to generate different estimations of cycling culture. These are:

i) Modal share of cycling, with the assumption that higher modal shares results in a reduced impact of darkness.,

ii) Total number of cyclists, with the assumption that the more cyclists there are in a location, the less the impact of darkness.,

iii) Cycling-Friendly Cities indexes, with the assumption that the higher the city is ranked on the list the higher the cycling culture, leading to its cyclists being less impacted by darkness.

The association between each proxy and ORs (established in chapter **3**) is explored below using a Spearman Rank correlation test (since ORs, the primary variable, were revealed not to be normally distributed), followed by a linear regression, ending with an exclusion of outliers where applicable.

4.2.2.1 Cycling modal share

The modal share of cycling in a city, typically expressed as a percentage, refers to the proportion of all cycling journeys relative to other modes of transportation used in that city. **Table 4.2** shows estimates of cycling modal shares for the 15 cities collected from various online sources, as it was not possible to find one source of data for all of the 15 cities.

Table 4.2 Modal shares of cycling in the 15 cities (arranged high to low) with sources of their estimation alongside ORs established in Chapter 3.

Location	Odds ratio	Modal share	Source of estimation
Münster, Germany	1.09	47.0%	City of Münster 2022 – Amt für Kommunikation https://www.muenster.de/pressemeldungen/web/frontend/design/kommunikation/show/1129447
Antwerp, Belgium	1.06	42.0%	UITP (Union Internationale des Transports Publics) 2022 https://www.uitp.org/news/smart-ways-to-antwerp-pioneering-sustainable-commuting/
Berlin, Germany	1.14	13.0%	Deloitte City Mobility Index 2018 https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/Berlin_GlobalCityMobility_WEB.pdf *
Paris, France	1.08	11.2%	Institut Paris Région 2024 https://www.institutparisregion.fr/mobilite-et-transports/deplacements/enquete-regionale-sur-la-mobilite-des-franciliens/
Helsinki, Finland	1.08	9.0%	City of Helsinki Bicycle action plan 2020 https://www.hel.fi/static/liitteet/kaupunkiymparisto/julkaisut/julkaisut/julkaisu-32-20.pdf
Dublin, Ireland	1.08	7.0%	Deloitte City Mobility Index 2020 https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/Dublin_GlobalCityMobility_WEB.pdf *
Oslo, Norway	0.87	6.0%	UPPER project 2022 https://www.upperprojecteu.eu/wp-content/uploads/2023/10/Overview-of-Oslo.pdf
Edinburgh, Scotland, UK	1.15	4.0%	Transport and Environment Committee, City of Edinburgh - City Mobility Plan 2021 https://democracy.edinburgh.gov.uk/documents/s40132/7.4%20-%20City%20Mobility%20Plan%20-%20Mode%20Share%20Target.pdf
Montreal, Canada	1.11	3.3%	Union Cycliste Internationale (UCI) 2020 https://www.uci.org/article/uci-bike-city-montreal-a-cycling-city-come-rain-shine-or-snow/4ox61lbv1VQKnDFES5TJD8?
Seattle, USA	1.74	3.0%	Commute Seattle survey 2022 https://www.commuteseattle.com

Location	Odds ratio	Modal share	Source of estimation
New York, USA	1.23	2.6%	NYC Department of Transportation 2022 https://nyc.streetsblog.org/2023/04/21/mayor-adams-wants-to-hit-the-brakes-on-citys-car-boom-encourage-sustainable-transit
Arlington, VA, USA	1.76	2.0%	MWCOG Regional Travel Survey 2017/2018, as reported in Uttley et al. [2023b]
Leeds, UK	1.18	1.1%	West Yorkshire 2016 – Transport Strategy Evidence Base https://www.westyorks-ca.gov.uk/media/2847/transport-strategy-evidence-base.pdf
Auckland, New Zealand	1.44	1.0%	Deloitte City Mobility Index 2020 https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/Auckland_GlobalCityMobility_WEB.pdf *
Birmingham, UK	1.51	1.0%	Deloitte City Mobility Index 2020 https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/Birmingham_GlobalCityMobility_WEB.pdf *

* Webpage no longer accessible

A Spearman Rank (r_s) correlation test between the ORs and modal shares reveals a coefficient of r_s = -0.752 (p=0.001), indicating a strong and statistically significant negative association [Dancey and Reidy, 2020, P. 183] – cycling modal shares tend to increase when OR decreases. Following this, a logarithmic regression model is employed to further explore the association between the two variables, as it provided a better fit (higher R^2) than the linear model and visually aligned more closely with the pattern observed in the scatterplot in **Figure 4.2**. This shows a negative association between ORs and cycling modal shares, confirming that ORs may decrease with an increase in cycling modal shares. However, the resulting equation OR = -0.119 *ln*(modal share) + 0.8766 suggests that this decrease is not at a steady rate. The model also suggests that 31.3% of variation in OR is explained by modal share, as revealed by an R^2 of 0.313 (p=0.03).

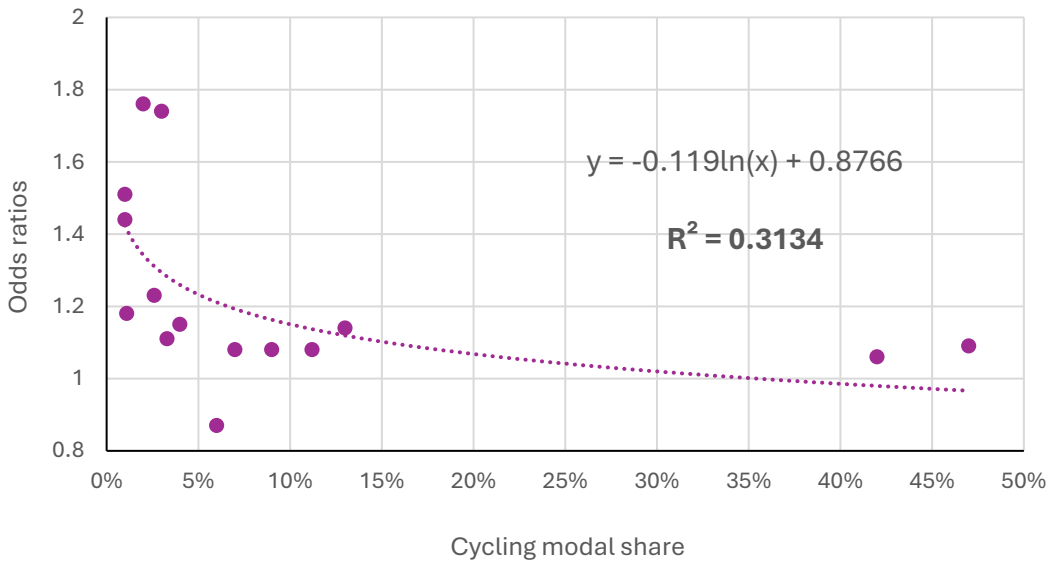


Figure 4.2 The relationship between odds ratios and cycling modal shares in the fifteen cities. A logarithmic trendline is fitted here.

To assess the influence of outliers, Münster and Antwerp are excluded due to their exceptionally high cycling modal shares compared to all other cities. This is shown to slightly increase the percentage of variation in ORs explained by modal share from 31.3% to 32.7% (**Figure 4.3**), with a marginal increase and no change in the strength of association when using the Spearman rank correlation (r_s = -0.750, p=0.001).

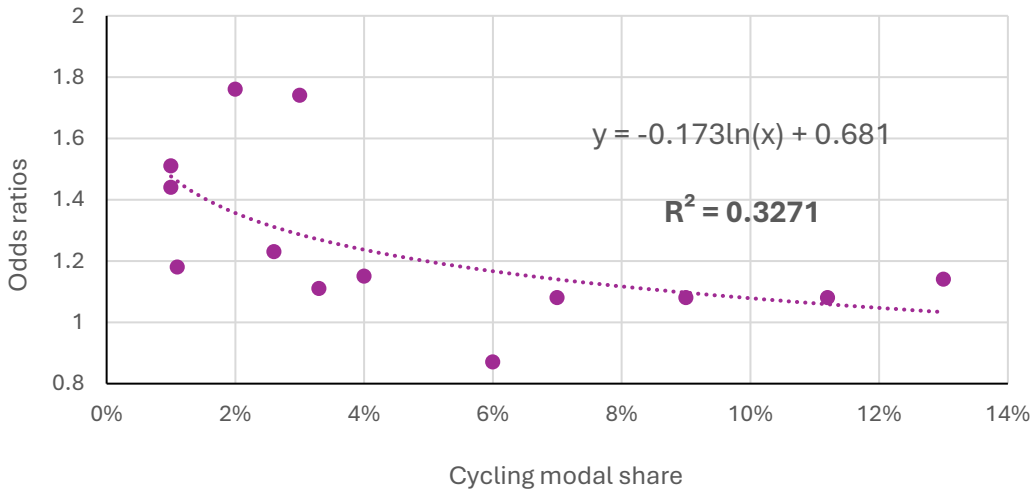


Figure 4.3 The relationship between odds ratios and cycling modal shares excluding outliers (Münster and Antwerp). A logarithmic trendline is fitted here.

4.2.2.2. Number of cyclists

An alternative approach to estimate a measure for cycling culture in a city is to use the number of cyclists in it as an indication. This number was established from automated cycling counter data, first as an annual average number of cyclists. However, to allow a fair comparison across different cities with different population sizes, these figures were normalized by population while also accounting for the number of counting sites used each year (as some cities installed additional counters over time). This is because more counters, more years, and a larger population will increase cyclist counts regardless of cycling culture. **Table 4.3** presents the number of cyclists per 1000 inhabitants in each city (see detailed calculations in **Appendix B**) alongside population estimates established using the *City Population* website [https://www.citypopulation.de/] and weighted ORs as established in Chapter **3**.

Table 4.3 Cyclists per 1000 inhabitants in each city (arranged highest to lowest) listed alongside corresponding ORs. Population and averaged cyclist counts per counter are shown for reference.

City	OR	Population*	Average cyclists count per counter per year	Cyclists per 1000 inhabitants
Münster, Germany	1.09	303,772	2103122	6923.36
Antwerp, Belgium	1.06	517,042	454584.9	879.20
Helsinki, Finland	1.08	635,181	469307.8	738.86
Arlington, VA, USA	1.76	238642	142810	598.43
Seattle, USA	1.74	737,018	419680.3	569.43
Dublin, Ireland	1.08	1,263,219	527083.8	417.25
Oslo, Norway	0.87	693,494	232501.7	335.26
Edinburgh, Scotland, UK	1.15	529,580	174365.1	329.25
Berlin, Germany	1.14	3,596,999	694355.4	193.04
Paris, France	1.08	2,113,705	222997.3	105.50
Montreal, Canada	1.11	1,743,687	259386.9	148.76
New York, USA	1.23	8804199	789456	89.67
Auckland, New Zealand	1.44	1,654,800	102620.5	62.01
Leeds, UK	1.18	809,479	36519.77	45.12
Birmingham, UK	1.51	1,074,283	35898.29	33.42

*As estimated in a year within or closest to the range of cycling data available, established using the *City Population* website [https://www.citypopulation.de/].

A Spearman Rank correlation coefficient of r_s = -0.373 (p=0.172) indicates a weak negative association between the two variables [Dancey and Reidy, 2020, P. 183], suggesting that as the number of cyclists per 1000 inhabitants increase, ORs tend to decrease slightly. This relationship is not statistically significant.

Following this, a logarithmic regression model is employed to further explore the association between the two variables, as it provided a better fit than a linear model and aligned with the pattern observed in the scatterplot in **Figure 4.4**. The model does not suggest a relationship between ORs and number of cyclists, as minimal variation in OR is explained by the number of cyclists, as revealed by an R^2 of 0.021 (p=0.608).

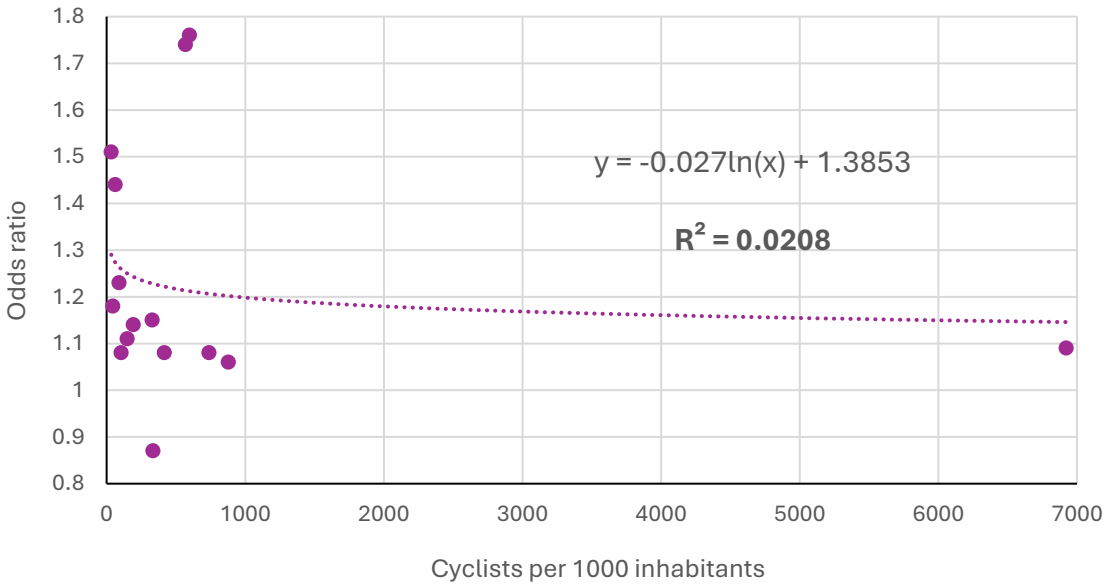


Figure 4.4 The relationship between odds ratios and cyclists per 1000 inhabitants. A logarithmic trendline is fitted here.

Münster shows an unusually high number of cyclists when compared to other locations. A scatterplot that excludes Münster as an outlier is shown in **Figure 4.5**. A reduced R^2 value of 0.0033 indicates that less than 1% of variation in ORs is explained by number of cyclists. No change in the strength of relationship or statistical significance is indicated with a Spearman rank correlation coefficient of r_s = -0.333 (p=0.225).

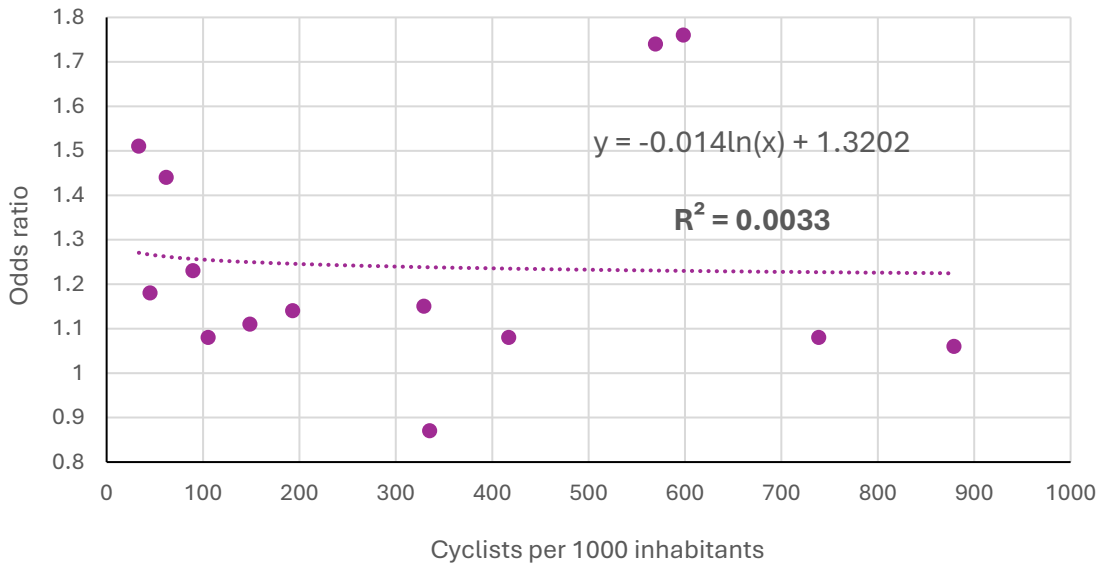


Figure 4.5 The relationship between odds ratios and cyclists per 1000 inhabitants, excluding Münster as an outlier.

4.2.2.3. Cycling friendliness

A third suggestion to estimate a measure of cycling culture in a city is to determine how cycling-friendly a city is compared to others. This information may be readily available from various ranking sources such as Luko's *Global Bicycle Cities Index* [Luko, 2022], Copenhagenize's *The Most Bicycle-Friendly Cities* [Copenhagenize, 2019], and PeopleForBikes' *Best Places to Bike* [Peopleforbikes, 2024]. Out of three mentioned, Luko's index has the clearest methodology and features the largest number of cities (n = 12) from the 15 included in this thesis. Therefore, it is used as the main source of cycling friendliness estimation in this analysis.

Luko's *Global Bicycle Cities Index 2022* [Luko, 2022] ranks 90 cities around the world for their cycling friendliness using six categories: City size, weather, bicycle usage, cycling infrastructure, bicycle sharing, and cycling events. **Table 4.4** shows the ranking of 12 cities out of the 15 in my analysis, as Arlington, Birmingham, and Leeds were not included in the ranking. While the data was initially accessed in 2023 through the Luko website (https://de.luko.eu/en/advice/guide/bike-index/), the page now redirects to *Getsafe*, a German digital insurance company, which has acquired Luko in October of

2023. However, data from Luko's website including the city ranking and its method were saved prior to the removal of the webpage. The document saved from Luko's website before its removal (see **Appendix C**) offers insight into the methodology followed by Luko to select and rank the 90 cities. The cities are chosen for their current and future investment in cycling and their willingness to improve infrastructure and safety. A weighted average is calculated for the following six categories:

- Weather: a score is generated using aggregate weather data (e.g. average annual precipitation per millimetre, number of days below 0° and above 30°) obtained from online sources such as *World Weather Online.*

- Bicycle usage: a percentage estimated from sources such as local statistical departments, UN, and others.

- Crime and safety: a score calculated from estimated crashes, fatalities, and bicycle theft per 100k cyclists in each city, estimated from multiple sources such as *World Bank*.

- Cycling infrastructure: a score calculated from estimates of total length of cycling paths, investment in infrastructure, bicycle ownership, and number of bicycle shops per 100k cyclists using sources such as Open Street Maps, Yellow Pages, and others.

- Bicycle sharing schemes: a score calculated from estimates of the number of available share bicycles and rental stations per 100k inhabitants using sources such as local bicycle sharing company websites.

- Cycling events: a score for the presence of cycling-friendly promotional events such as No Car Day, and the number of people attending such events.

Table 4.4 Available ranking of 12 cities showing the score for each item in the six categories evaluated by Luko. Shaded columns indicate the final score of the six categories.

Rank	City	Size*	Weather score	Bicycle usage	Crime and safety				Infrastructure				Sharing			Events			Total Score
					Fatalities**	Accidents**	Bicycle theft score	**Safety score**	No. of Bicycle shops**	Road quality score	Infrastructure investment	**infrastructure score**	Bike sharing station**	no. of shared bicycles**	**sharing score**	No car day?	Critical mass score	**Event score**	
#2	Munster	S	58.74	39.10%	0.53	445.58	83.04	88.43	28.15	53.05	88.04	51.23	35.52	26	31	N	23.84	445.58	65.93
#3	Antwerp	S	62.67	28.90%	1.61	1165.81	84.61	77.05	73.57	53.37	75.31	34.28	78.87	100	89	Y	14.12	1165.81	60.51
#16	Montreal	L	49.60	18.20%	0.42	986.47	94.79	87.51	19.05	44.12	72.73	45.91	7.42	3.67	6	Y	8.82	986.47	43.68
#19	Berlin	L	57.69	15.00%	0.58	407.56	86.91	89.86	14.82	50.79	92.81	48.71	10.36	24.43	17	N	69.79	407.56	42.59
#32	Paris	L	66.31	3.00%	0.75	318.14	69.64	84.28	29.51	58.51	91.61	63.15	69.24	93.33	81	Y	32.67	318.14	37.53
#35	Helsinki	M	47.16	10.00%	1.05	222.36	88.75	90.19	25.97	51.96	91.61	45.89	36.87	42.18	40	N	12.41	222.36	36.62
#49	Auckland	L	74.64	8.00%	0.25	453.72	98.01	94.54	11.3	38.83	74.28	33.73	1.08	1.07	1	N	1.48	453.72	33.04
#50	Seattle	M	71.92	3.50%	0.67	1688.20	82.14	75.3	32.59	56.73	90.4	56.92	10.84	4.62	8	Y	4.23	1688.20	32.93
#54	Edinburgh	S	62.56	3.00%	0.95	1175.78	84.37	79.84	53.07	52.85	78.04	43.82	11.57	10.59	11	Y	3.02	1175.78	31.32
#55	Oslo	M	47.45	7.00%	0.53	226.40	83.65	90.79	20.07	38.58	71.03	30.31	42.86	46.15	45	N	10.13	226.40	31.31
#60	Dublin	M	68.72	3.00%	0.63	517.05	81.95	86.92	66.19	43.56	49.21	35.91	47.07	37.14	42	N	7.44	517.05	29.97
#67	New York	L	60.75	1.20%	0.66	2157.77	85.19	71.76	7.58	48.2	90.4	48.21	23.98	16.33	20	Y	2.52	2157.77	28.1

* Size interpretation: S (small) refers to cities with less than 500,000 inhabitants, M (medium) refers to cities with inhabitants between 500,000 and 999,999, and L (large) refers to cities with 1 million inhabitants or more.

** Per 100k cyclists

Scores for the six categories used in Luko's index are presented in **Table 4.5** alongside corresponding ORs for 12 available cities (out of the fifteen in this thesis). A Spearman Rank correlation test is employed to explore the association between the six categories and the ORs; the resulting coefficients are presented in **Table 4.6.** The findings suggest that bicycle-sharing score has the strongest association with ORs (r_s = -0.859, p<0.001) and is also statistically significant – as sharing score increases, ORs decrease.

Weather and Event scores are shown to have a positive association with moderate strength, suggesting an increase in these scores might be associated with an increase in ORs, however, out of the two associations, only event score is statistically significant (p=0.028). The remaining three categories and the overall Luko score are shown to have a negative associating with weak strength and no statistical significance.

To account for multiple comparisons across the six Luko categories and the final score, a Bonferroni correction was applied by dividing the original threshold of p<0.05 by the number of comparisons (n = 7), resulting in an adjusted significance threshold of α=0.007. Following this correction only the association with bicycle sharing remains statistically significant, while the previously significant Event score no longer meets the threshold (see **Table 4.6**).

Table 4.5 Scoring for all six categories defined in Luko's Global Bicycle Cities index 2022 (arranged from lowest to highest total score) alongside weighted ORs for each city and variance in OR as explained by each category.

City	OR	Weather score	Bicycle usage	Safety score	infrastructure score	Sharing score	Event score	Total score	Luko rating
Münster	1.09	58.74	0.39	88.43	51.23	31	445.58	65.93	2
Antwerp	1.06	62.67	0.29	77.05	34.28	89	1165.81	60.51	3
Montreal	1.11	49.6	0.18	87.51	45.91	6	986.47	43.68	16
Berlin	1.14	57.69	0.15	89.86	48.71	17	407.56	42.59	19
Paris	1.08	66.31	0.03	84.28	63.15	81	318.14	37.53	32
Helsinki	1.08	47.16	0.10	90.19	45.89	40	222.36	36.62	35
Auckland	1.44	74.64	0.08	94.54	33.73	1	453.72	33.04	49
Seattle	1.74	71.92	0.04	75.3	56.92	8	1688.2	32.93	50
Edinburgh	1.15	62.56	0.03	79.84	43.82	11	1175.78	31.32	54
Oslo	0.87	47.45	0.07	90.79	30.31	45	226.4	31.31	55
Dublin	1.08	68.72	0.03	86.92	35.91	42	517.05	29.97	60
New York	1.23	60.75	0.01	71.76	48.21	20	2157.77	28.1	67

Table 4.6 Interpretations of the correlation coefficients calculated between weighted ORs and the six categories in the Luko index.

Category	Correlation with ORs (r_s)	Relationship strength*	Statistical significance (Bonferroni adjusted, p>0.007)
Weather	0.43	Moderate (positive)	p=0.110, not significant
Bicycle use	-0.25	Weak (negative)	p=0.372, not significant
Safety	-0.25	Weak (negative)	p=0.372, not significant
Infrastructure	0.34	Weak (positive)	p=0.218, not significant
Bicycle sharing	-0.86	Strong (negative)	p=0.000, significant
Events	0.59	Moderate (positive)	p=0.028, not significant
Overall score	-0.20	Weak (negative)	p=0.481, not significant

* Interpreted using descriptions established in Dancey and Reidy [2020].

Next, the relationship between the ORs and each of the six Luko categories is explored in the scatterplots in **Figure 4.6**, where polynomial trendlines appear to show R^2 values ranging from 0.08 to 0.53. These are detailed further in **Table 4.7**. The findings suggest that among the six categories, weather score showed the strongest relationship with ORs, with an R^2 value of 0.535 (over 53% of variation explained). Sharing score followed closely with an R^2 value of 0.471 (47.1% of variation explained). However, while initially only weather score was found statistically significant ($p<0.05$), as sharing score was just above the threshold of 0.05 ($p=0.057$), correcting for multiple comparisons adjusts the significance threshold to $\alpha=0.007$, which means that none of the relationships remain statically significant after correction. Additionally, the direction of relationships was here reversed, where higher ORs were associated with a higher weather score but a lower sharing score. The variables with the next biggest influence were safety, event, and infrastructure scores with a range of 11% to 27% of variation explained.

These results highlight that Weather and Sharing scores have the most influence on the impact of darkness on cyclists among the six categories explored, although this influence may be limited once multiple comparisons are accounted for. The U-shaped trendline shown in the scatterplots may suggest that these relationships are not linear – scores may decrease around the mid-range of ORs but increase towards higher and lower ORs.

Table 4.7 Variance in OR as explained by each category and the total score. None of the models remain statistically significant after Bonferroni correction (p<0.007).

	Weather score	Bicycle usage	Safety score	infrastructure score	Sharing score	Event score	Total score
Explained variance in OR (R^2)	0.535	0.071	0.272	0.112	0.471	0.261	0.057
P-value	0.032	0.717	0.239	0.586	0.057	0.256	0.769

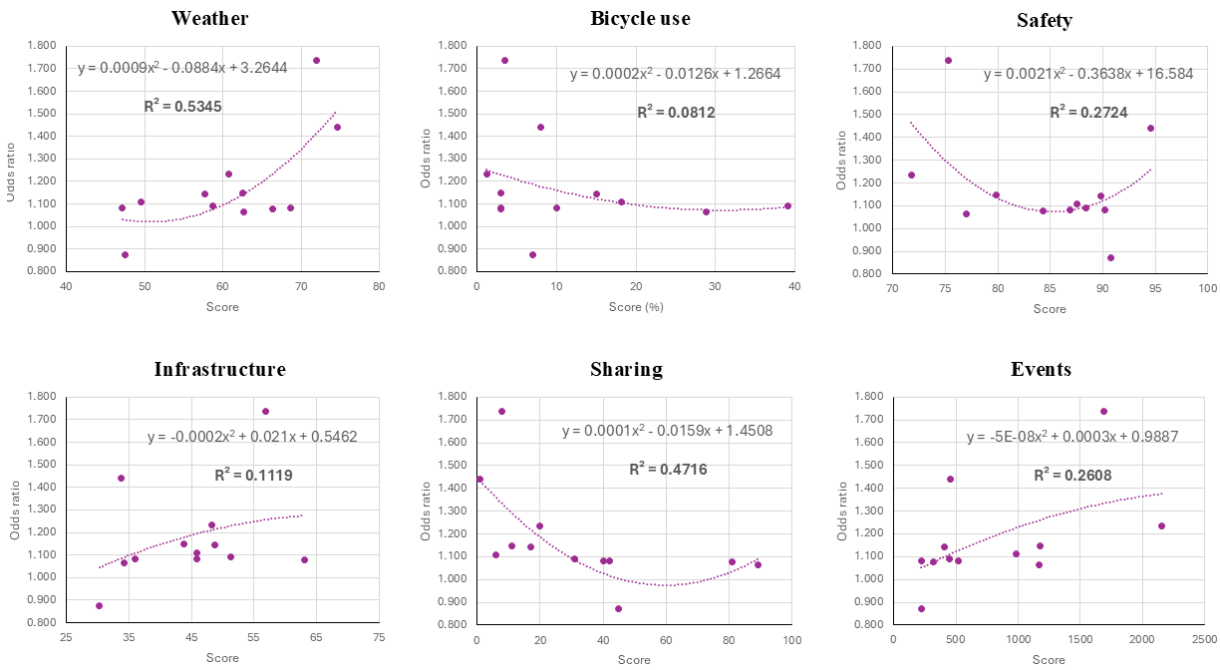


Figure 4.6 The relationship between weighted ORs and Luko's six scoring categories. A polynomial trendline is fitted on all scatterplots.

4.3. Summary

This chapter presents an exploration of the association between the weighted ORs (established in chapter **3**) and records of latitude and estimates of cycling culture. This is done to understand the influence these macroscale factors may have on the effect of darkness on cyclists across the 15 cities.

Normality of data was assessed, revealing that the main outcome variable (OR) is not normally distributed. Thus, a Spearman Rank correlation test was employed going forward. The results (summarized in **Table 4.8**) suggest that ORs may significantly decrease in higher latitudes and with higher cycling modal shares – the impact of darkness on cyclists tends to decrease in locations higher in latitude and locations with a higher modal share of cycling (as an estimate of cycling culture).

Additionally, from the Luko scores, bicycle-sharing was strongly associated with variation in ORs, revealing that ORs may decrease with a higher sharing score – the impact of darkness on cyclists is reduced in locations where bicycle-sharing is prevalent. This relationship is statistically significant. Weather and event score were the next to show association with ORs, with moderate strength, indicating that ORs may increase with higher scores, but out of the two, only event score had a statistically significant association.

The final step was the application of linear regression analysis to model the relationships between ORs and each variable. The summary results shown in **Table 4.8** suggest that the top attributes for explaining significant variation in ORs may be Luko's weather score (53.5% explained), Luko's bicycle-sharing score (47.1% explained), latitude (37% explained), and cycling modal share (31% explained). However, only latitude, modal share, and weather score are statistically significant, with sharing score just slightly above the threshold (p=0.057).

In conclusion, the results presented in Chapter **4** suggest that the variation in ORs observed in the 15 cities may be associated with latitude and cycling culture (when using modal share as proxy). Bicycle-sharing was also shown to be associated; thus, it may be reasonable for future work to include it as a proxy for cycling culture. While here the focus was on the geographical and cycling culture scope, influences from factors such as weather and cycling promotional events emerged as attribute that require further investigation in the 15 cities.

Chapter **4** explored two macroscale factors (latitude and cycling culture) to support hypotheses H3 and H4, which state that locations at higher latitudes and a greater cycling culture will show less of a deterrent effect of darkness on cycling. Chapters **5** and **6** explore the influence of microscale factors.

Table 4.8 Summary of findings from analysing the relationship between weighted ORs against latitude records (first results row) and cycling culture estimates (remaining rows).

Attribute			Correlation tests (Monotonic association)			Linear Regression		Summary interpretation
			Correlation coefficient (r_s)	Statistical significance *	Relationship Direction and strength	R^2	R^2 after removing outliers	
Latitude			-0.53	**0.040**	negative moderate	0.367, p=**0.017**	n/a	ORs tend to decrease moderately with higher latitudes.
Cycling culture	Modal share		-0.75	**0.001**	negative strong	0.313, p=**0.03**	0.327	ORs tend to decrease strongly with higher modal shares.
Cycling culture	Cyclists per 1000 inhabitants		-0.37	0.172	negative weak	0.021, p=0.608	0.003	ORs tend to minimally dectrease with higher cyclist numbers. This relationship is not statistically significant.
Cycling culture	Luko	weather score	0.43	0.110	positive moderate	0.535, p=0.032	n/a	ORs tend to decrease with a higher bicycle-sharing score. This relationship is statistically significant. ORs increase with higher weather then event scores. The relationship is only significant for event score.
Cycling culture	Luko	Bicycle use	-0.25	0.372	negative weak	0.081, p=0.717		
Cycling culture	Luko	Safety score	-0.25	0.372	negative weak	0.272, p=0.329		
Cycling culture	Luko	Infrastructure score	0.34	0.218	positive weak	0.112, p=0.586		
Cycling culture	Luko	Sharing score	-0.86	**p<0.001**	negative strong	0.471, p=0.057		
Cycling culture	Luko	Event score	0.59	0.028	Positive moderate	0.261, p=0.256		
Cycling culture	Luko	Overall score	-0.20	0.481	negative weak	0.057, p=0.769		

* Statistically significant values (p<0.05) are shown in **bold** numbering. For Luko categories, a Bonferroni adjustment of p<0.007 is applied

Chapter 5. Within-cities analysis of the impact of darkness: Method

5.1. Introduction

Chapter **3** focused on improving the case-control method used to quantify the effect of darkness on cycling and presented the results of its application on 15 cities, as weighted ORs. Chapter **4** focused on exploring the influence of macroscale (across cities) factors on these ORs.

Chapter **5** describes the process of investigating the influence of several microscale (within cities) factors on the effect of darkness on cyclists. This is done at the scale of individual counting sites rather than the scale of the entire city as a unit. The results of this are presented in chapter **6**.

This exploration aims to address the remaining research hypotheses H5-H7, which state:

H5: Locations with a higher proportion of utilitarian cycling will show a smaller deterrent effect of darkness.

H6: Locations further from the city centre will show a larger deterrent effect of darkness than locations closer to it

H7: Locations where street lighting is present will show a smaller deterrent effect of darkness than locations where no lighting is present.

Each of these hypotheses targets one mediating microscale factor that may influence the effect of darkness on cyclists. These are: *journey type*, *presence of street lighting,* and *distance from city centre*. Additionally, while *latitude* and the *number of cyclists* were investigated at the macroscale level in chapter **4** to address H3 and H4, this chapter includes them alongside the three other factors at the microscale level investigation to understand their influence at individual counting sites.

5.2. Procedure

While previous chapters (Chapters **3** and **4**) focused on assessing the deterrent effect of darkness across cities, establishing one weighted OR per city for the macroscale analysis, Chapters **5** and **6** instead assess this effect within cities, establishing weighted ORs for individual counting sites rather than one general OR per city. Five out of the fifteen cities were selected for this exploration: Auckland, Edinburgh, Münster, Oslo, and Seattle. One reason for this choice was the ability to identify data for individual locations in the available count data.

All available counting sites were used within the five cities: a total of 74 locations. The coordinates of these sites are listed in **Tables 5.1-5.5** and highlighted in the corresponding maps in **Figures 5.1-5.5**. In instances where coordinates were not included in the data package (e.g. Seattle), they were instead estimated using other information available in the source material (i.e. guide map) or by exploring Google street views of the location using details about the counter name to trace for visible cycle counters (see example in **Figure 5.6**).

Using the same cycling datasets and process described in chapter **3**, weighted ORs were established for each individual counting site within the five cities. Next, the association between ORs and data established for the five factors (*journey type*, *presence of street lighting, distance from city centre*, *latitude,* and the *number of cyclists*) was explored through linear regressions to model the relationships and understand the strength of association. Following this, multi-collinearity was examined in preparation to use all variables in a stepwise regression. If any variables exceed the threshold of a variance inflation factor (VIF) above 5.0, they are excluded [Brooks and Barcikowski, 1999]. Finally, the stepwise regression analysis was performed using SPSS to identify predictors of variation in ORs. Here ORs are set as a dependent variable and all five factors as independent variables. The five factors and their data are described in the following sections.

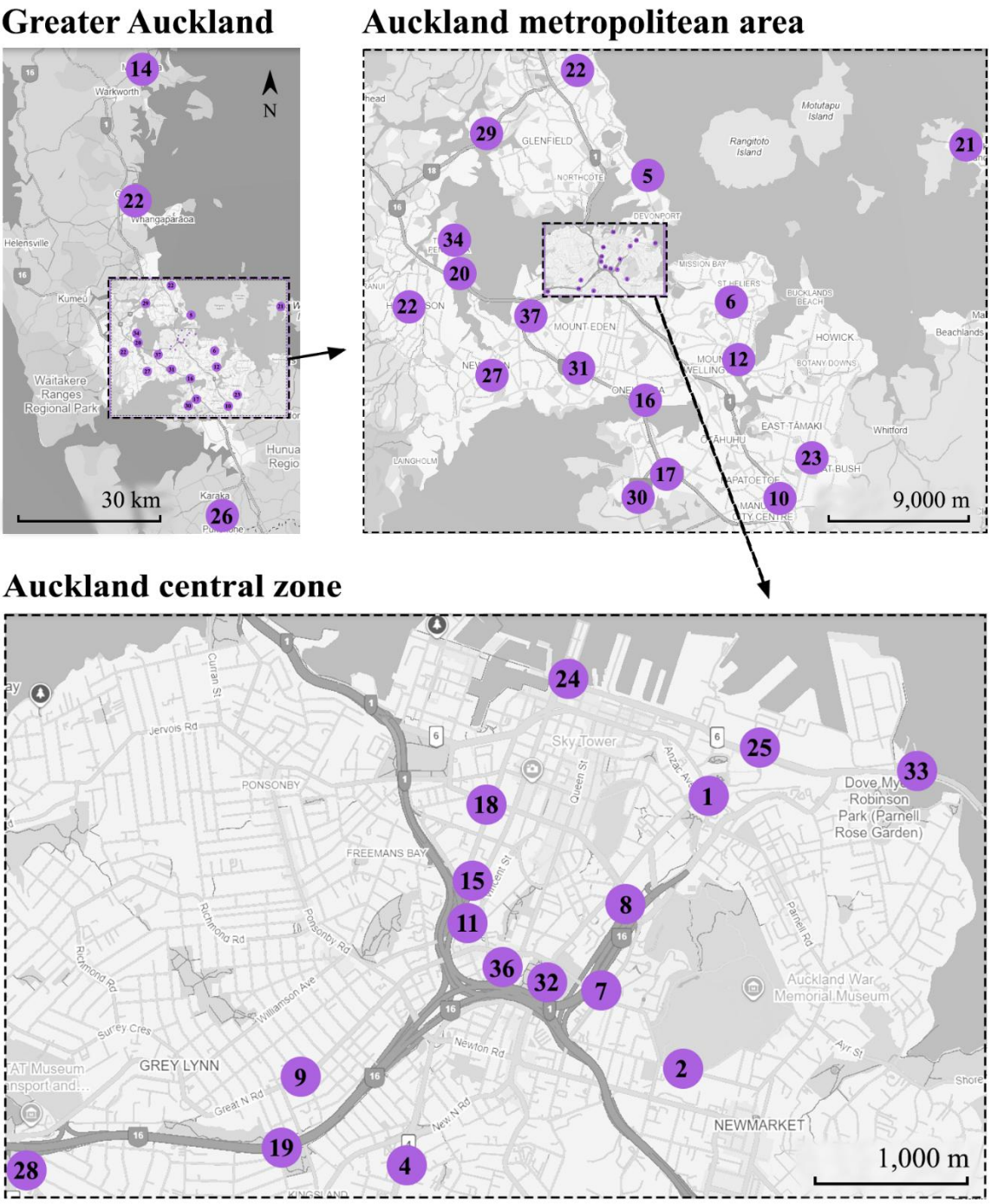


Figure 5.1 Map of **Auckland** showing 37 counting sites (overlay added by author). See Table 5.2. for key information. *Base map source: © Google Earth: data from Google (accessed June 2025).*

Table 5.1 A list of counting sites in Auckland, New Zealand, arranged by order of appearance in source data. The number of years data is available for varies between locations.

ID	Counter location	Data range	Coordinates (DMS)	
1	Beach Road	2015-2019	36°50'57.79"S	174°46'27.93"E
2	Carlton Gore Road	2016-2019	36°51'51.60"S	174°46'21.18"E
3	Curran Street	2016-2019	36°50'21.90"S	174°44'21.77"E
4	Dominion Road	2018-2019	36°52'13.40"S	174°45'10.59"E
5	East Coast Road	2013-2019	36°44'30.35"S	174°44'28.67"E
6	Glenn Innes to Tamaki Drive Section	2017-2019	36°52'25.11"S	174°51'2.61"E
7	Grafton Bridge	2013-2019	6°51'36.32"S	174°45'59.39"E
8	Grafton Gully	2015-2019	36°51'19.90"S	174°46'6.89"E
9	Great North Road	2017-2019	36°51'53.83"S	174°44'43.91"E
10	Great South Road Manukau	2018-2019	36°59'13.68"S	174°52'54.47"E
11	Hopetoun Street	2016-2019	36°51'21.96"S	174°45'27.09"E
12	Lagoon Drive	2013-2019	36°54'25.71"S	174°51'27.23"E
13	Lake road	2012-2019	36°48'9.54"S	174°47'14.81"E
14	Leigh Road	2018-2019	36°21'6.96"S	174°43'6.36"E
15	Lightpath 2	2016-2019	36°51'12.54"S	174°45'27.39"E
16	Mangere Bridge	2012-2019	36°55'56.46"S	174°47'10.64"E
17	Mangere Safe Routes	2017-2019	36°58'20.35"S	174°47'58.40"E
18	Nelson Street	2016-2019	36°50'59.61"S	174°45'32.50"E
19	Nw Cycleway Kingsland	2012-2019	36°52'8.88"S	174°44'38.47"E
20	Nw Cycleway Teatatu	2014-2019	36°51'30.33"S	174°39'13.46"E
21	Oceanview Road	2018-2019	36°47'1.35"S	175° 0'41.43"E
22	Orewa Path	2012-2019	36°35'46.89"S	174°41'38.59"E
23	Ormiston Road	2018-2019	36°57'54.64"S	174°54'33.45"E
24	Quay Street Eco Display Classic	2017-2019	36°50'34.26"S	174°45'53.43"E
25	Quay Street Spark Arena	2016-2019	36°50'47.40"S	174°46'40.31"E
26	Queen Street Pukekohe	2018-2019	37°12'13.13"S	174°54'3.49"E
27	Rankin Avenue	2019	36°54'43.45"S	174°40'55.59"E
28	Saint Lukes Road	2018-2019	36°52'16.17"S	174°43'32.74"E
29	SH18 Upper Harbour Drive	2013-2019	36°46'56.22"S	174°40'31.17"E
30	SH20A	2019	36°58'40.14"S	174°47'11.40"E
31	SW SH20	2013-2019	36°54'43.52"S	174°44'24.33"E
32	Symonds Street	2015-2019	36°51'35.16"S	174°45'45.61"E
33	Tamaki Drive Wb	2013-2019	36°50'52.59"S	174°47'20.56"E
34	Teatatu Peninsula	2019	36°50'59.60"S	174°39'5.03"E
35	Twin Streams	2013-2019	36°52'43.69"S	174°37'26.82"E
36	Upper Queen Street	2016-2019	36°51'33.42"S	174°45'38.34"E
37	Waterview Unitec	2018-2019	36°52'57.98"S	174°42'16.87"E

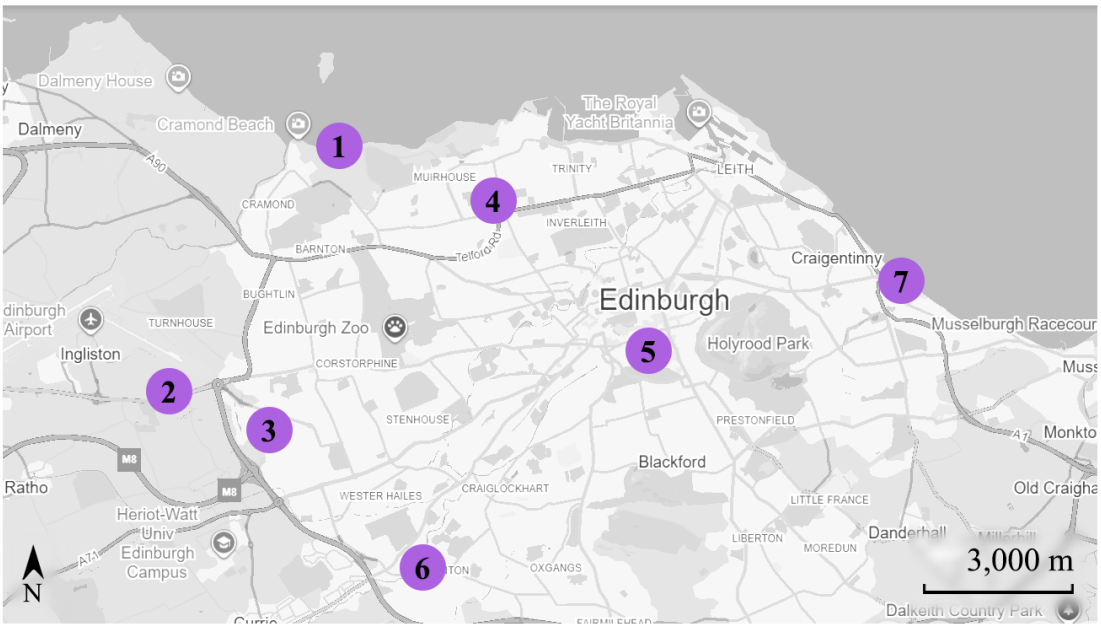


Figure 5.2 Map of **Edinburgh** showing 7 counting sites (overlay added by author). See Table 5.2. for key information. *Base map source: © Google Earth: data from Google (accessed June 2025).*

Table 5.2 A list of counting sites in **Edinburgh**, Scotland, arranged by order of appearance in source data. Data for all locations is available for one year only.

ID	Counter location	Data range	Coordinates (DMS)	
1	Silverknowes	2019	55°58'44.19"N	3°17'18.64"W
2	RBS Gogar	2019	55°56'11.83"N	3°20'13.13"W
3	Cultins Road	2019	55°55'44.31"N	3°18'23.49"W
4	North Edinburgh Access Road	2019	55°58'6.10"N	3°14'21.09"W
5	Middle Meadow Walk	2019	55°56'33.72"N	3°11'28.90"W
6	Spylaw Park	2019	55°54'23.70"N	3°15'41.76"W
7	Portobello Prom	2019	55°57'24.10"N	3° 6'56.24"W

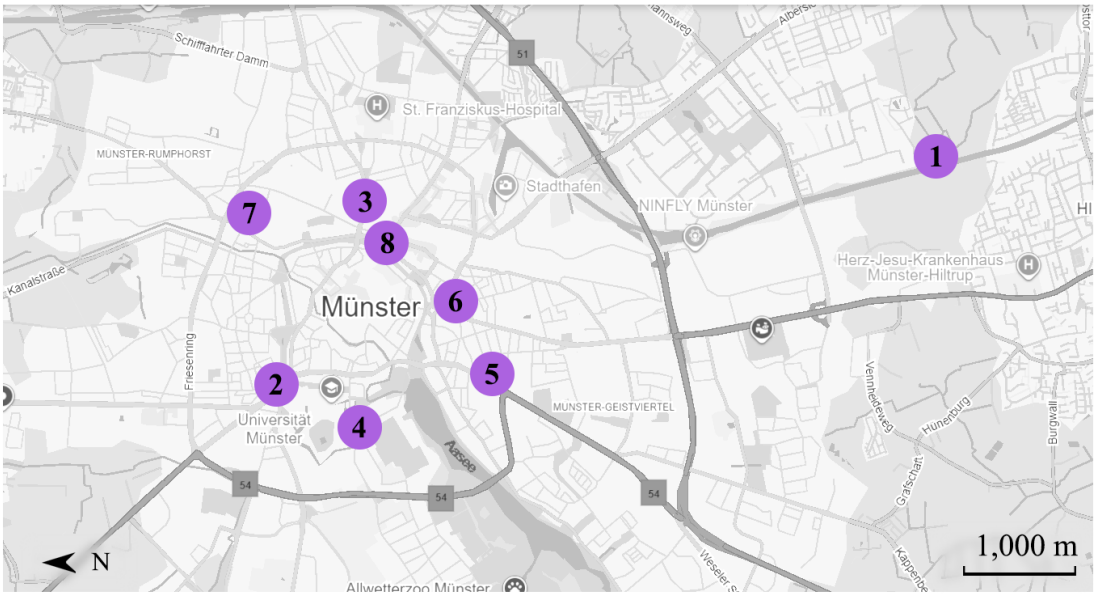


Figure 5.3 Map of **Münster** showing 8 counting sites (overlay added by author). See Table 5.3. for key information. *Base map source: © Google Earth: data from Google (accessed June 2025).*

Table 5.3 A list of counting sites in **Münster**, Germany, arranged by order of appearance in source data. Data for all locations is available for one year only.

ID	Counter location	Data range	Coordinates (DMS)	
1	Kanalpromenade	2019	51°55'2.52"N	7°38'57.00"E
2	Neutor	2019	51°58'1.15"N	7°36'55.58"E
3	Warendorfer Straße	2019	51°57'42.73"N	7°38'15.14"E
4	Hüfferstraße	2019	51°57'42.73"N	7°36'39.23"E
5	Weseler Straße	2019	51°57'2.06"N	7°37'3.75"E
6	Hammer Straße	2019	51°57'16.24"N	7°37'34.61"E
7	Gartenstraße	2019	51°58'17.48"N	7°38'8.12"E
8	Promenade	2019	51°57'38.15"N	7°38'2.54"E

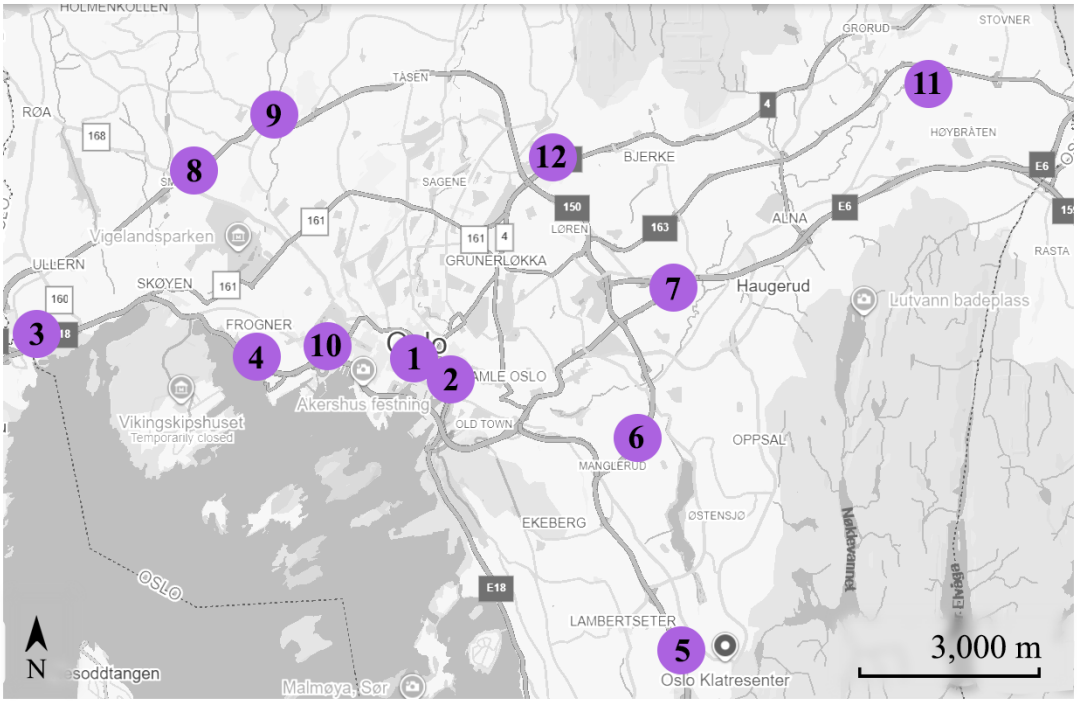


Figure 5.4 Map of **Oslo** showing 12 counting sites (overlay added by author). See Table 5.4. for key information. *Base map source: © Google Earth: data from Google (accessed June 2025).*

Table 5.4 A list of counting sites in **Oslo**, Norway, arranged by order of appearance in source data. Data for all locations is available for two years.

ID	Counter location	Data range	Coordinates (DMS)	
1	Dr Eufemias vest	2018-2019	59°54'31.47"N	10°45'17.27"E
2	Dr Eufemias ost	2018-2019	59°54'31.18"N	10°45'14.35"E
3	lysaker	2018-2019	59°54'48.10"N	10°38'32.41"E
4	frognerst	2018-2019	59°54'40.26"N	10°42'14.26"E
5	Skullerod	2018-2019	59°52'9.11"N	10°49'46.91"E
6	Bryn	2018-2019	59°54'7.42"N	10°49'10.01"E
7	Breivol	2018-2019	59°55'23.02"N	10°49'52.95"E
8	Smestad	2018-2019	59°56'19.56"N	10°41'13.92"E
9	Gaustad	2018-2019	59°56'44.78"N	10°42'48.22"E
10	Munkedamsvein	2018-2019	59°54'40.38"N	10°43'32.44"E
11	Grorud	2018-2019	59°57'1.94"N	10°53'46.14"E
12	Akkersyke	2018-2019	59°56'24.48"N	10°47'31.32"E

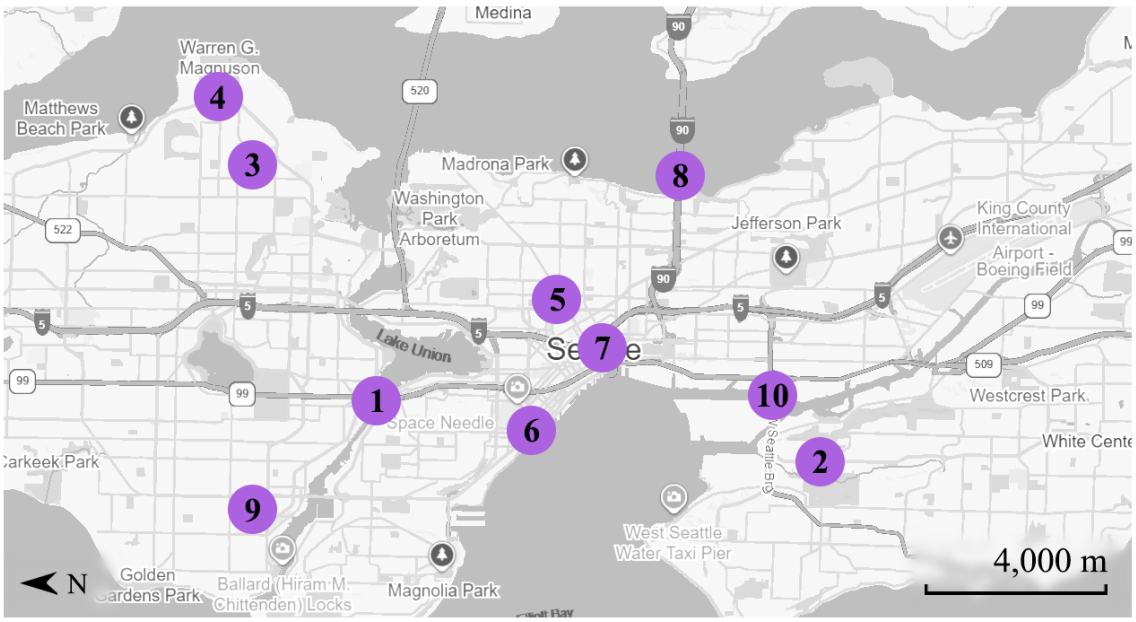


Figure 5.5 Map of **Seattle** showing 10 counting sites (overly added by author). See Table 5.5. for key information. *Base map source: © Google Earth: data from Google (accessed June 2025).*

Table 5.5 A list of counting sites in **Seattle**, WA, USA, arranged by order of appearance in source data. The number of years data is available for is similar for all locations except 2nd Ave.

ID	Counter location	Data range	Coordinates (DMS)	
1	Fremont Bridge	2014-2019	47°38'52.98"N	122°20'59.57"W
2	26th Ave – Delridge greenway	2014-2019	47°33'46.14"N	122°21'55.62"W
3	39th Ave	2014-2019	47°40'26.10"N	122°17'9.30"W
4	BGT North	2014-2019	47°40'45.99"N	122°15'55.27"W
5	Broadway	2014-2019	47°36'48.67"N	122°19'14.45"W
6	Elliot Bay	2014-2019	47°37'5.89"N	122°21'34.31"W
7	2nd Ave	2015-2019	47°36'18.44"N	122°20'5.99"W
8	MTS Trail (I-90)	2014-2019	47°35'25.83"N	122°17'11.67"W
9	NW 58TH St Greenway	2014-2019	47°40'15.62"N	122°23'5.50"W
10	Spokane St. bridge	2014-2019	47°34'17.90"N	122°20'42.29"W

Figure 5.6 Google street views showing examples of visible automated counters in two cycling sites in **Seattle**, WA, USA: pneumatic hoses in Delridge Greenway (left) and an inductive loop with a display screen on Fremont Bridge (right). *Images source: Google Street View, ©2019 Google (accessed June and October 2025).*

5.3. Journey type

5.3.1. The proportion of leisure journeys

The impact of darkness on cyclists may vary depending on the purpose of their journey [Wessel, 2022], with the assumption that cyclists commuting to and from work are more resilient to low light levels than those cycling for leisure. This assumption is based on the understanding that utilitarian journeys are typically necessary trips taken for the purpose of reaching a specific destination (e.g. work, education, or shops), often requiring travel regardless of ambient light and other conditions. Leisure journeys on the other hand, where the journey itself is the purpose, allow for more flexibility in choice of time and preferred ambient conditions.

One limitation that hindered investigation into journey types in previous work is that cyclist count data from automated counters captures only the cyclist, not the purpose of cycling.

To estimate journey type, whether leisure or utilitarian, the method proposed originally by Miranda-Moreno et al. [2013] and later adapted by Wessel [2020] was used. This presumes that weekday cyclists tend to be utilitarian journeys and weekend cyclists tend to be leisure journeys. This separation is based on the assumption that people are more likely to cycle to and from work on weekdays than on weekends, and more likely to cycle for leisure on weekends than weekdays, implying that weekdays will be more

dominated by utilitarian cycle journeys and weekend will be more dominated by leisure cycle journeys. These assumed trends are reflected in the patterns of cyclist numbers by hour of the day for weekdays and weekends shown in **Figure 5.7**. In the five cities selected for the site-specific analysis, cycling on weekdays displays a concentration of journeys in peak hours where people are typically commuting to and from employment or education, while on weekends this bimodal trend is largely absent, with peak cyclist volumes around lunchtime and early afternoon hours. Thus, as a first step, cycle counts for each location within the five cities are separated into weekdays and weekends counts using the =WEEKDAY function in Excel.

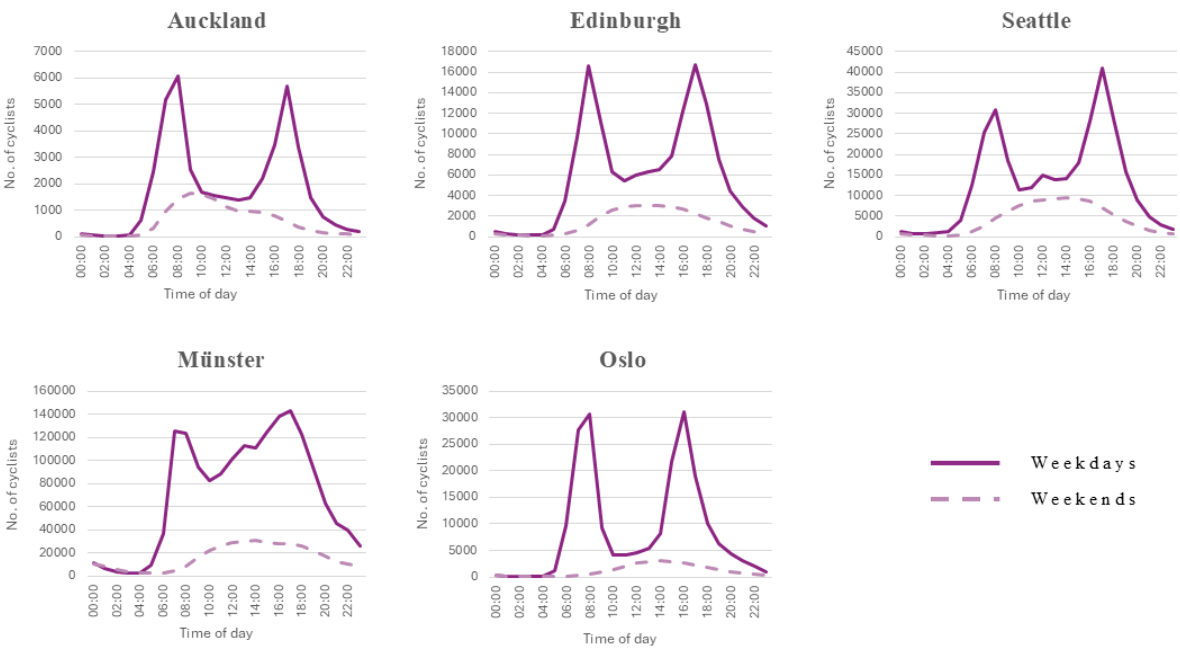


Figure 5.7 Hourly averages of cyclists per counter per years of data for weekends and weekdays in five cities.

The proportion of leisure journeys (P_L) at a given site was established using **Equation 6**. The resulting proportion would indicate that all journeys are utilitarian if P_L=0, or all journeys are for leisure if P_L=1.0.

$$P_L = \frac{N_L}{N_L + N_U} \qquad (6)$$

Where,

N_L = Average daily cyclist numbers at weekends (proxy for leisure journeys)

N_U = Average daily cyclist numbers for weekdays (proxy for utilitarian journeys)

5.3.2. Verification of journey type by visual assessment

Using weekday vs. weekend cycling to denote utilitarian vs. leisure cycling is an estimate demanded by the limited nature of count data. Clearly it is not always accurate because some people may cycle to work at weekends and some may undertake leisure cycling in weekdays. To provide some verification of this approach, a visual assessment of counting sites was carried out. In which the likely predominant journey type in a counting site was visually assessed using Google Street Views. Locations were classified as utilitarian, leisure, or mixed, using the criteria developed in **Table 5.6**.

Table 5.6 Proposed criteria for visual classification of locations. If a leisure and utilitarian conditions are met in the same location, then a location is classified as mixed.

Condition	Proposed journey type
If location is off-road (through a park, along a river, etc.)	Leisure
If location is in an area that promotes physical activity (i.e. fitness park, multi-use recreational areas)	Leisure
If location is in a residential area	Utilitarian
If location is in a highway	Utilitarian
If location is in an offices-dominant commercial street	Utilitarian
If location is in a shops-dominant commercial street	Mixed
If location is on a bridge connecting two areas	Utilitarian
If path is not buffered from vehicles	Utilitarian

To verify the efficacy of the criteria shown in **Table 5.6**, an inter-rater validation exercise was carried out where 20 PhD student colleagues were shown images of 10 cycling sites and asked to state if they thought each site was predominantly used for

leisure cycling, utilitarian cycling, or mixed. The sites were all from Seattle, WA, USA. Their answers were then compared to the classification proposed using the criteria described. Each validator was shown ten slides; each containing one to two street views and a satellite image of one counting site (see example in **Figures 5.8-5.10**). Names of locations were obscured to avoid influencing responses in instances where the name could suggest the use. For example, *Elliot Bay Cycling Trail in Myrtle Edwards Park* may influence validators to assume that it is a destination for leisure cycling since it includes the words *trail* and *park*. Overall, in 73% of cases the validators agreed with the results determined according to the criteria shown in **Table 5.6**, which is higher than chance level (33%).

Figure 5.8 Example *A* of slides shared with validators for visual classification. These images show Fremont Bridge in Seattle, WA. This site was classified utilitarian dominant using the criteria. 70% of validators were in agreement with this. *Images source: top left - Google Earth, data from Google, ©2024 (accessed October 2025); top right and bottom - Google Street View, ©2019-2023 Google (accessed June and October 2025).*

Figure 5.9 Example *B* of slides shared with validators for visual classification. These images show Elliot Bay Trail in Myrtle Edwards Park in Seattle, WA. This site was classified leisure dominant using the criteria. 70% of validators were in agreement with this. *Images source: top left - Google Earth, data from Google, ©2022 (accessed June 2025); top right and bottom - Google Street View, ©2019-2024 Google (accessed June and October 2025).*

Figure 5.10 Example *C* of slides shared with validators for visual classification. These images show 2nd Ave PBL in Seattle, WA, USA. This site was classified utilitarian dominant using the criteria. 90% of validators were in agreement with this. *Images source: top left - Google Earth, data from Google, ©2022 (accessed June 2025); top right and bottom - Google Street View, ©2021 Google (accessed June 2025).*

After validating the efficacy of the criteria using the visual classification method, these criteria were applied to all counting sites. Two approaches were then used to assess the reliability of the *proportion of leisure journeys*.

First, weighted ORs were calculated for all sites categorized as Utilitarian, Mixed, and Leisure, respectively. The assumption is that ORs would be higher for utilitarian sites, validating the reliability of the proportions.

Second, a bar chart was created to visually inspect whether grouping the data according to my visual classification produces consistent trends (i.e. higher *proportion of leisure journeys* for sites categorized as leisure dominant). These approaches would give an indication as to the validity of using *proportion of leisure journeys* method.

5.4. Distance to city centre

To explore the influence of proximity to city centre on ORs, 'city centre' must first be defined. Here, City Hall was used, suggested by Holian [2019], as a point to define the city centre and use to measure distance to each counter location. Two alternative methods to establish distance between the city centre and each counter location are used. These are described below. **Figure 5.11** illustrates an example of the two approaches, showing the distance between the Seattle City Hall and one of the cycling counter locations.

i) The Euclidean distance (km) between city hall and counting location. This distance is measured as a straight line using Google Maps' *measure distance* function.

ii) The cycling network distance (km) between city hall and each location. This is measured using the *Directions* function on Google Maps, choosing cycling as the mode of navigation and calculating the shortest distance of travel from counter location to city hall. An attempt was made record these navigation distances in off-peak morning hours (10:00-12:59) to avoid peak hour traffic.

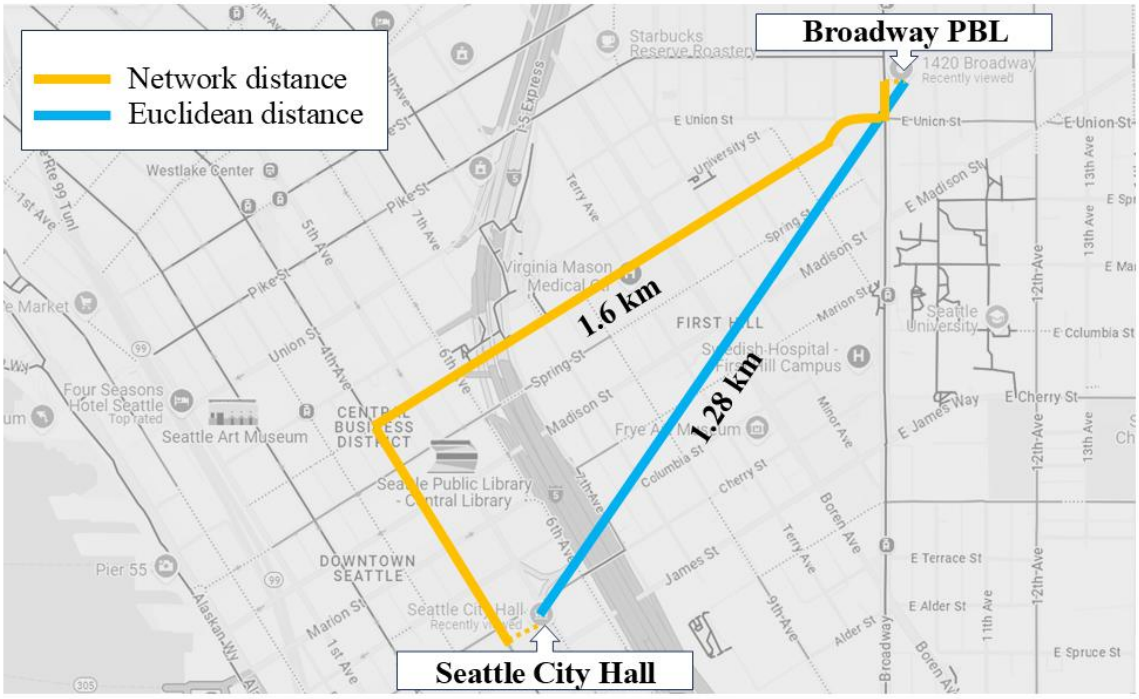


Figure 5.11 Example of the two approaches of calculating distance on a Google cycling map of Seattle, WA, USA (data overlay by author). Network distance refers to the shortest cycling distance between two points as suggested by Google and Euclidean distance refers to a line measured between two points on a map. *Base map source: © Google Maps, map data ©2025 Google (accessed August 2025).*

5.5. Presence of street lighting

To explore the influence of the presence of street lighting on OR variation, each counting location was visually assessed for the presence of street lighting (i.e. checking for a visible lamp post) in Google street views. Where this was not possible, an image search on Google was used to find pictures taken by visitors of the location. The street views used were captured by Google in the period between November 2017 and December 2024.

The cycling path was examined for a distance of 50m in both directions from the coordinates recorded for a counter. If installed street lighting fixtures were observed, the site was designated as *lit*. If street lighting was not observed, the site was designated as *unlit*. Locations with no lighting installed but are minimally lit by light spill from adjacent areas are initially flagged as *partially lit* but ultimately classified as *unlit* for the regression analysis. Examples of the three cases are shown in **Figure 5.12**.

Figure 5.12 Examples of locations identified as lit and unlit after dark in Auckland, NZ (data overlay by author). Left: East Cost Road. Middle: Archibald Park. Right: Curran Street. Locations are checked for the presence of street lighting for a distance of 50m in both direction of the coordinates available for the site. *Images source: left - Google Street View, ©2023 Google (accessed August 2025); middle - Google Street View, ©2018 Google (accessed August 2025); right – Google Street View, ©2024 Google (accessed August 2025).*

While this approach was chosen for practical reasons, it is a crude representation of lighting conditions that does not take into account the impact of the different characteristics of the lighting provided. Such characteristics were shown to influence the impact of darkness to different degrees in previous work. For example, Uttley et al., [2020] compared ORs from 48 locations in Birmingham, UK, with records of lantern density and relative brightness of street lighting (estimated from aerial images). They reported that the effect of darkness on cycling varied depending on how bright a street was lit and the density of lamps on that street, suggesting the influence of lighting on cycling after dark is nuanced and may not be entirely represented by the simple presence or absence of street lighting. Thus, further research is required to more comprehensively assess the influence of street lighting and its characteristics on the impact of darkness beyond the crude measure of the presence or absence of lighting.

To test other measures, a pilot study was carried out as a part of this PhD research (see **Appendix G**). Its aim was to establish measurements of street lighting characteristics (i.e. illuminance) using an experimental method which follows a suggestion by Greffier [2022] in using HDRI (High Dynamic Range Imaging) with a specialised post processing software to capture and analyse road surface luminance. This offers several benefits when compared to using an illuminance metre, such as the ability to analyse an entire field of vision with a single capture rather than the time-consuming point-based

measurement of the metre. A comparison of the process of both methods is illustrated in **Figure 5.13**.

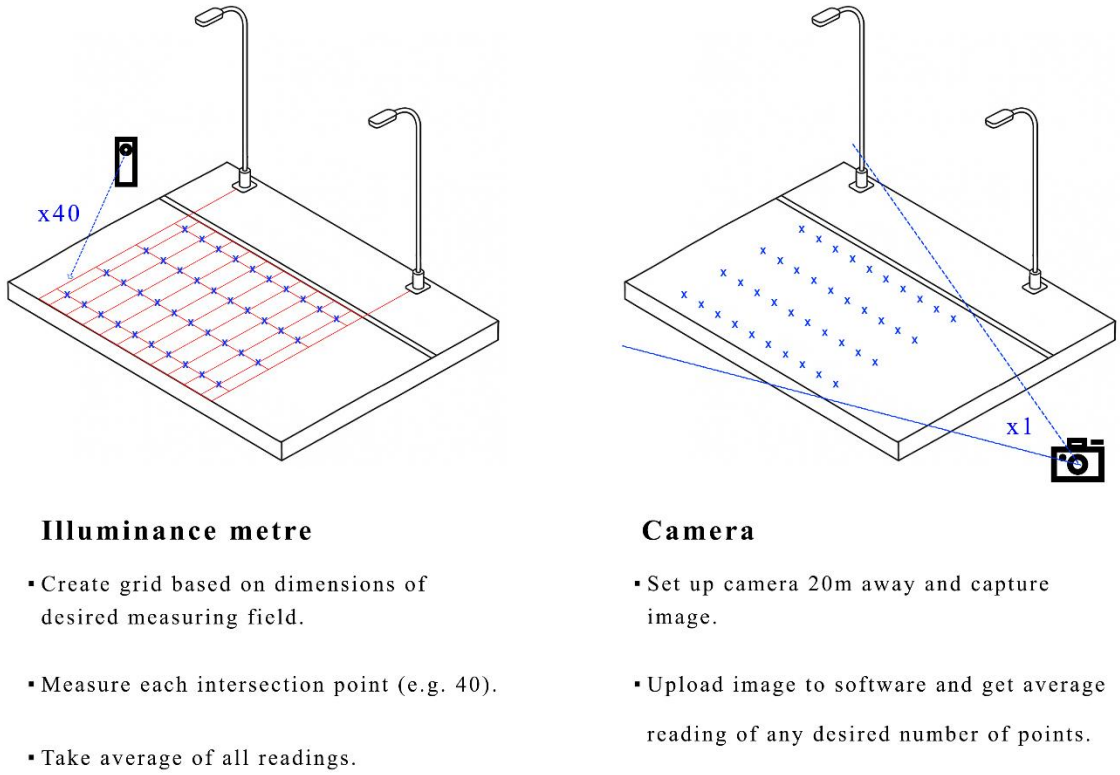


Figure 5.13 A Comparison between the process of using an illuminance metre to measure illuminance vs. using an HDR camera and a post-processing software to measure luminance. Here an example of a 15m x 6m measuring field is given, which generates approx. 40 measuring points**.**

However, due to several challenges regarding the correct process of using the equipment and software, this study was not completed, and no assumptions were made about its effectiveness in lieu of the measure presented in this thesis. The documented trials made herein should provide the framework for a future study using the same method.

5.6. Latitude and the number of cyclists

The influence of both latitude and the number of cyclists on OR variation across different cities were explored in chapter **4**, where latitude showed significant correlation, but the number of cyclists did not. The influence of these two factors is explored here again but within the five select cities.

Latitudes for each counting site in the five cities were established from the coordinates provided in or estimated from the publicly accessible counter data (see **Table 5.1** to **5.5** in section **5.2**).

For the number of cyclists, an annual average is established from the count data obtained for each city. While in chapter **4** the number of cyclists was weighted by city population (see section **4.2.2**) to enable a comparison between cities of different sizes, this approach may not be appropriate here. Weighting cyclist counts by population assumes that the volume of cycling at a counting site is constrained by the wider population of the city, but at the level of the individual counting site, volumes may be influenced more strongly by site-specific aspects like infrastructure or network connectivity. Population weighting could therefore give misleading patterns, making cycling on a street in a large city appear less substantial than a similarly busy street in a smaller city. Alternative approaches for weighting, such as using path width, may be possible; however, the use of raw counts is adopted here as a direct representation of cycling activity at each location.

5.7. Summary

This chapter described the method followed to investigate microscale factors that may influence the level of deterrence caused by darkness on cyclists. The chapter began by selecting five cities to focus on: Auckland, Edinburgh, Münster, Oslo, and Seattle. It listed a total of 74 cycle counting sites within them and proceeded to describe the procedure followed for analysis as follows:

1. Weighted ORs are established for each individual counting sites.
2. Records and estimated measures of four factors are collected for each site. These factors are *journey type*, *distance from city centre*, *presence of street lighting*, *latitude*, and *the number of cyclists.*
3. Linear regression is performed to model the relationships and understand the strength of association between ORs and each factor.
4. Multicollinearity is examined, and variables above the threshold are excluded from the next step.
5. A stepwise regression analysis is performed to identify predictors of variance in ORs and their levels of influence.

Chapter **6** presents the findings from these five steps.

Chapter 6. Within-cities analysis of the impact of darkness: Results

6.1. Introduction

Chapter **5** described the process of investigating the influence of microscale factors on the effect of darkness on cyclists. It detailed a five-step process for this, beginning with establishing weighted ORs for individual counting sites in five cities, followed by establishing data for five factors in order to enable linear and stepwise regression analyses between them.

Chapter **6** begins by presenting the weighted ORs for each location (n = 74) within the five cities to understand the general impact of darkness on cyclist numbers in them. Next, results of the linear regression between ORs and each of the five factors are shown. The last section contains multicollinearity checks and the final stepwise regression models.

6.2. Odds ratios

Weighted odds ratios are established for each counting location in Auckland (n = 37), Edinburgh (n = 7), Münster (n = 8), Oslo (n = 12), and Seattle (n = 10). These are shown below in **Tables 6.1** to **6.5** and are calculated using all possible case and control hour combinations established for each city (see example of detailed calculations for Seattle in **Appendix D**) as described in Chapter **3**. The majority of ORs shown are greater than 1.0, with only ten ORs below 1.0 (Edinburgh, n = 2, and Oslo, n = 8) and one equal to 1.0 in Auckland. This suggests that outside of those eleven locations, darkness reduces the number of people cycling compared to daylight periods. The impact of darkness varies significantly across the five cities as shown in **Figure 6.1**, with the smallest OR established being 0.75 (Lysaker in Oslo) and the largest being 8.72 (Leigh Road in Auckland).

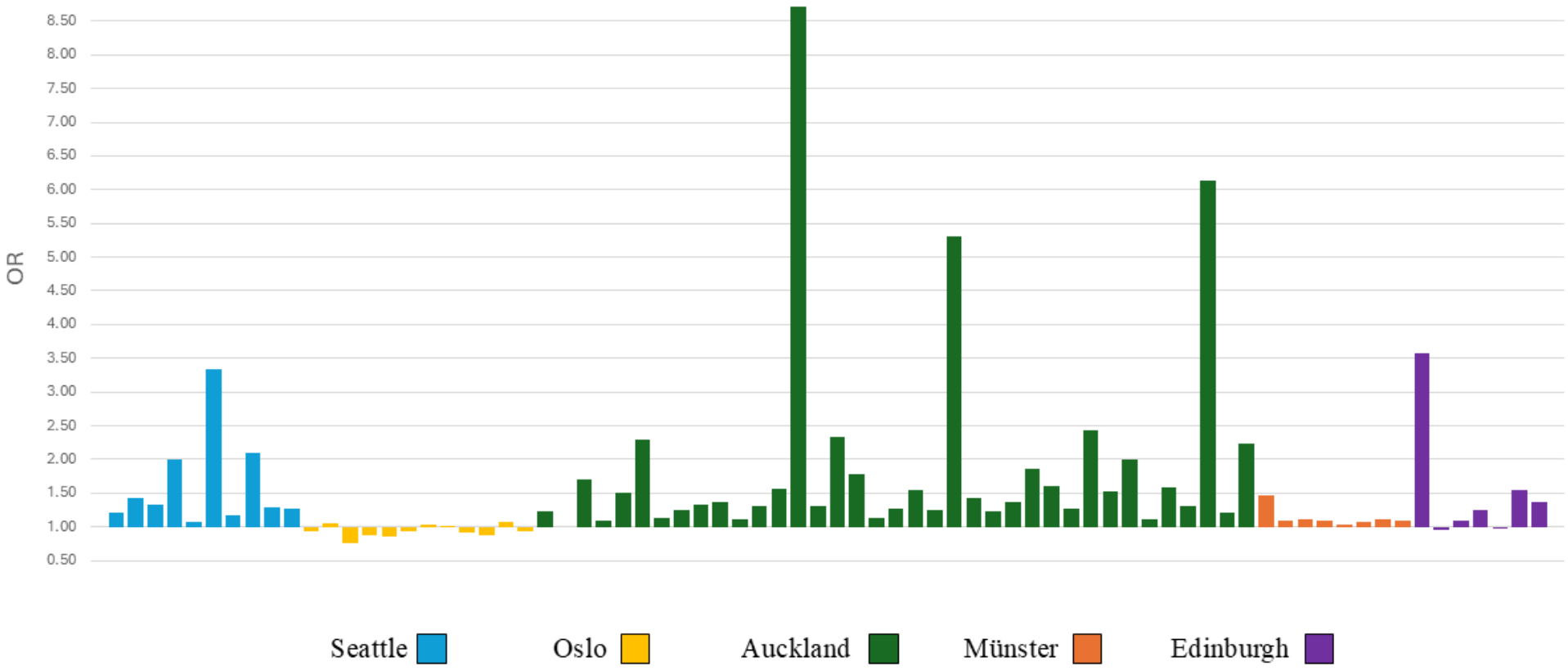


Figure 6.1 All 74 weighted ORs established across five cities. Only Oslo and Edinburgh have locations with ORs lower than 1.0.

Table 6.1 Weighted ORs for 37 sites **in Auckland**, NZ, arranged low to high, alongside estimates for each microscale factor (shaded columns) established through the methods described in chapter 5.

Site	OR	Effect size*	Microscale factors					No. of cyclists
			P_L	Euclidean distance (km)	Network distance (km)**	Street lighting presence	Latitude	
Carlton Gore Road	1.00		0.25	1.53	1.9	Yes	-36.864	324913
Dominion Road	1.09		0.27	2.16	2.4	Yes	-36.870	233301
Symonds Street	1.11		0.28	0.78	0.95	indirect	-36.860	650985
Hopetoun Street	1.12	Negligible	0.25	0.63	0.9	Yes	-36.856	218979
Grafton Bridge	1.14		0.29	0.87	1.1	Yes	-36.860	128643
Nelson Street	1.14		0.29	0.5	0.8	Yes	-36.850	678620
Upper Queen Street	1.20		0.31	0.76	0.75	Yes	-36.859	239369
Quay Street Eco Display	1.22		0.43	1.13	1.5	Yes	-36.843	106134
Beach Road	1.22		0.36	1.07	1.9	Yes	-36.849	539342
Oceanview Road	1.24		0.53	23.39	Excluded	Yes	-36.784	99802
Grafton Gully	1.25		0.38	0.57	0.9	Yes	-36.856	651043
Saint Lukes Road	1.26		0.38	3.91	5.3	Yes	-36.871	147445
Nw Cycleway Kingsland	1.27		0.33	2.5	2.8	Yes	-36.869	183547
Teatatu Peninsula	1.30		0.38	9.98	12.8	indirect	-36.850	66509
Lagoon Drive	1.30		0.55	10.37	13.3	Yes	-36.907	486423
Lightpath 2	1.31	Small	0.39	0.51	1.1	Yes	-36.853	591887
Great N. Road	1.33		0.33	2.07	2.3	Yes	-36.865	121033
Great S. Road Manukau	1.36		0.45	18.28	20.3	Yes	-36.987	25693
Quay Street Spark Arena	1.37		0.44	1.48	2.1	Yes	-36.847	123447
Ormiston Road	1.43		0.49	18.02	27.1	indirect	-36.965	39808
East Coast Road	1.51		0.55	12.5	Excluded	Yes	-36.742	309523
SH20A	1.53		0.45	14.06	17.2	indirect	-36.978	12103
Nw Cycleway Teatatu	1.54		0.50	9.77	12.0	indirect	-36.858	117893
Lake road	1.56		0.45	5.98	Excluded	Yes	-36.803	414794
Tamaki Drive Wb	1.59		0.51	2.36	3.2	Yes	-36.848	113050
Rankin Avenue	1.61		0.44	9.79	11.1	Yes	-36.912	12353
Curran Street	1.70		0.53	2.59	4.3	indirect	-36.839	120756
Mangere Safe Routes	1.79		0.50	13.68	17.7	No	-36.839	36400
Queen Street Pukekohe	1.86		0.49	40.89	53.3	Yes	-37.204	8098
SW SH20	2.00		0.55	6.91	9.9	indirect	-36.912	339850
Waterview Unitec	2.23	Medium	0.57	6.15	7.4	Yes	-36.883	160174
Glenn Innes to Tamaki	2.29		0.57	8.13	10.8	No	-36.874	30258
Mangere Bridge	2.34		0.63	9.59	11.1	No	-36.932	116194
SH18 Upper Harbour	2.44		0.71	11.08	26.1	indirect	-36.782	392246
Orewa Path	5.30		0.61	29	29.17	Yes	-36.596	888308
Twin Streams	6.13	Large	0.62	12.71	17.8	Yes	-36.879	300995
Leigh Road	8.72		0.73	55.78	95.3	indirect	-36.356	15963

* These effect size interpretations are based on categories described by Olivier and Bell [2013].

** Some values were excluded because the journey requires a mix of modes (i.e. ferry).

Table 6.2 Weighted ORs for 7 counting sites in **Edinburgh**, Scotland, UK, arranged from low to high, alongside estimates for each microscale factor (shaded columns).

Site	OR	Effect size*	Microscale factors					
			P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
RBS Gogar	0.96	Negligible	0.30	9.26	10.2	Yes	55.937	41784
Middle Meadow Walk	0.99		0.34	0.84	1.0	Yes	55.943	497591
Cultins Road	1.10		0.17	7.62	9.0	Yes	55.929	66731
N. Edinburgh Access Rd.	1.24	Small	0.35	3.65	4.7	Yes	55.968	300594
Portobello Prom	1.36		0.42	4.7	5.5	Yes	55.957	191277
Spylaw Park	1.55		0.50	6.58	8.2	No	55.907	50894
Silverknowes	3.58	Medium	0.61	6.89	8.8	No	55.979	72405

* These effect size interpretations are based on categories described by Olivier and Bell [2013].

Table 6.3 Weighted ORs for 8 counting sites in **Münster**, Germany, arranged from low to high, alongside estimates for each microscale factor (shaded columns).

Site	OR	Effect size*	Microscale factors					
			P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
Weseler Straße	1.04	Negligible	0.35	1.42	1.6	Yes	51.951	116093
Hammer Straße	1.07		0.39	0.79	0.9	Yes	51.955	271583
Neutor	1.09		0.34	1.06	1.3	Yes	51.967	439025
Promenade	1.09		0.37	0.41	1.1	Yes	51.961	510327
Hüfferstraße	1.10		0.31	1.19	1.3	Yes	51.962	208906
Warendorfer Straße	1.11		0.39	0.64	0.85	Yes	51.962	237161
Gartenstraße	1.11		0.36	1.22	1.5	Yes	51.972	965303
Kanalpromenade	1.47	Small	0.41	5.46	1.1	Yes	51.918	123761

* These effect size interpretations are based on categories described by Olivier and Bell [2013].

Table 6.4 Weighted ORs for 12 counting sites in **Oslo**, Norway, arranged from low to high, alongside estimates for each microscale factor (shaded columns).

Site	OR	Effect size*	Microscale factors					
			P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
Lysaker	0.75	Negligible	0.18	5.11	6.6	Yes	59.913	390753
Skullerud	0.86		0.33	7.18	9.7	Yes	59.869	59478
Munkedamsveien	0.88		0.24	0.47	1.1	Yes	59.911	116005
Frognerst.Sykkel 03	0.88		0.28	1.67	2.4	Yes	59.911	145787
Gaustad	0.91		0.23	3.89	4.9	Yes	59.946	684285
Bryn	0.93		0.25	4.91	6.4	Yes	59.901	150452
Akersyke l 03	0.93		0.24	4.48	5.5	Yes	59.940	500724
Dr. Eufemias Vest	0.94		0.32	1.23	1.4	Yes	59.909	424761
Smestad	1.02		0.18	3.93	5.5	Yes	59.939	263612
Breivoll	1.03		0.20	5.57	6.5	Yes	59.923	97138
Dr. Eufemias Øst	1.06		0.31	1.19	1.6	Yes	59.909	341870
Grorud	1.07		0.28	9.87	12.4	Yes	59.951	49053

* These effect size interpretations are based on categories described by Olivier and Bell [2013].

Table 6.5 Weighted ORs for 10 counting sites in **Seattle**, WA, USA, arranged from low to high, alongside estimates for each microscale factor (shaded columns).

Site	OR	Effect size*	Microscale factors					
			P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
Broadway	1.08	Negligible	0.37	1.28	1.6	Yes	47.614	657868
2nd Ave	1.17		0.25	0.4	0.45	Yes	47.605	155909
Fremont Bridge	1.21		0.31	5.13	5.6	Yes	47.648	617738
Spokane	1.26	Small	0.34	3.76	4.6	Yes	47.572	177089
NW 58TH St Greenway	1.29		0.51	8.52	10.0	Yes	47.671	429671
39th Ave	1.32		0.36	8.45	11.3	Yes	47.674	334503
26th Ave	1.42		0.38	5.32	8.0	Yes	47.563	365493
BGT North	2.00	Medium	0.56	9.49	13.6	No	47.679	371568
MTS Trail	2.10		0.58	3.58	4.9	No	47.591	175169
Elliot Bay	3.33	Large	0.50	2.7	3.3	No	47.683	796974

* These effect size interpretations are based on categories described by Olivier and Bell [2013].

6.3. Journey type

After a weighted OR was established for each location, data for the five proposed microscale factors were recorded or estimated, the first of which being a classification of the dominant type of journey undertaken in a location (i.e. utilitarian or leisure). This is presented in section **6.3.1**, and its validity is assessed in section **3.6.2**.

6.3.1. The proportion of leisure journeys

Tables 6.1 to **6.5** (see section **6.2**) presented the P_L established for all sites within the five cities and their corresponding weighted ORs. A P_L of 1.0 indicates a completely leisure journey dominant site and a P_L of 0 indicates a completely utilitarian journey dominant site. Most tables appear to show an upward trend when inspected visually, where P_L may increase with a higher OR, except for a few mid-range values that occasionally deviate from this. This may initially suggest that the deterrence from darkness on cyclists is increased with a higher proportion of leisure journeys in Auckland, Edinburgh, Münster, and Seattle.

The relationship is explored further using linear regression, where **Figure 6.2** suggests a positive association – ORs increase with a higher P_L. However, the variation in ORs explained by P_L appears to vary across cities, with the lowest R^2 (Oslo) explaining only 2% of the variation which is substantially a weaker relationship when compared to the other cities with a range of 31% to 64% variation explained.

A linear regression analysis was also applied to data for all five cities combined (n = 74). This also displayed a positive association ($R^2 = 0.41$, $p<0.001$) – ORs tended to increase with a higher P_L (**Figure 6.3**). To explore the influence of outliers, they must first be identified. Here, the general guideline that z-scores above the common threshold of 3.00 are considered outliers is used, particularly due to the sample size not being very large (where a z-score cutoff is typically >4.00) or very small (a cutoff of >2.50) [Stevens, 2009]. This means that ORs larger than 5.00 were excluded. This relationship, shown in **Figure 6.4**, displays an improved association ($R^2 = 0.53$, $p<0.001$).

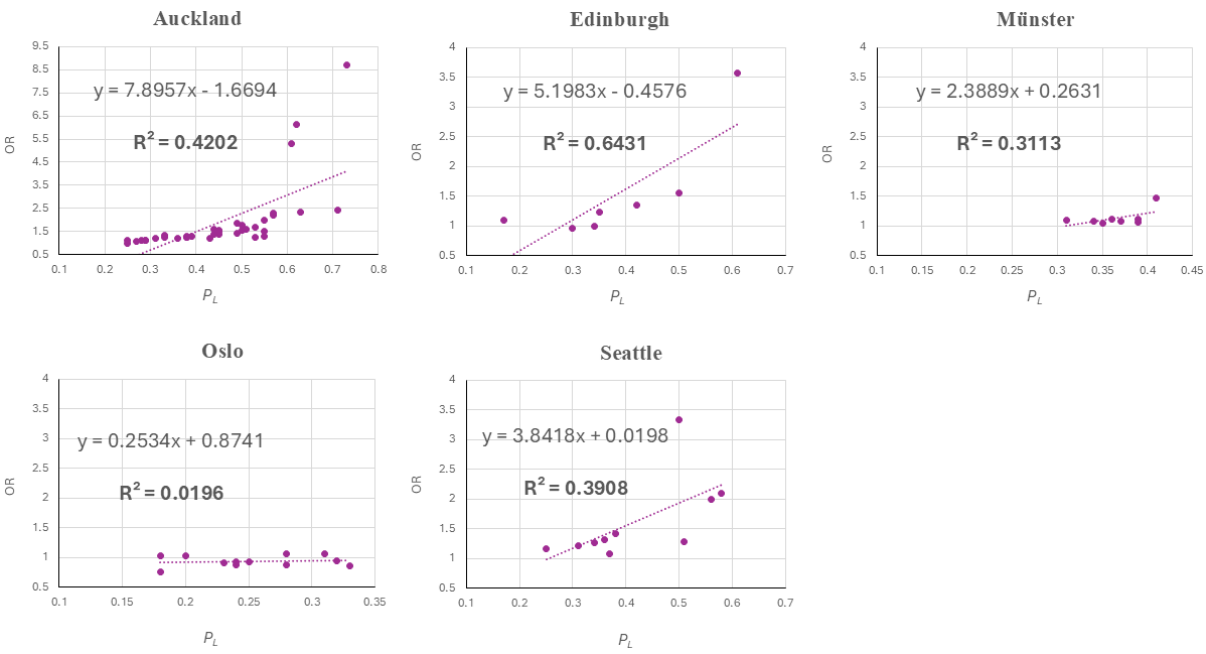


Figure 6.2 The relationship between odds ratios and the proportion of leisure journeys in the five cities.

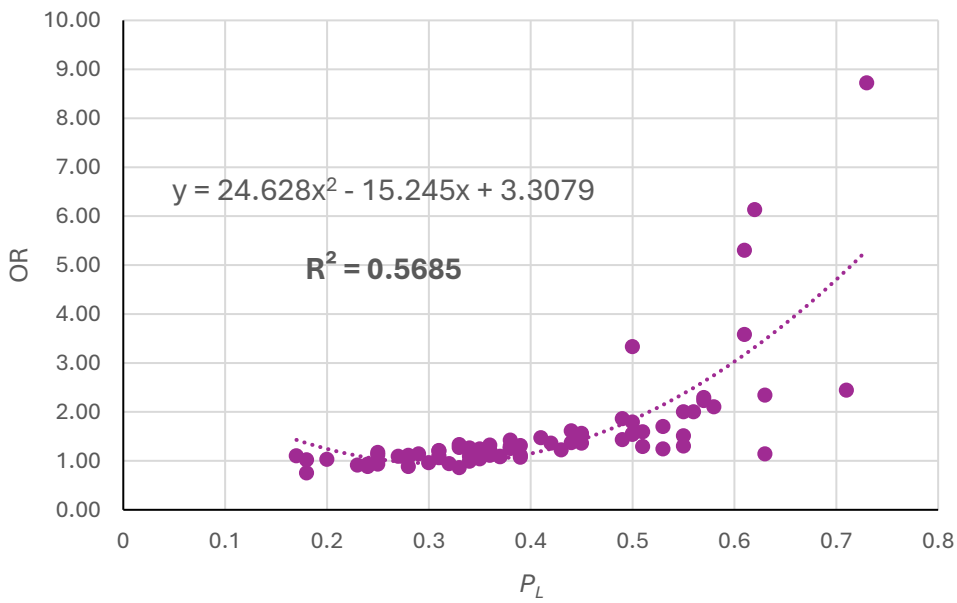


Figure 6.3 The relationship between odds ratios and the proportion of leisure journeys across locations in all five cities.

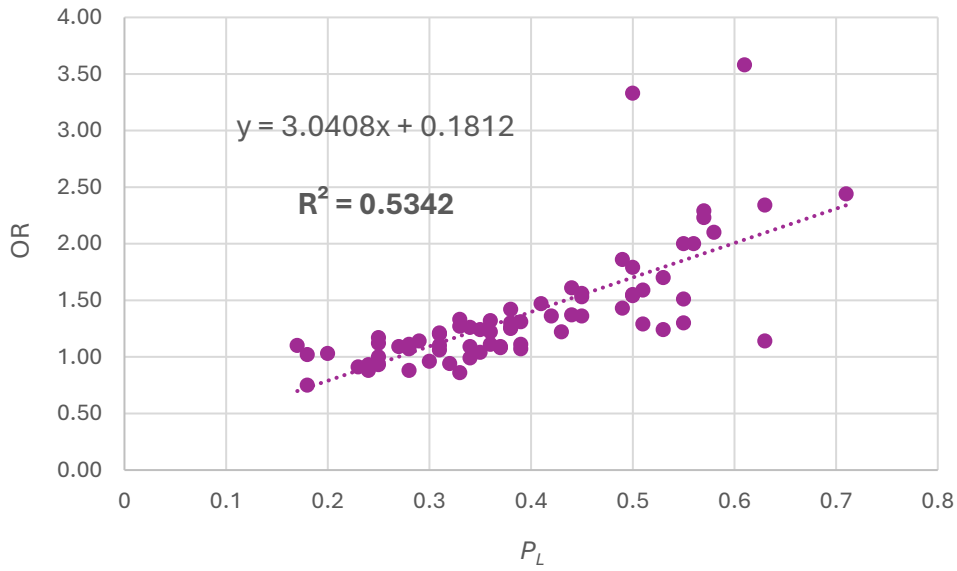


Figure 6.4 The relationship between odds ratios and the proportion of leisure journeys across locations in all five cities, with ORs larger than 5.00 excluded as outliers.

6.3.2. Verification of journey type by visual assessment

This step was used to assess the validity of the *proportion of leisure journeys* (P_L). All counting locations in the five cities were visually assessed and classified between utilitarian, mixed, and leisure dominant locations. These classifications are presented in **Appendix E**. Following this, two assessments were carried out.

First, an overall weighted OR was established from the combined data for the category (**Table 6.6**). This initially shows that leisure locations are associated with higher ORs, suggesting that the *proportion of leisure journeys* (P_L) may be a suitable method to identify leisure locations. For utilitarian and mixed locations, ORs were close to each other with only a 0.04 difference.

Table 6.6 Range of ORs calculated for locations, grouped by journey type classification.

Item	U	M	L
Number of locations	25	35	14
Min OR	0.94	0.75	1.47
Max OR	1.61	2.44	8.72
Weighted OR	1.19	1.15	2.73

Next, **Figure 6.5** presents the proportion of leisure journeys for all sites within the three groups. The chart shows that on average, the *proportion of leisure journeys* (P_L) appears to increase from utilitarian sites to mixed sites, to leisure sites. While there is some variation within each group, the pattern provides additional support for the validity of using the *proportion of leisure journeys* method to estimate the dominant journey type in counting sites.

Figure 6.5 The proportion of leisure journeys for sites based on their visual classification. A P_L closer to 1.0 indicates a concentration of leisure journeys in the counting site. A linear trendline reflects an increase from utilitarian to mixed to leisure

6.4. Distance to city centre

The distance between counting sites and the city hall in each city was presented in **Tables 6.1** to **6.5** (see section **6.2**) using two alternative measurements: Euclidean distance and cycling network distance.

Linear regression analyses reveal positive relationships with ORs in nearly all scatterplots (**Figures 6.6-6.10**) except for network distance in Münster, suggesting that ORs tend to increase the further away the journey is from city centre in almost all locations. The OR variation explained using the two approaches can vary significantly from city to city and sometimes within the same city as is the case in Münster (see **Figure 6.8**), which shows an unusually high R^2 value for euclidean distance contrasted by a very low R^2 value for network distance (0.90 and 0.04 respectively). There could

be a number of reasons behind this and the reversed relationship direction between the two approaches in Münster, such as the density of built environment in the city centre requiring longer routes to be proposed by Google, or a discrepancy in the measurement.

For all cities but Auckland, the number of data points may be very low for meaningful results. Thus, a further linear regression analysis is performed on data from all locations combined. The two scatterplots in **Figure 6.11** confirm a positive relationship – ORs tend to increase the further away the location is from city centre. The R^2 values shown are 0.46 ($P<0.001$) for euclidean distance and 0.59 ($P<0.001$) for Network distance, explaining 45.7% and 58.7% of variation in ORs respectively.

To explore the influence of outliers, defined here as values with a z-score larger than 3.00, ORs larger than 5.00 and distances larger than 50km are excluded. This reduces the R^2 values drastically to 0.20 ($P<0.001$) for Euclidean and 0.13 ($P=0.003$) for network distances.

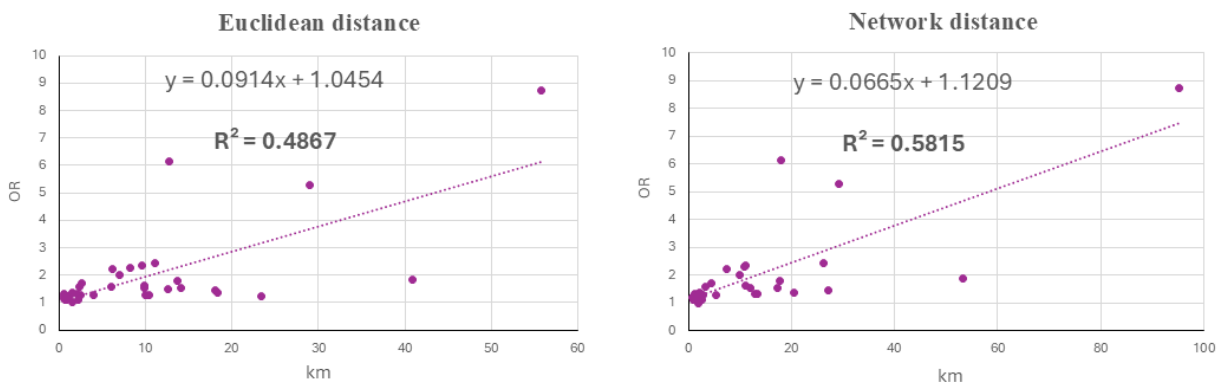


Figure 6.6 The relationship between odds ratios and two approaches to measure distance to city centre in **Auckland**, New Zealand.

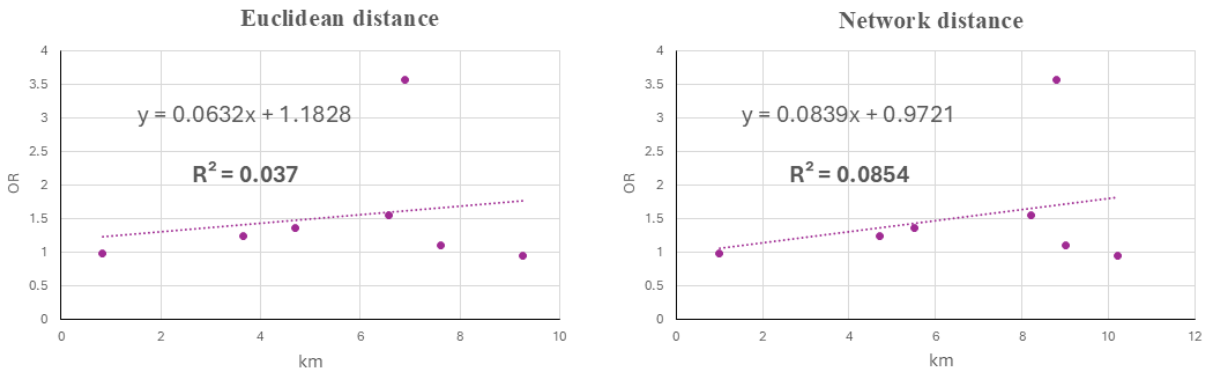


Figure 6.7 The relationship between odds ratios and two approaches to measure distance to city centre in **Edinburgh**, SCT, UK.

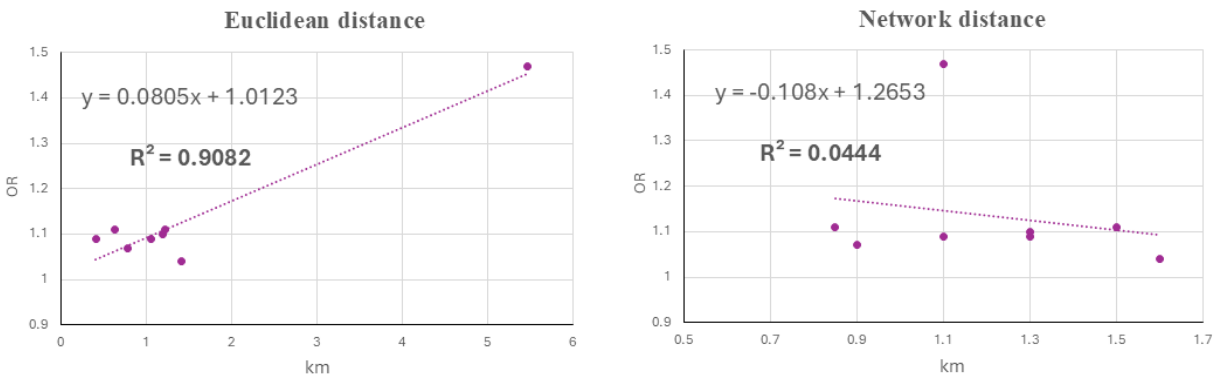


Figure 6.8 The relationship between odds ratios and two approaches to measure distance to city centre in **Münster**, Germany.

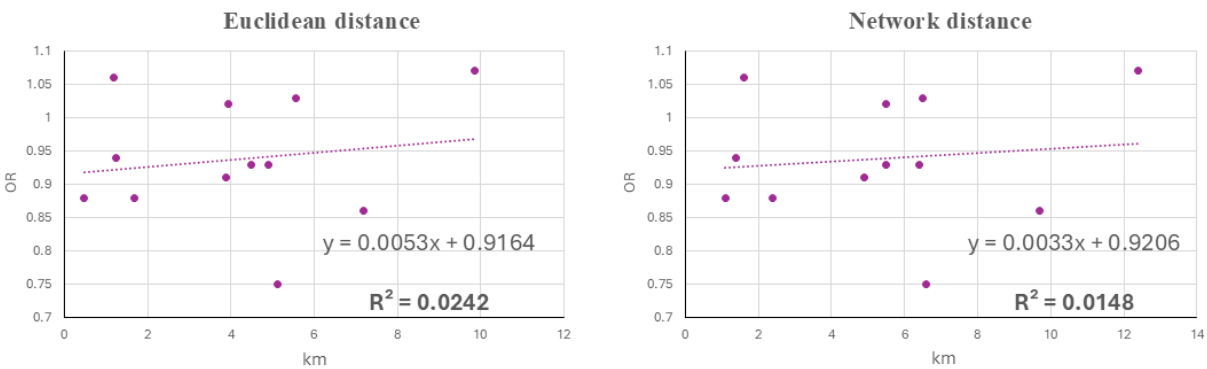


Figure 6.9 The relationship between odds ratios and two approaches to measure distance to city centre in **Oslo**, Norway.

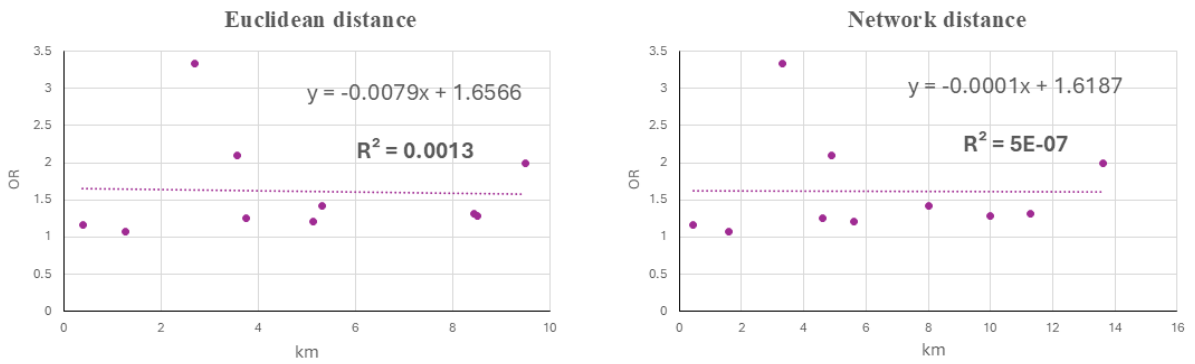


Figure 6.10 The relationship between odds ratios and two approaches to measure distance to city centre in **Seattle**, WA, USA.

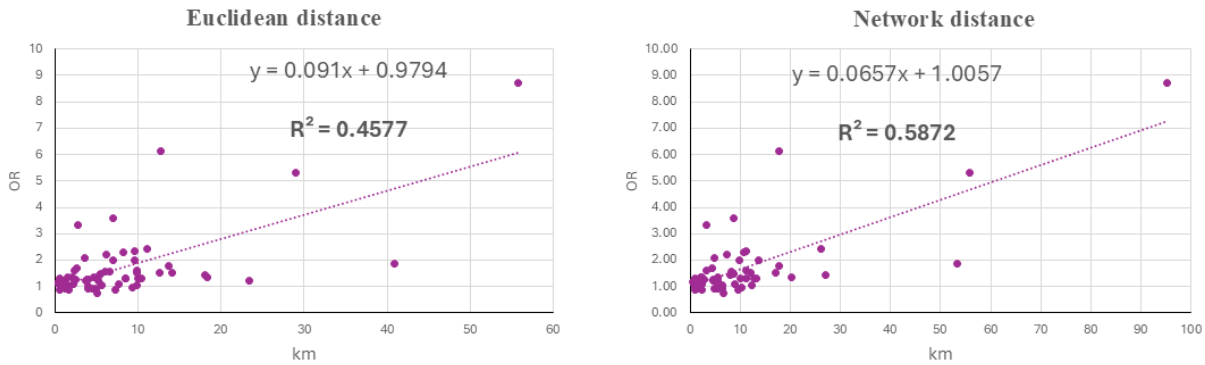


Figure 6.11 The relationship between odds ratios and two approaches to measure distance to city centre in **all five cities combined**.

6.5. Presence of street lighting

The presence or absence of street lighting was presented in **Tables 6.1** to **6.5** (see section **6.2**) for all counting sites, alongside their corresponding ORs. Despite this, the majority of cities have a small sample of data and that may prevent a meaningful outcome. It may therefore be beneficial to perform a linear regression analysis on the combined data for all cities, similarly to all previous factors.

The R^2 values for individual cities range from 0.03 to 0.73 (3% to 73% variation explained). However, it was not possible to calculate this for all five cities, since Oslo and Münster had only one type of assigned binary entries (i.e. all 1s or all 0s). The combined data for all cities shows an R^2 value of 0.12 (p=0.002), explaining 12% of

variation in ORs, which may be a better representation since linear regression was not possible for all cities when done individually. Removing outliers, here defined as values with a z-score higher than 3.00, excludes OR>5.00, which increases R^2 value to 0.33 ($p<0.001$),). explaining 33% of variation in ORs. A negative relationship here suggests that locations with street lighting tend to have lower ORs – The presence of lighting may reduce the impact of darkness.

6.6. Latitude and the number of cyclists

Linear regression analyses between the latitudes of cycle counting sites and their corresponding ORs (**Tables 6.1** to **6.5**) reveal a positive relationship for all cities but Münster as shown in **Figure 6.12** – ORs may increase at higher latitudes within Auckland, Edinburgh, Oslo, and Seattle, with R^2 values ranging from 0.15 to 0.40 (15%-40% of the variation in OR is explained), and at lower latitudes within Münster, with an R^2 value of 0.73 (73% of variation in OR explained). However, due to the low number of entry points for most of the cities, and the very small variations in latitude between counting sites within the same city, the reliability of these coefficients may be impacted. Thus, the linear regression is repeated on data for all five cities combined (n = 74 entries). This reveals a negative association, as shown in **Figure 6.13**, suggesting that ORs tend to decrease at higher latitudes. However, only 7% of OR variation is explained by latitude here ($R^2=0.07$, $p=0.019$). This weak association on the microscale does not match the strong association established in chapter 4 for the macroscale, suggesting that for small differences in latitude, the impact is not meaningful. One reason for this may be that small within-city differences in latitude do not significantly change the amount of ambient light levels across different locations. Repeating the regression with absolute latitude values (thereby removing the negative southern-hemisphere values for Auckland) resulted a in and additional minimal improvement of 0.02 to the R^2 value. To explore the influence of outliers, here defined as values with a z-score larger than 3.00, ORs greater than 3.50 were removed. This improved the R^2 value further to 0.12 ($p=0.003$) and is statistically significant (**Figure 6.14)**.

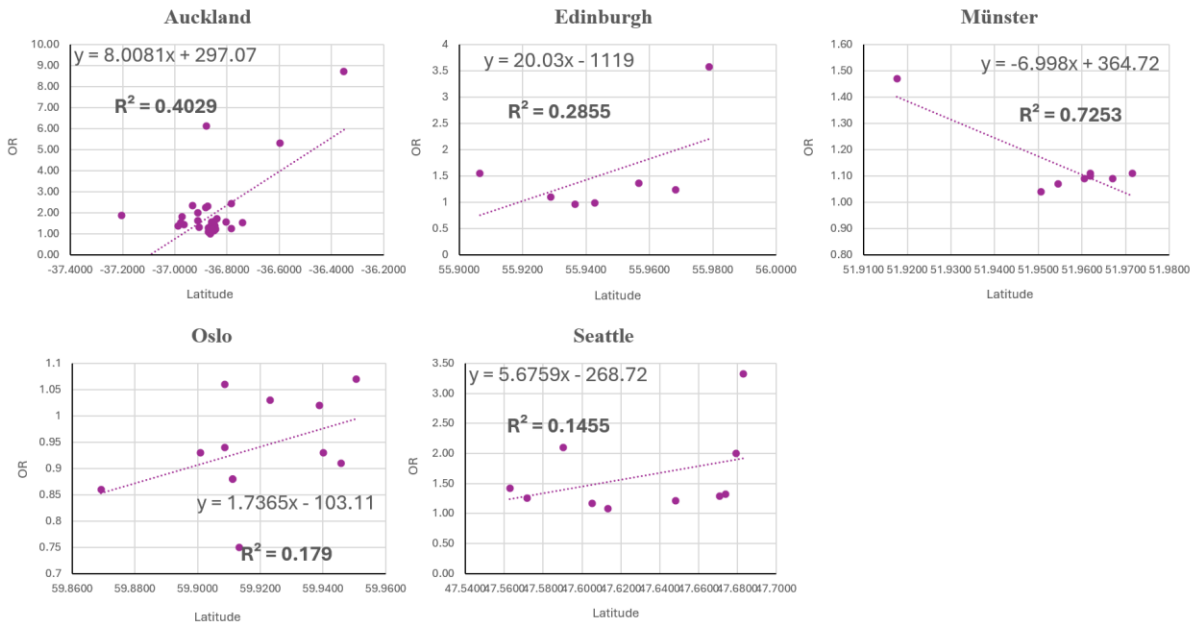


Figure 6.12 The relationship between odds ratios and counter latitude for each of the five cities.

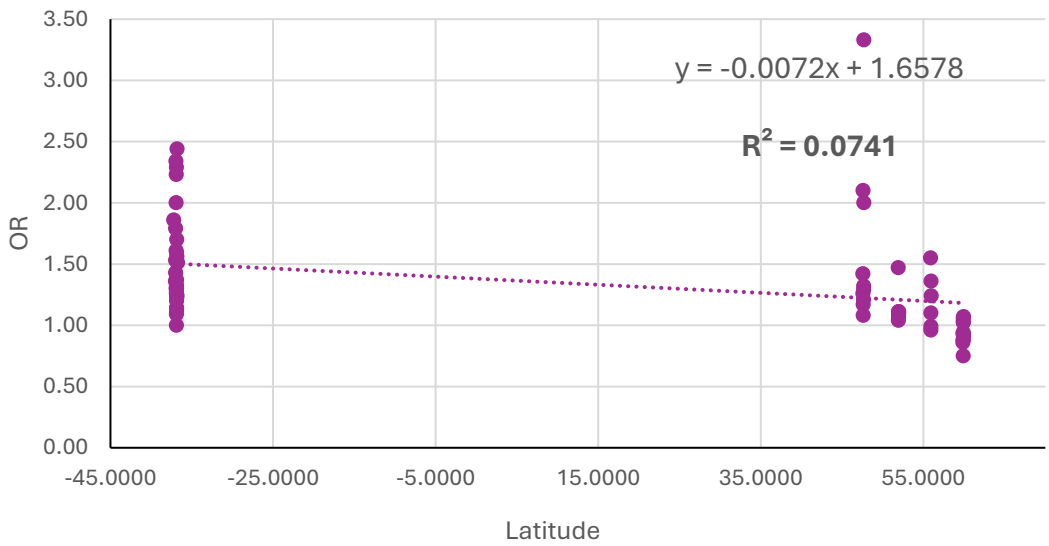


Figure 6.13 The relationship between odds ratios and counter latitude for all five cities combined.

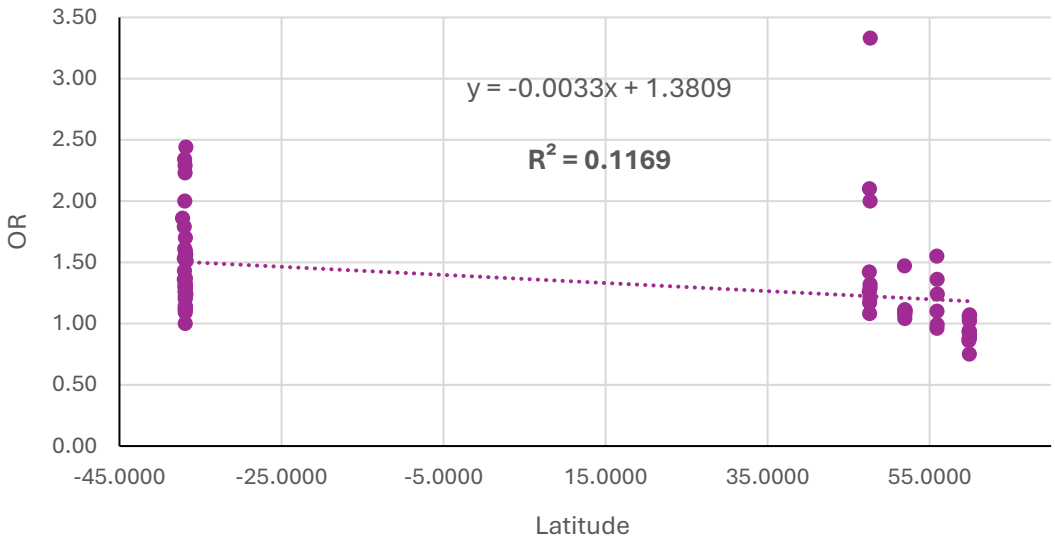


Figure 6.14 The relationship between odds ratios and counter latitude for all five cities combined after removing outlies.

The total number of cyclists was presented in **Tables 6.1** to **6.5** (see section **6.2**) for all counting sites, alongside their corresponding ORs. Due to the highly skewed distribution of the number of cyclists, a logarithmic transformation was applied prior to regression analysis, A linear regression analysis on these variables reveals a negative relationship for all cities but Seattle as shown in **Figure 6.15** – ORs may decrease as the number of cyclists increase, but this trend is reversed in Seattle. The R^2 values range from 0.04 to 0.72 (4%-72% of the variation in OR is explained). However, due to the low number of entry points for most of the five cities, the reliability of these coefficients may be impacted. Thus, the regression is repeated on data for all five cities combined (n = 74 entries), and here a polynomial trendline provided a closer visual fit to the data and improved the R^2 value to 0.07 (p=0.085), explaining 7% of the variation in ORs, but the relationship is not statistically significant (**Figure 6.16**). To explore the influence of outliers, here defined as values with a z-score larger than 3.00, ORs greater than 3.50 were removed. This improved the R^2 value to 0.11 (p=0.005) and is now statistically significant (**Figure 6.17**).

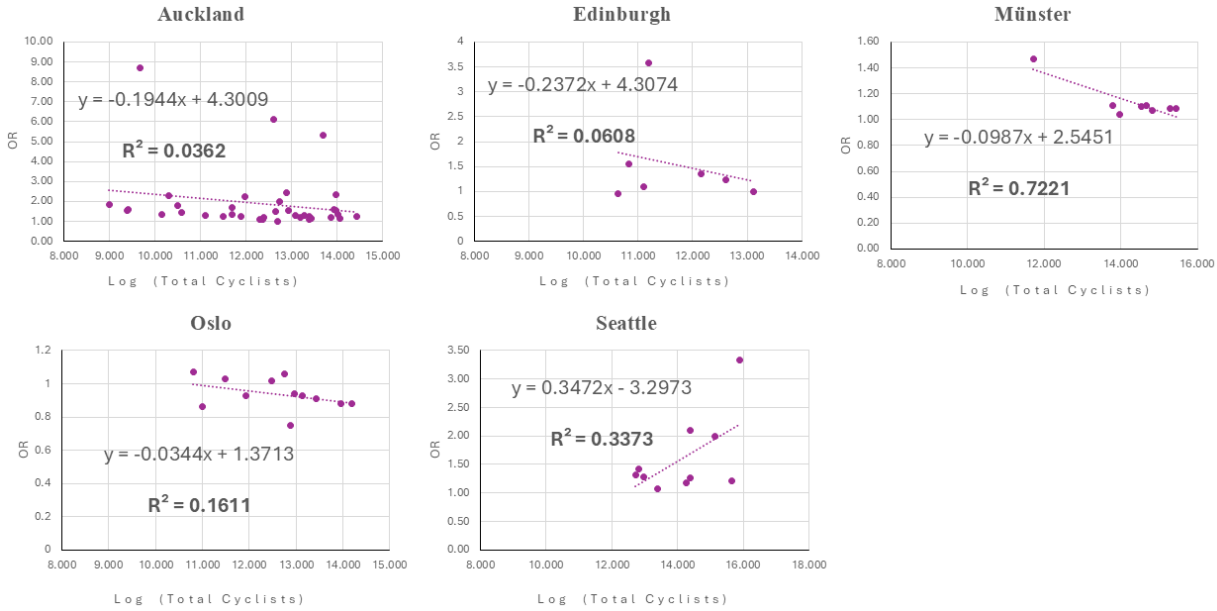


Figure 6.15 The relationship between odds ratios and the number of cyclists as a proportion of city population for each of the five cities.

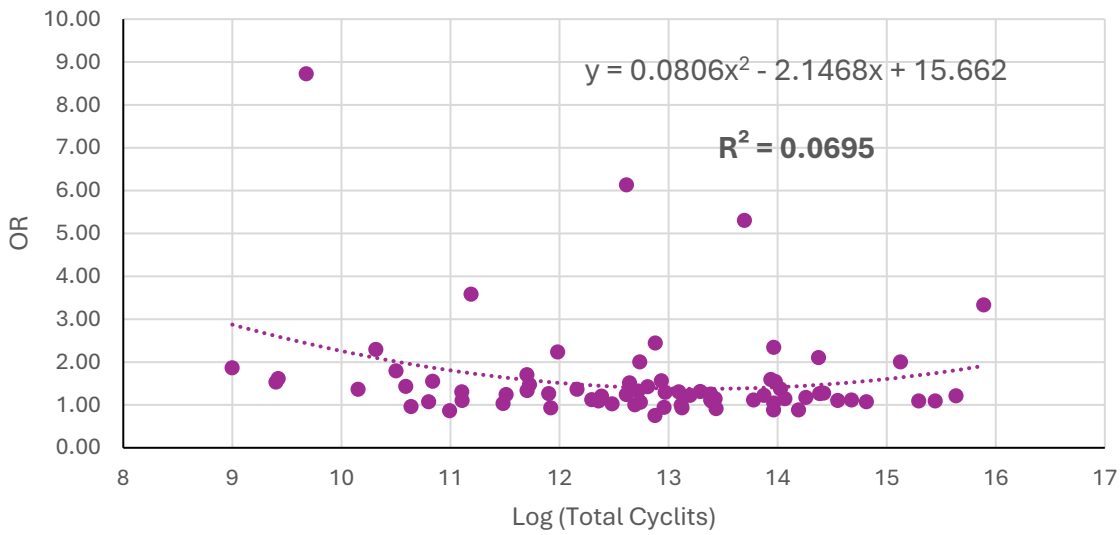


Figure 6.16 The relationship between odds ratios and the number of cyclists as a proportion of city population for all five cities combined, fitted with a polynomial trendline

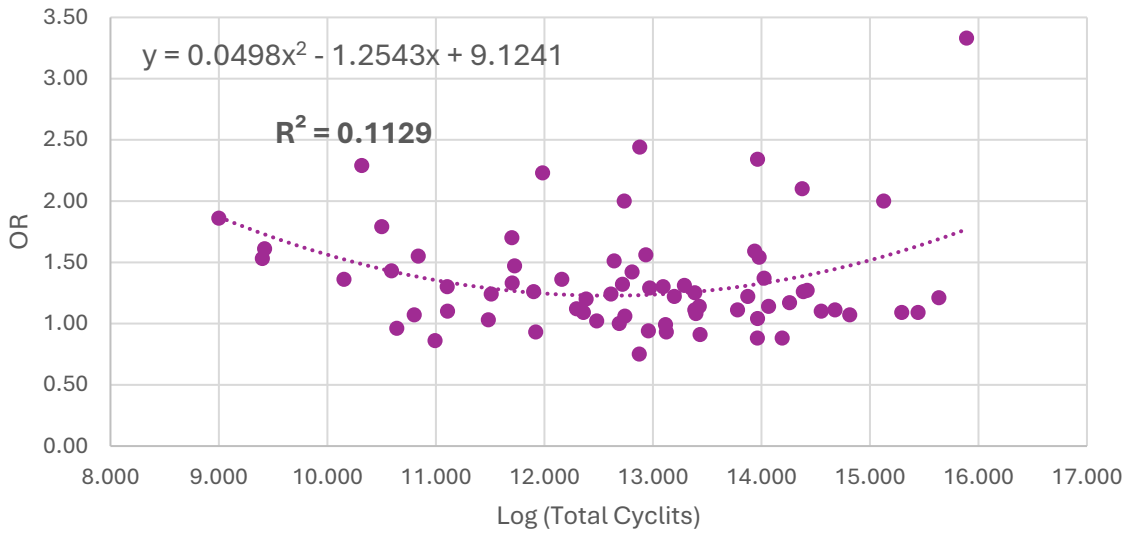


Figure 6.17 The relationship between odds ratios and the number of cyclists as a proportion of city population for all five cities combined after removing as outliers, fitted with a polynomial trendline

6.7. Stepwise regression

Sections **6.3** to **6.6** explored the degree to which variance in ORs could be explained by journey type, distance to city centre, presence of lighting, latitude, and cyclist numbers. Stepwise regression is next used to integrate those factors into a single model.

Out of these five factors, distance to city centre was established using two approaches: Euclidean Distance and Network Distance. Section **6.4** showed that the association between ORs and network distance was stronger when compared to euclidean distance, with R^2 values of 0.59 and 0.46 respectively. Thus, out of the two options, Network Distance is retained for the stepwise regression.

Variance Inflation Factors (VIFs) for the five independent variables were calculated in SPSS to assess multicollinearity. These values ranged from 1.04 to 1.36 (see **Appendix F**). Since all values were below the common threshold of 5.0, all variables were retained for the stepwise regression analysis [Brooks and Barcikowski, 1999].

Table 6.7 presents the models resulting from the stepwise regression analysis. Stepwise regression typically begins by evaluating individual variables first, and here, *distance to city centre* was the strongest single predictor from all variables, with an R^2 value of 0.587, $p<0.001$ (0.581 when adjusted). Subsequently, stepwise introduces the other variables to the base model to assess for improvement, and here, adding *journey type* Improved the R^2 value, raising it to 0.681, $p<0.001$ (0.672 when adjusted). While in some cases stepwise regression can identify improvements from adding more than two predictors, here no additional improvement to the models was found beyond two.

Table 6.7 The resulting models from the stepwise regression analysis.

Model No.	Dependant variable	Independent variable inserted					Predictors	R^2	Adjusted R^2	sig. of change in model
1	ORs	Distance to city centre: (*Network distance*)	Journey type: (*Proportion of leisure*)	Presence of lighting	Latitude	No. of cyclists	(constant), Network distance	0.587	0.581	<0.0001
2							(constant), Network distance, proportion of leisure	0.681	0.672	<0.0001

Table 6.8 shows the coefficient of terms in the model, where and the *constant* refers to the predicted value of the dependant variable (OR) when all independent variables are equal to zero. This constant is essential in establishing the equations for the model (**Equation 7**), which can be useful in predicting ORs in locations outside of the 74 used here.

The findings suggest that proximity to the city centre might have the largest influence on the impact of darkness from the five variables. This is then followed by the type of journey undertaken (utilitarian or leisure). The remaining three variables, the *presence of lighting*, *latitude*, and the *number of cyclists* were shown to be excluded from the model, suggesting that for locations in the five cities, their influence is not strongly associated with a variation in ORs. When testing the equation to predict ORs ($R_{odds,p}$) and then compare them to the weighted ORs established from cyclist counts (see Chapter **3**), a simple linear regression (**Figure 6.18**) confirms that the equation is able to explain 68% of variation.

Table 6.8 Coefficients the final model.

Model No.		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% CI for B	
		B	Std. error	beta			Lower	Upper
2	(Constant)	-0.182	0.283	-	-0.642	0.523	-0.746	0.383
	Distance to city centre	0.050	0.007	0.583	7.306	0.000	0.036	0.064
	Journey type	3.325	0.742	0.358	4.482	0.000	1.845	4.805

$$R_{odds,p} = -0.182 + 0.050D + 3.325P_L \quad (7)$$

Where,

$R_{odds,p}$ = The predicted weighted OR.

D = Distance to city centre.

P_L = Journey type (proportion of leisure journey)

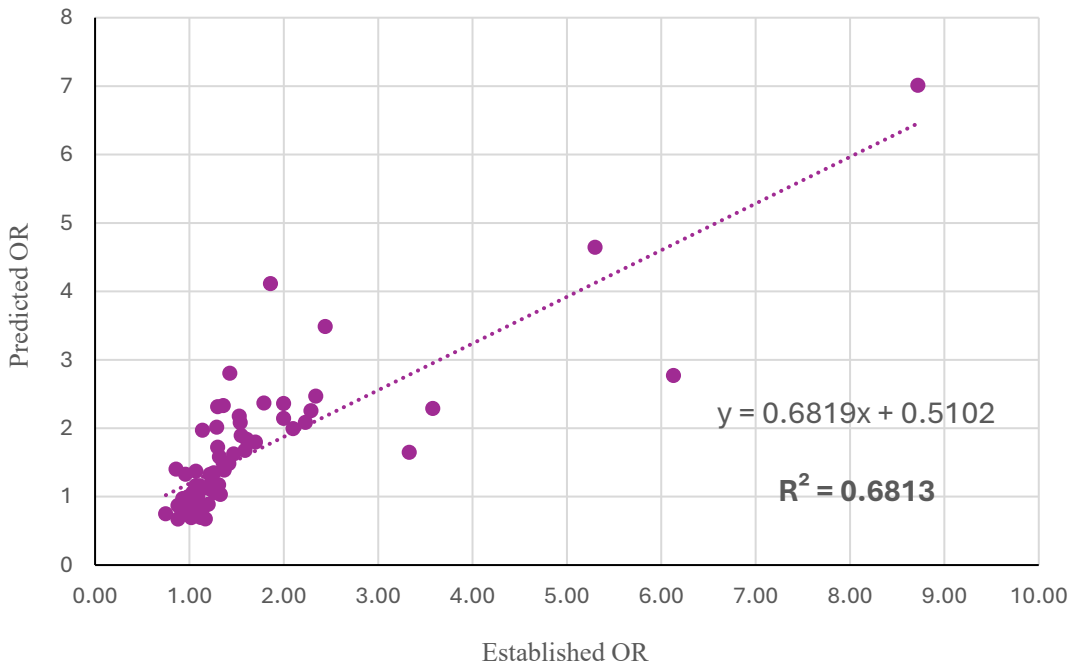


Figure 6.18 The relationship between predicted ORs ($R_{odds,p}$) and weighted ORs ($MH_{w\text{-}odds}$) for all locations.

To explore the influence of outliers, here defined as values with a z-score larger than 3.00, the four following sites were removed from the stepwise analysis: Fremont Bridge, Elliot Bay, Leigh Road, and Twin Streams. This did not improve the model performance, as it lowered the R^2 value from 0.681 to 0.620 and reversed the order of the top predictors, with Journey type becoming the strongest predictor followed by proximity to city centre. Variables previously excluded were still not retained, suggesting that the model behaviour was not impacted by those values.

6.8. Summary

Five out of the fifteen cities assessed for the effect of darkness on cycling numbers were selected for further exploration. Here, the aim was to investigate the influence of microscale factors on the effect of darkness within those cities, and five such factors were identified. These are: *journey type*, *distance from city centre*, the *presence of street lighting*, *latitude*, and the *number of cyclists*. This chapter began with establishing weighted ORs for each counting location (n = 74) within the five cities. ORs ranged from 0.75 to 8.72, suggesting a very wide effect of darkness across those cities. Next, records and estimates for the five factors were collected and their relationship with ORs explored through linear regression.

The findings from the linear regression (summarized in **Table 6.9**) suggest that the several factors may influence the effect of darkness as hypothesized. Higher ORs are shown to be associated with locations that are:

i) Leisure journey dominant,

ii) Further away from the city centre,

iii) Without street lighting present.

Associations with the remaining two factors, latitude and the number of cyclists, are also observed but are weaker. For both variables however, the exclusion of outliers improved the performance.

The strongest association across all factors was that between the *network distance to city centre* and ORs (approx. 59% of variation explained) and the weakest was the *number of cyclists*. However, these observations are made when combining data from all cities, as the reliability of observations on the influence on individual cities is hindered by the low count of locations within some of the cities.

To explore the weights of influence from the five factors further, a stepwise regression analysis was performed where the factors were inserted as independent variables. The resulting model broadly reflects the findings of the linear regression, suggesting that ORs may be best predicted by *distance to city centre,* followed by *Journey type*. Additionally, *the presence of street lighting, latitude,* and the *number of cyclists* were not retained in any of the models, which is consistent with the weaker associations observed in the linear regression analyses. Excluding outliers did not improve the model.

Finally, ORs predicted using the model equation were assessed against ORs previously established for all locations. The findings show that up to 68% of the variation in ORs can be explained by the model.

In conclusion, the findings from the linear and stepwise regression analyses presented in chapter **6** indicate that the suggested microscale factors may influence the deterrent effect from darkness to varying degrees. While these findings represent a consistent pattern across the combined data from these specific five cities, this may not be equally reliable for these cities when examined individually. Furthermore, it is unknown if a combination of other cities outside of those five would fit the models established in this chapter. Chapter **7** discusses such limitations and includes a comparison of models established in this chapter to models established in coauthored work that examines five different cities.

Table 6.9 Summary of the findings from linear regression analyses.

Variable	Approach	R^2 range (across 5 cities)	R^2 (all cities combined)	R^2 excluding outliers	Additional steps	Interpretation
Journey type		0.02-0.64	0.41 (p<0.001)	0.53 (p<0.001)	Additional analysis was performed to assess the validity of using the proportion of leisure journeys (P_R) as an estimate of the dominant journey type in a location.	ORs tend to increase with higher a P_L. – Leisure cycling is more deterred by darkness.
Distance to city centre	Euclidean distance	0.00-0.90	0.46 (p<0.001)	0.20 (p<0.001)	Excluded from stepwise regression.	ORs tend to increase with distance from the city centre – Locations further away from the centre are more deterred by darkness.
	Cycling network distance	0.00-0.58	0.59 (p<0.001)	0.13 (p=0.003)	-	ORs increase with distance from the city centre – Locations further away from the centre are more deterred by darkness.
Presence of street lighting		N/A for all cities	0.12 (p=0.002)	0.33 (p<0.001)	Pearson correlation to verify the direction of the relationship reveals it is negative.	ORs show a moderate tendency to increase in locations where street lighting is not present.
Latitude		0.15-0.73	0.07 (p=0.019)	0.12 (p=0.003)	-	ORs show a weak tendency to decrease at higher latitude. This suggests that small differences in latitudes between counting sites within the city do not contribute meaningfully to OR variation as the do between cities as discussed in chapter 4.
Number of cyclists		0.04-0.72	0.07 (p=0.085)	0.11 (p=0.005)	Due to the highly skewed distribution of the number of cyclists, a logarithmic transformation was applied prior to the regression analyses.	ORs show a weak tendency to decrease with a larger number of cyclists in the five cities. This confirms the findings in chapter 4, suggesting that the number of cyclists may not meaningfully contribute to OR variation within cities or across cities.

Chapter 7. Discussion

7.1. Introduction

The overall aim of this thesis was to investigate the effect of darkness on cyclist numbers. This was divided into three focused aims based on the literature reviewed in chapter **2**:

i) Improve the method of analysis for quantifying the impact of darkness.

ii) Assess whether darkness deters cycling.

iii) Explore causes of variance in the impact of darkness on cycling.

The three aims were addressed through seven research hypotheses. Chapter **7** begins by assessing how the hypotheses were supported by the findings of the analyses described in chapters of this thesis.

It then discusses how these findings relate to previous work and addresses the limitations faced. It concludes by making recommendations for future research.

7.2. Assessment of hypotheses

This section presents an assessment of each of the seven hypotheses to determine whether they are supported or refuted by findings of the analyses described in earlier chapters. Where relevant, further exploration and recommendations for future work are discussed.

7.2.1. Hypothesis 1

H1: Choice of case and control hour significantly influences ORs produced.

The limitation of selective case and control hours identified in previous studies using the case-control method was addressed in chapter **3**. An array of ORs was established from all possible combinations of case and control hours for the 15 cities to explore the influence of different choices of case and control hours. Rather than the two

combinations used in previous work, this analysis identified from 45 to 72 case and control hour combinations per city.

Figure 7.1 illustrates the distribution of all ORs per city and their effect size, arranged by case periods (morning or evening case hours) against control periods (daylight or darkness control hours). The figure shows that ORs tend to generally increase towards later hours in the evening case periods in most cities. For example, the hours 18:00 to 19:59 are often in the small to medium effect size threshold, while the hours 20:00 to 21:59 are often in the medium to large threshold, but this trend is more pronounced in the daylight control period than in the dark period. Additionally, early morning case hours – typically 05:00 to 06:59 – show lower ORs across most cities, compared to other hours of the day. This trend is clearer when ORs are illustrated as line plots (see **Figures 3.2** to **3.16**) Edinburgh generally shows a reversed trend, with an increase in ORs in morning case hours and a decrease in evening case hours. For control periods, some cities show an increase towards later hours of the period, while others remained contained within the negligible threshold. Control hours in midday may lead to lower ORs when compared to other hours in the same period, but this trend is not consistent across all cities.

The trends observed between case and control hours suggest that the choice of hours matters. Specifically, choosing a case hour in the morning period may lead to a substantially lower OR than a case hour in the evening period. This supports H1 which states that the choice of case and control hours significantly impact the OR produced.

For this reason, a method that summarizes OR arrays into one summary figure is recommended.

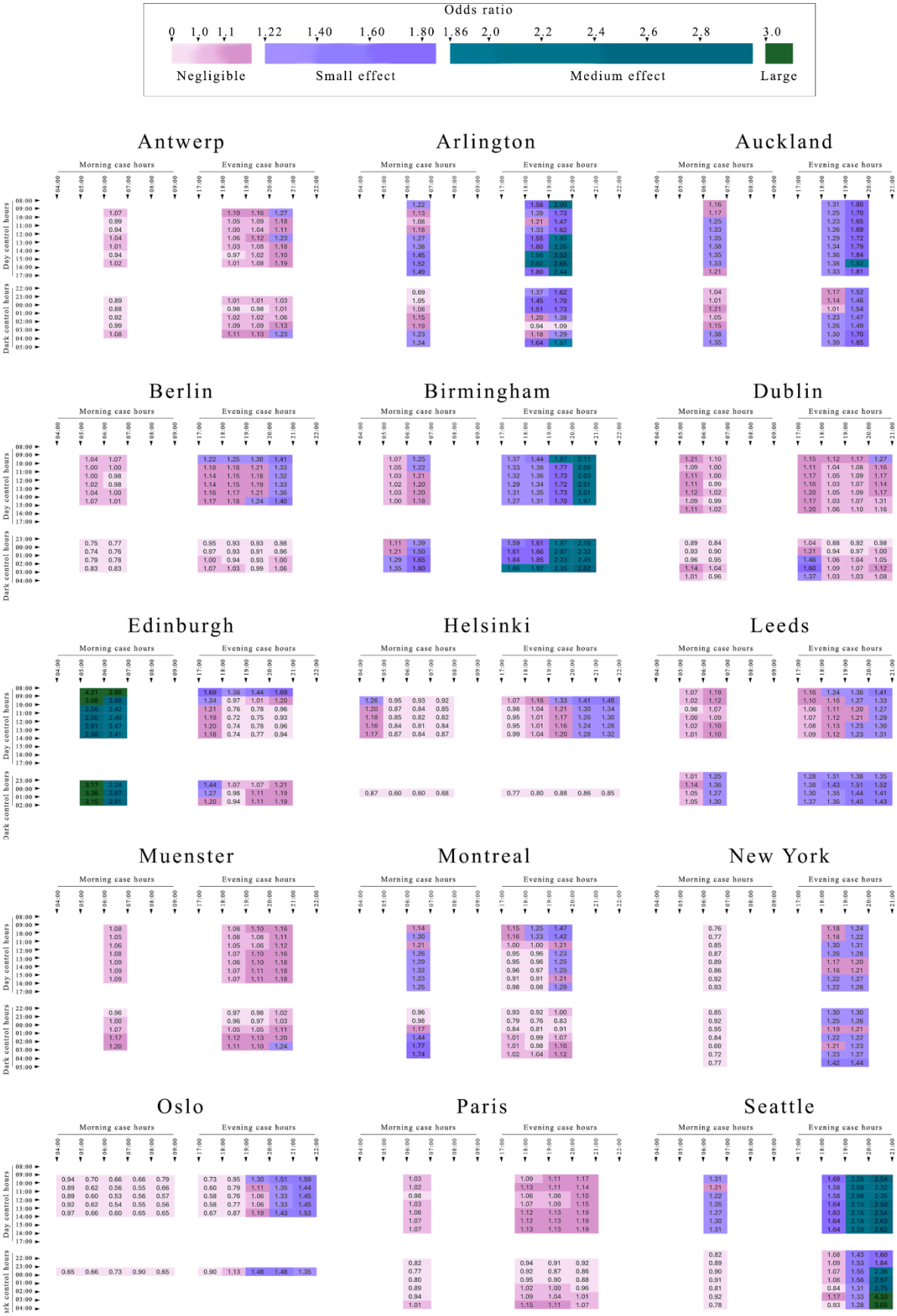


Figure 7.1 ORs for all case and control hour combinations in each city with their effect size (threshold based on interpretations by Olivier and Bell [2013].

7.2.2. Hypothesis 2

H2: Darkness reduces the number of cyclists.

With the increase of ORs towards later case hours illustrated in **Figure 7.1**, it is reasonable to conclude that darkness can bring a reduction in cyclist numbers when compared to daylight.

To make OR arrays easily legible and provide one general OR that quantifies the impact of darkness for each city, each array was summarized into a single figure, weighted by the number of cyclists in each case and control hour combination. These *Mantel-Haenszel* weighted ORs, illustrated in **Figure 7.2**, suggest that with the exception of Oslo, the number of cyclists is reduced after dark when compared to daylight in all cities. This aligns with findings from the nine revealed-preferences studies reviewed in chapter **2** [Chen et al., 2018; Fotios et al., 2019; Fotios et al., 2023; Fotios & Robbins, 2021; Uttley et al., 2020; Uttley et al., 2023b; Uttley & Fotios, 2017; Wessel, 2022; Zacharias & Meng, 2021], which suggested a general deterrence of cycling associated with darkness and low light levels, particularly case-control studies which reported a reduction in cycling numbers with ORs ranging from 1.05 to 1.67 (see **Table 2.6**)

This supports H2 which states that darkness reduces the number of cyclists.

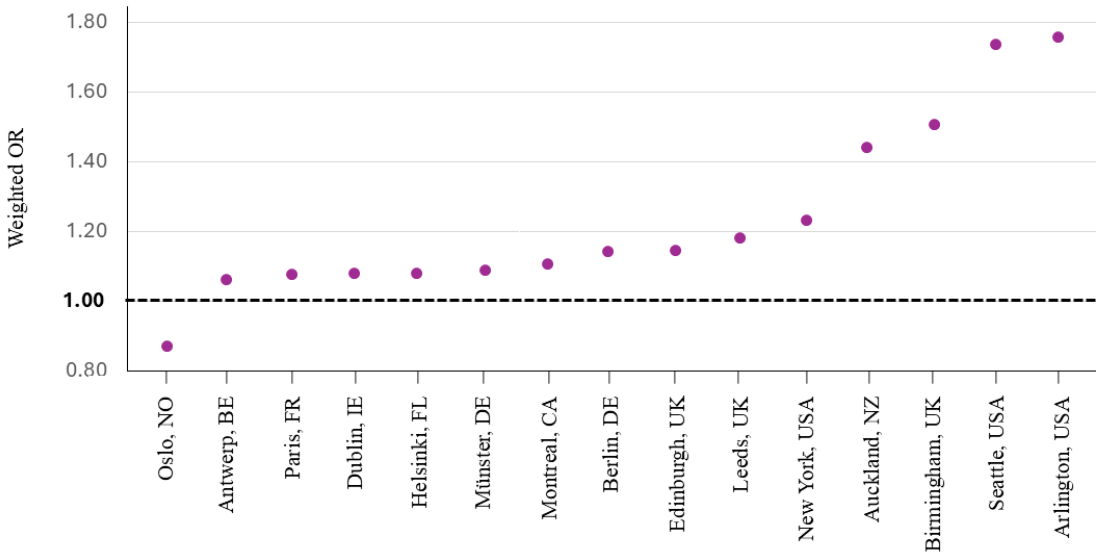


Figure 7.2 Weighted ORs for fifteen cities, arranged ascendingly. An OR significantly above 1.0 ($P<0.05$) for all cities except Oslo indicates that cycling is reduced after dark in those cities.

Oslo was the only city where the established OR (0.87) suggested an increase in cycling activity after dark. It is unknown why the impact of darkness on cyclists is reversed in Oslo, but there could be several reasons behind this, including Oslo's extensive cycling promotion efforts (see examples in **Table 7.1**), its infrastructure, its latitude, or simply the locations where the counters are installed.

Table 7.1 Examples of cycling promotional efforts implemented in Oslo, Norway [Copenhagenize, 2019; Oslo Kommune, 2019].

Effort	description
The Car-free liveability program, 2019	Initially launched in 2017, this program aimed to make Oslo's city centre greener and promote active travel. The initiative included multiple measures to increase cycling in the city centre, including enhanced cycling infrastructure, street lighting improvements, and a car-free central area connected to Oslo's main station.
Subsidies	The city offers many subsidies for cyclists and potential cyclists, including financial support for purchase of cargo bicycles
Winter support	Winter-ready bicycle sharing (Oslo Bysykkel) and loaning programs. Financial support for studded winter tyres purchase.

The examples given for the efforts implemented in Oslo are not exclusive to it. For instance, the next three cities with the lowest ORs all have car-free zones in central areas, which suggest that this may play a role in influencing the impact of darkness. Moreover, Oslo's latitude might mean that its cyclists are more resilient to darkness and weather because they spend more time in darkness in wintertime compared to the other cities on the list. A comparison of total time spent in darkness (as defined in this thesis) in the upcoming 2025 winter solstice of this year is presented in **Table 7.2** and illustrated in **Figure 7.3**, offering some support for the proposal that resilience to darkness may be association with time spent in it. The general influence of latitude and distance from city centre on the deterrent impact of darkness on cyclists were explored further in the thesis. These are addressed in H3 and H7 (subsections **7.2.3** and **7.2.5**).

Table 7.2 Hours spent in darkness in the shortest day of this year for all cities analysed in this thesis, arranged descendingly. Winter Solstice falls on Sunday 21 December 2025 for all cities except Auckland, where winter solstice falls on Saturday 21 June 2025. These durations were calculated using www.timeanddate.com

City	Hours of darkness in winter solstice
Oslo	16hr 16m
Helsinki	16hr 14m
Edinburgh	15hr 27m
Leeds	15hr 08m
Dublin	15hr 04m
Berlin	14hr 58m
Birmingham	14hr 57m
Münster	14hr 53m
Antwerp	14hr 48m
Paris	14hr 31m
Seattle	14hr 22m
Montreal	14hr 10m
New York	13h 43m
Arlington	13h 26m
Auckland	13h 23m

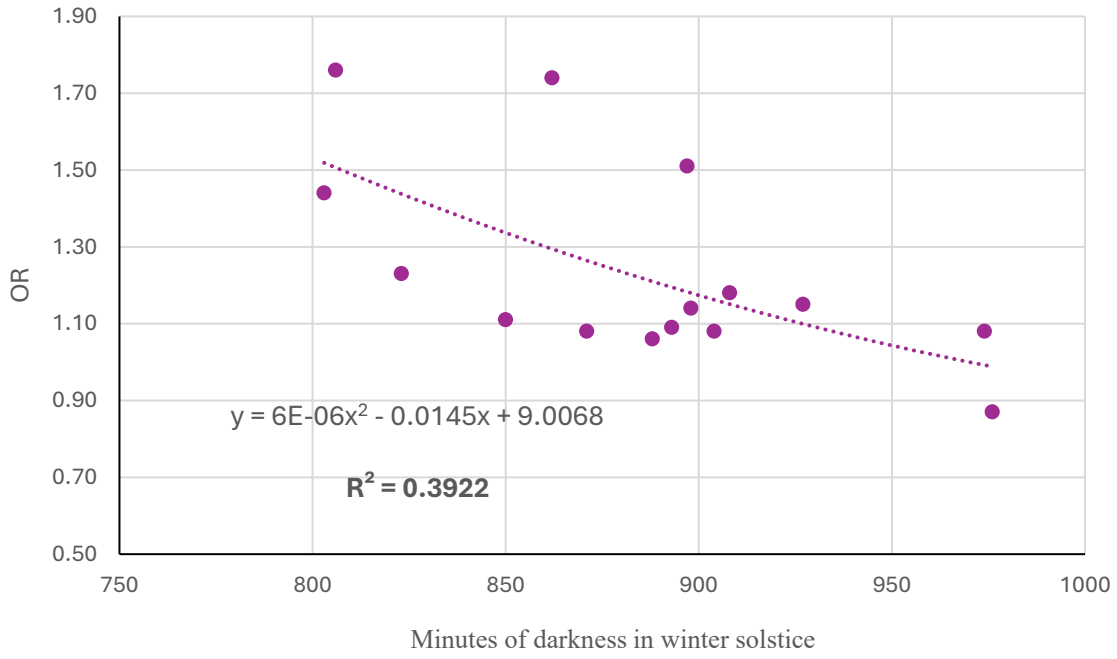


Figure 7.3 The relationship between ORs and time spent in darkness in winter solstice (converted to minutes from hours presented in Table 7.2).

7.2.3. Hypothesis 3

H3: Locations at higher latitudes will show a smaller deterrent effect from darkness on cycling.

Latitude contributes towards a city's climate and the amount of daylight it receives during a year [Schmal et al., 2020]. Both climate and the amount of daylight can significantly influence cycling (see section **2.7**). An exploration of the association between the weighted odds ratios established for the fifteen cities and their latitude revealed that ORs may significantly decrease with higher latitudes (r_s = -0.534, p=0.040). A linear regression model (see **Figure 4.1**) suggested that for every 1° of increase in latitude the OR is predicted to decrease by approximately 0.022. The model also suggests that 36.7% of variation in OR is explained by latitude (R^2=0.367, p=0.017).

Following this exploration across the 15 cities, the influence of latitude was also explored within select cities. A linear regression analysis between weighted odds ratios for 74 counting sites within five cities and their latitudes revealed a weak association (R^2=0.074, p=0.019). Although when exploring this effect within each city individually, Münster yields a high R^2 value (R^2=0.725, p=0.007), indicating a strong relationship, this should not be interpreted as a meaningful effect. With only eight counting sites and a narrow span of approximately 0.05° (around 6 km north to south), the regression may be sensitive to fluctuations in ORs. Additionally, latitude failed to be retained in the stepwise regression analysis as a predictor of OR variation.

These findings suggest that while latitude can have an influence on the impact of darkness on cyclists, this influence may be more relevant across cities, where difference in it can meaningfully impact ambient light and weather variations. This supports H3 which states that locations at higher latitudes will show a smaller deterrent effect from darkness on cycling, but it should be noted that this influence is applicable primarily when changes in latitude are substantial. These findings also align with the suggestion made by Uttley et al. [2023b] that the latitude of Norway is one reason behind its cyclists' resilience to darkness, which may also contribute to explaining the reversed impact of darkness reported in Oslo, the capital of Norway, in this thesis (see subsection **7.2.2**).

7.2.4. Hypothesis 4

> H4: Locations with a greater cycling culture will show a smaller deterrent effect from darkness on cycling.

Three proxies were proposed to quantify cycling culture and explore if it influences the impact of darkness on cyclists. The first proxy used was cycling modal shares, where an exploration of its association with ORs revealed a strong and statistically significant relationship (r_s = -0.752, p=0.001), indicating that higher modal shares are associated with lower ORs. A linear regression model (see **Figure 4.2**) suggested that 31.3% of variation in ORs is explained by modal shares (R^2 = 0.313, p=0.03).

The second proxy, the number of cyclists per 1000 inhabitants, showed a weaker association with OR, which is also not statistically significant (r_s = -0.373, p=0.172), and explains only 2% of variation in ORs (see **Figure 4.4**).

The third proxy used was a comprehensive ranking index of 90 cycling-friendly cities by the now-defunct insurance company *Luko*, where the association was explored between ORs established for the 12 out of 15 cities in my analysis and the scores for multiple *Luko* categories. While the overall *Luko* score given to a city showed a weak and statistically insignificant association with ORs (r_s = -0.20, p=0.481), bicycle sharing score was shown to have the strongest association with ORs (r_s = -0.859, p<0.050), which suggests lower scores (indicating less bicycle sharing) are associated with higher ORs. A linear regression model shows that up to 47% of variation in ORs can be explained by the bicycle sharing score (see **Figure 4.6**). However, this is just above the threshold of statistical significance (p=0.057).

In conclusion, for the three proxies used as a measure of cycling culture, only modal shares directly support H4, which states that locations with a greater cycling culture will show a smaller deterrent effect from darkness on cycling. This also supports the suggestions made by previous work [Haustein et al., 2020; Uttley et al., 2023b] that cycling culture may be a reason behind differences in cycling rates across different cities.

7.2.5. Hypotheses 5-7

H5: Locations with a higher proportion of utilitarian cycling will show a smaller deterrent effect from darkness on cycling.

H6: Locations further from the city centre will show a larger deterrent effect of darkness than locations closer to it.

H7: Locations where street lighting is present will show a smaller deterrent effect of darkness than locations where no lighting is present.

The analysis used to address H1-H4 explored the influence of macroscale factors on the impact of darkness on cyclists across 15 cities. Out of those cities, 5 were chosen for the next step of the analysis, which explores the influence of microscale factors to address the remaining hypotheses (H5-H7). Three such factors were identified: *journey type*, *distance from city centre*, and the *presence of street lighting*. Additionally, two more factors, *counter latitude* and the *number of cyclists*, were reintroduced at the microscale to explore their influence within cities.

Using the revised case-control method, weighted ORs for each individual counting site (n = 74) within the five cities were established. ORs ranged from 0.75 to 8.72, suggesting a very wide effect of darkness within those cities. The association between ORs and the five factors was explored in two types of regression analyses.

First, linear regression analyses suggested that counting sites with lower ORs are associated with:

i) A higher proportion of utilitarian journeys (up to 53% of variation explained), suggesting that the impact of darkness on cyclists may be reduced in sites that are predominantly used for utilitarian cycling. This supports H5, which states that locations with a higher proportion of utilitarian cycling will show a smaller deterrent effect from darkness on cycling. These findings also align with work by Wessel [2022], which suggested that improved lighting conditions may impact utilitarian journeys less than other types; and work by Duren et el. [2023], which reported that utilitarian cyclists are generally less affected by factors that deter other types of cyclist and non-cyclists.

ii) Closer proximity to the city centre (up to 59% of variation explained), suggesting that the impact of darkness on cyclists may be reduced in sites that are closer to the city centre. This supports H6, which states that locations further from the city centre will show a larger deterrent effect of darkness than locations closer to them. These findings are not directly supported by existing work, as none of the studies reviewed in chapter **2** reported on this directly. Those studies only reported that central locations may experience fewer cycling barriers due to infrastructure connectivity, access to public transportation, and environmental zones, among other factors.

iii) Presence of street lighting (up to 33% of variation explained), suggesting that the impact of darkness on cyclists may be reduced in sites where street lighting is installed. This supports H7, which states that locations where street lighting is present will show a smaller deterrent effect of darkness than locations where no lighting present. This aligns with findings reported in previous studies [Fotios et al., 2019b; Uttley et al., 2020], reporting a reduced impact of darkness in locations lit after dark.

iv) Higher latitude and a higher number of cyclists (only 7% of variation explained for each variable), suggesting that to a much lesser degree, the impact of darkness on cyclists may be reduced in sites higher in latitude and with a higher number of cyclists. However, only the relationship with latitude was statistically significant (p=0.19). In contrast to other factors, these two appear to have a weaker influence.

Second, a stepwise regression echoed these findings, suggesting that ORs may be best predicted by *distance to city centre* followed by *Journey type*. However, *the presence of street lighting, latitude,* and the *number of cyclists* failed to be included in any of the models, which may suggest a reduced influence in the five cities. These findings generally support H5 and H7.

7.3. Limitations

The research presented in this thesis has several limitations. These limitations can be grouped into three categories: sample size and limited representation of the sample, reliability of supporting data, and further unexplored factors that may influence the impact of darkness. These are discussed in the following subsections.

7.3.1. Sample size and limited representation

While this thesis made an effort to expand the geographical scope beyond that of previous work, the 15 cities analysed in it are within the same socioeconomic range. All cities are in high-income industrialized countries with access to multiple modes of transportation. While these cities can offer insight into cycling behaviour in a developed urban context, analysing cities with lower-income, different infrastructure, and less support for cycling could show very different trends and results.

Additionally, inconsistencies within the sample size of the available data between different cities may significantly impact the accuracy of the reported cycling trends and the ORs established. The number of counting locations and years the data was collected for varied greatly between cities, ranging from 5 counting locations (e.g. New York) to 55 counting locations (Paris), and a single year of data (e.g. Dublin) to 10 years of Data (Leeds). This may impact the results of the analysis, particularly in chapter **6**, where across the five cities, Auckland has more than three times the number of counters compared to the other four cities. **Table 7.3** shows a comparison between Münster and Auckland as an example of sample size inconsistencies. The low number of 8 counting locations in Münster might mean that they are strategically installed in areas with better infrastructure and higher cycling traffic, as all counters in Münster are located on cycling infrastructure buffered from traffic but only 27 locations out of the 37 in Auckland are buffered from traffic. In Münster, all counting locations have street lighting and the average distance from counting location to city centre is 2.17 km, while in Auckland 32% of locations are not lit after dark and the average distance is 13.33

km. These reasons might contribute to the difference in findings from both cities, particularly the ORs established for them.

Table 7.3 Comparison of counting location characteristics between Münster and Auckland.

	Münster, DE	**Auckland, NZ**
Total number of counters	8	37
Years data available for	2019	2012-2019
Locations buffered from traffic*	8/8	27/37
Average network distance from location to city centre	2.17 km	13.33 km
Locations with street lighting	8/8	25/37
Weighted OR	1.09	1.44

*Established using visual assessment of counting location on Google street view

7.3.2. Reliability of supporting data across all cities

While automated cycle counters can provide a valuable quantitative input about cycling volumes, they offer no information about the nature or purpose of the recorded journeys. Thus, this thesis tried to establish estimates of such information from multiple sources to understand how it influences the impact of darkness. However, the accuracy of these estimates and their method of collection can impact the results. The following are examples of how this might be a possible limitation.

1) ***Modal shares***: Estimates of cycling modal shares were collected from various sources that used varying methods, sample sizes, and timeframes. This can significantly impact their comparability across all 15 cities. For example, some estimates were established from official sources such departments of transportation or city surveys (e.g. Helsinki, New York, Oslo, and Münster), while others were established from third-party reports (e.g. Dublin, Berlin, Auckland, and Birmingham). Some are established using GPS data (e.g. Paris) or official surveys (e.g. Münster), while others are less transparent about how these figures were established (e.g. Montreal).

Additionally, these modal shares were established for different years, ranging from 2016 to 2024. With the exception of Berlin and Leeds, the year the modal shares were established for were outside the range of years for the collected cycling counts. One reason for this was that several of them were established in 2020 and 2021, which are years excluded from my analysis to avoid confound from the impact of the Covid-19 Pandemic on cycling patterns.

2) ***Luko's Global Bicycle City index:*** Several proxies were introduced in this thesis to quantify cycling culture in the 15 cities, since it is not directly measurable. These proxies were modal share, number of cyclists, and cycling-friendliness indexes. One index that had comprehensive data for 12 cities out of the 15 in my analysis was Luko's *Global Bicycle City Index 2022*. This index ranked a list of 90 cities based on scores given for multiple categories such as safety, infrastructure, bicycle-sharing, and more. While Luko's data is no longer accessible after being acquired by another company in 2023, the information on the page was successfully saved before its removal (see **Appendix C**). The information on the page gives description of the methodology Luko followed to calculate their city index scores. However, some missing information and inconsistencies might impact the reliability of this index. For example, while the scores for each category and subcategory are provided, the scoring system for each isn't explained, nor is the weight given to each category in the final score.

   Additionally, this index was established in 2022, likely using the most recent data aggregates. It is possible that infrastructures, bicycle sharing, and other cycling attributes improved in the cities included in this analysis since the last year the collected counts, possibly causing an increase or decrease in cycling in that is not captured by the count data. **Figure 7.3** illustrates the differences in daily average cyclist numbers per counting site in Paris, France, between my analysis period and Luko's index.

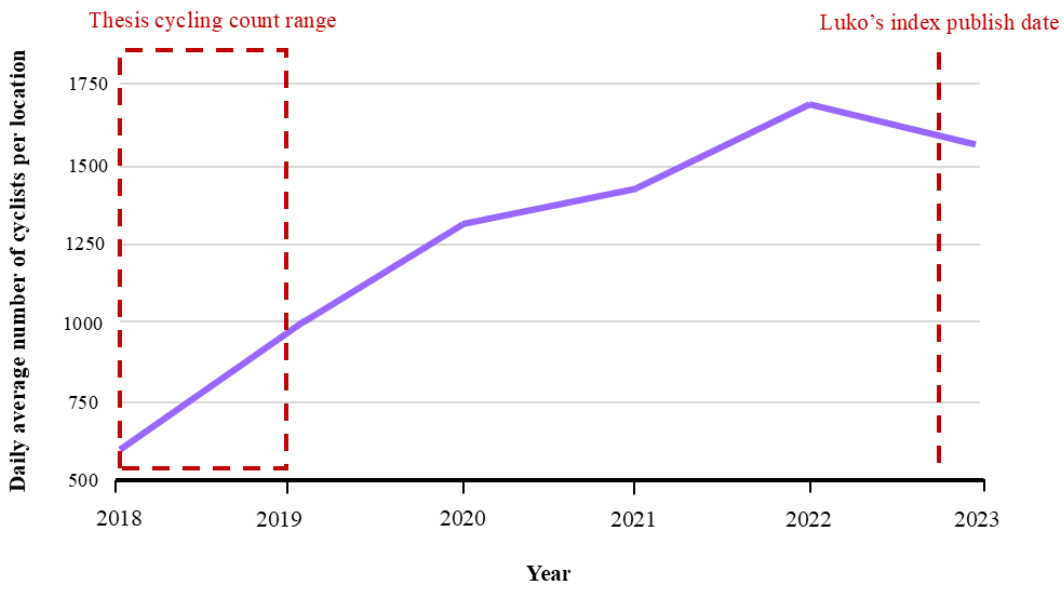


Fig. 7.3. Paris' mean daily average number of cyclists per counting site, averaged by year. Chart source: Paris Open Data [retrieved June 2025]. Recreated by author with overlay from data described in this thesis.

Another limitation concerns the number of contextual variables in the index. Multiple potentially intercorrelated measures relating to weather, safety, infrastructure, and policy context were included. In principle, dimension reduction techniques such as Principal Component Analysis (PCA) could be applied to summarize the variables into a smaller number of components. However, in this case the variables used in the thesis were already consolidated category scores (n = 6) derived from multiple underlying indicators (n = 10), and further reduction may offer limited analytical benefit. It is possible that analysing the ten underlying indicators in addition to the categories can offer beneficial insight into their individual contribution. However, the relatively small number of cities included in the analysis may limit the reliability of PCA, which typically requires larger sample sizes to produce stable and interpretable components [Osborne & Costello, 2004]. In addition to this, an issue was identified in the Luko scores themselves, where two reported values, *Events* (score category) and *Accidents per 100k cyclists* (indicator for *Safety* score), are exact duplicates of each other (see **Table 4.4**). It is unclear which of these two values is the one accurately reported, but this duplication can potentially impact the results, especially since *Events* score was shown to be associated with ORs (**Table 4.7**).

3) ***Google street views:*** By visually assessing Street Views of cycle counting sites on Google Maps, an estimation about two factors that may influence the impact of darkness is established. These are the journey type dominant in the site and whether street lighting is installed. However, the accuracy of these estimates might be limited. For example, classifying journey type visually using the criteria proposed (see **Table 5.6**) can be subjective or inaccurate, as it may be unfair to classify a site as utilitarian-dominant just because it is in residential area might. It is reasonable to assume that residents of the area might feel safer riding their bicycle for leisure within their neighbourhood, as they are more familiar with traffic patterns and what to expect. It may also be unjustified to classify a site as utilitarian-dominant if it's in a commercial street with offices, but as leisure-dominant if it's in a commercial street with shops. Sites that had both offices and shops would potentially meet both criteria, introducing a degree of subjectivity in allocating the site to one journey type over the other.

   Additionally, the other limitation of using Google Street View to assess microscale factors affecting cycling in darkness is the potential for a discrepancy between the imagery date and the cycle count data collection period. For example, if a change in building or land use occurred during the cycle count period but wasn't reflected in the Street View imagery, it could change the journey type classification for that site. Similarly, evaluating the presence or absence of street lighting via Google Street View might be inaccurate if lighting was installed or removed between the Street View image date and the cycle counter data collection dates for that location.

7.3.3. Further unexplored factors

This thesis explored the influence of several city-scale and site-scale factors on the impact of darkness on cyclists. However, these factors are likely not the only ones to have an influence. For example, it may be reasonable to assume that people may be more resilient to darkness or reduced lighting conditions if the journey is short. While the association between *distance travelled* and darkness is yet to be explored, previous studies have confirmed that longer distances may generally lead to less cycling [Heinen et al, 2010].

Other possible factors might include *journey duration*, as it may also be reasonable to assume that if a person can reach their destination faster by bicycle than car (due to a shorter network), they may choose to cycle, particularly if not deterred by other factors such as weather. Lastly, while previous studies did explore the influence of weather [Miranda-Moreno & Nosal, 2011], heavy traffic [Lee & Moudon, 2008; Segadilha & Sanches, 2014], and harsh topography [Harris et al., 2013; Parkin et al., 2008; Vandenbulcke et al., 2011] (see chapter **1**), the association between these factors and the impact of darkness is not yet explored. Although the analysis in this thesis briefly considered the association of weather and infrastructure (using the Luko's weather and infrastructure scores), more research is needed to explore their influence on the impact of darkness on cyclists.

Additionally, including more factors may introduce further complexity, including potential interactions between variables, thereby increasing modelling limitations. Although the stepwise regression presented in this thesis explored the independent influence of each microscale factor on variation in ORs, it did not examine potential interactions between the factors. Such interactions would imply that the influence of one factor may depend on the level of another. For example, the influence of distance from city centre could differ depending on the dominant journey type in a location. While it is reasonable to assume that such interactions exist, they were not tested in this analysis, and no direct evidence for their presence was established within the scope of this study. Including these interaction terms (e.g. distance from city centre vs. journey type) could therefore provide additional insight into compounded patterns. However, introducing interactions substantially increases model complexity and requires a wider range of data for each variable, which may be difficult given the limited number of counters in each individual city. Thus, these were not considered in the analysis presented in the thesis, but it is recommended that they are explored in future work.

7.3.4. Summary of limitations

Three categories of limitations are identified in this thesis. First, sample size limitations, where inconsistencies in the range of years and number of locations in the data available for the 15 cities might impact the ORs established, and subsequently the results reached.

Second, several types of supporting data collected are estimates that may not reflect accurate real-life cycling patterns. For example, some sources of collection lacked the transparency to show how estimates were collected, while others had obvious mistakes in the reported data (e.g. Luko having duplicate scores for two categories).

Third, the thesis explored the influence of several macroscale and microscale factors on the impact of darkness on cyclists, but these factors are likely not the only ones to have an impact. Other factors that require more research include the distance travelled, the duration of cycling journey, infrastructure condition, and topography.

7.4. Assessment of regression assumptions and sensitivity analysis

This thesis relies on regression modelling to explore the association between the impact of darkness on cycling and factors that may influence it at the macro and micro scales. These models are typically subject to underlying assumptions, including normality, homoscedasticity, and multicollinearity, and it is therefore important to consider the extent to which these assumptions are met. While the previous section discussed limitations related to the data used in the analysis, this section aims to understand the sensitivity of their findings to the assumptions of linear regression. This is addressed through a re-estimation of all regression models reported in this thesis using log-transformed ORs, rather than a detailed examination of residual diagnostics for each of the 16 models. Alternative specifications (e.g. polynomial terms) were retained only where statistically significant, or where model fit improved when no specification was statistical significance. **Tables 7.4** and **7.5** compare the results from the original models presented in chapters **4** and **5-6**, respectively, to those from the log-transformed models. Additional details including a list of log-transformed ORs and scatterplots are provided in **Appendix H**.

The sensitivity comparison shows that re-estimating the models using log-transformed ORs does not change the main conclusion from the initial findings, but it does affect the strength and significance of some relationships. At the macroscale (Chapter **4**), log-transformation led to similar or improved explanatory power for most factors, as reflected by R^2 values; however, fewer of these associations remained statistically significant. This notably affects the initial finding from the thesis that cycling modal

shares are associated with variations in ORs, as this relationship is no longer statistically supported under the revised specification. At the microscale (Chapters **5** and **6**), log-transformation generally improved R^2 values across all factors. Model performance improved for all but distance variables, where small reductions in R^2 values were observed, although statistical significance was retained. Journey type was particularly sensitive to outlier removal, as statistical significance was not retained.

Finally, for the stepwise regression reported at the end of chapter **6**, using log-transformed ORs as the dependent variable improved the R^2 value from 0.681 to 0.862, and the model remained statistically significant. The two retained predictors, distance to city centre and journey type, remained the same, although their order were reversed, with journey type emerging as the top predictor. A comparison of diagnostic residuals for the original and re-estimated models (**Figures 7.4-7.6**) suggests the using log-transformed ORs improved conformity to the assumptions of regression, as reflected in the histograms and normal P-P plots. Improvements in the residuals vs. fitted scatterplots are minimal, suggesting that some heteroscedasticity remains.

Table 7.4 Comparison of regression findings for models using raw ORs (Chapter 4) and log-transformed ORs. The latter are highlighted in grey, with dark shading indicating changes in statistical significance.

Macroscale factor			Linear Regression (raw ORs) *		Linear Regression (with log-transformed ORs) *		Specification
			R^2	R^2 after removing outliers	R^2	R^2 after removing outliers	
Latitude			0.367, p=**0.017**	n/a	R^2= 0.393, **p=0.012**	-	Linear
Cycling culture	Modal share		0.313, p=**0.030**	0.327, p=**0.041**	0.341, p=0.747	0.440, p=0.289	Polynomial
Cycling culture	Cyclists per 1000 inhabitants		0.021, p=0.608	0.003, p=0.854	0.032, p=0.521	0.012, p=0.707	Logarithmic
Cycling culture	Luko	weather score	0.535, p=0.032	n/a	0.532, p=0.293	-	Polynomial
Cycling culture	Luko	Bicycle use	0.081, p=0.717		0.067, p=0.303		
Cycling culture	Luko	Safety score	0.272, p=0.329		0.272, p=0.189		
Cycling culture	Luko	Infrastructure score	0.112, p=0.586		0.139, p=0.689		
Cycling culture	Luko	Sharing score	0.471, p=0.057		0.507, p=0.077		
Cycling culture	Luko	Event score	0.261, p=0.256		0.274, p=0.740		
Cycling culture	Luko	Overall score	0.057, p=0.769		0.049, p=0.966		

* Statistically significant values ($p<0.05$) are indicated in **bold** numbering. For Luko categories, a Bonferroni adjustment of $p<0.007$ is applied

Table 7.5 Comparison of regression findings for models using raw ORs (Chapters 5 & 6) and log transformed ORs. The latter are highlighted in grey, with dark shading indicating changes in statistical significance. This table only shows R^2 values for the combined data of the five cities.

Microscale factor		Linear Regression (raw ORs) *		Linear Regression (with log-transformed ORs) *		Specification
		R^2	R^2 after removing outliers	R^2	R^2 after removing outliers	
Journey type		0.41, **p<0.001**	0.53, **p<0.001**	0.682, **p<0.001**	0.644, p=0.300	Polynomial
Distance to city centre	Euclidean distance	0.46, **p<0.001**	0.20, **p<0.001**	0.380, **p<0.001**	0.107. **p=0.005**	Linear
	Cycling network distance	0.59, **p<0.001**	0.13, **p=0.003**	0.466, **p<0.001**	0.165, **p<0.001**	Linear
Presence of street lighting		0.12, **p=0.002**	0.33, **p<0.001**	0.202, **p<0.001**	0.303, **p<0.001**	Linear
Latitude		0.07, **p=0.019**	0.12, **p=0.003**	0.190, **p<0.001**	0.185, **p<0.001**	Linear
Number of cyclists **		0.07, p=0.085	0.11, **p=0.005**	0.083, **p=0.045**	0.103, **p=0.009**	Polynomial

* Statistically significant values (p<0.05) are indicated in **bold** numbering.

** Raw numbers of cyclists were log-transformed to reduce skewness before the regression.

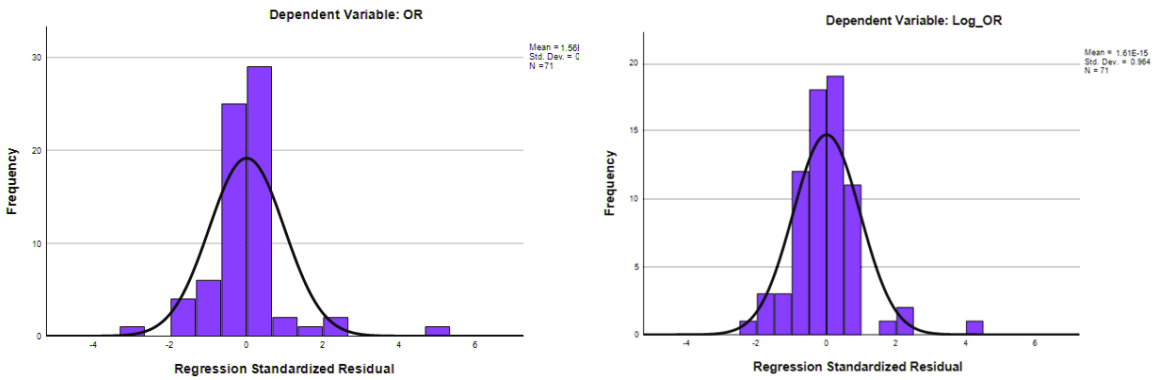


Figure 7.4 Comparison of residual histograms for models using raw ORs (left) and log-transformed ORs (right).

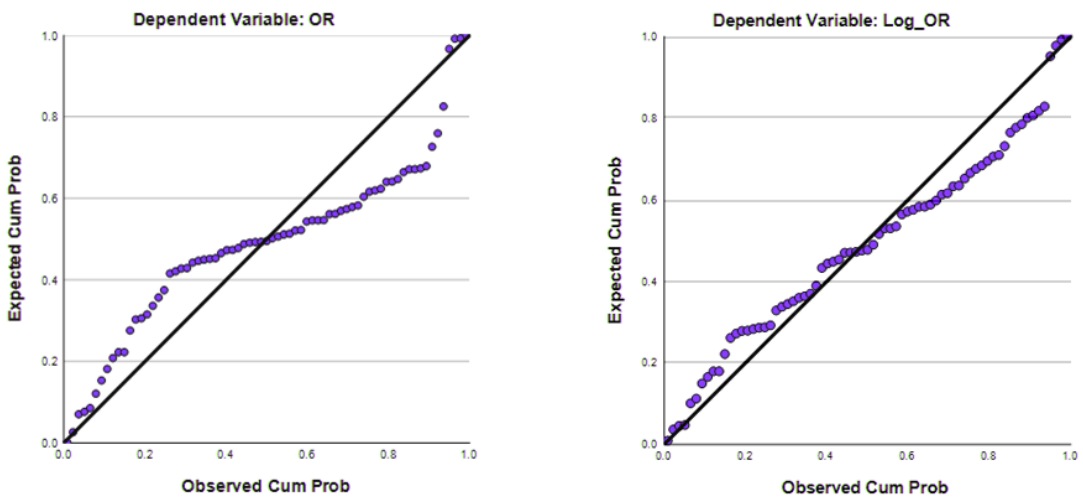


Figure 7.5 Comparison of Normal P-P plots for models using raw ORs (right) and log-transformed ORs (right).

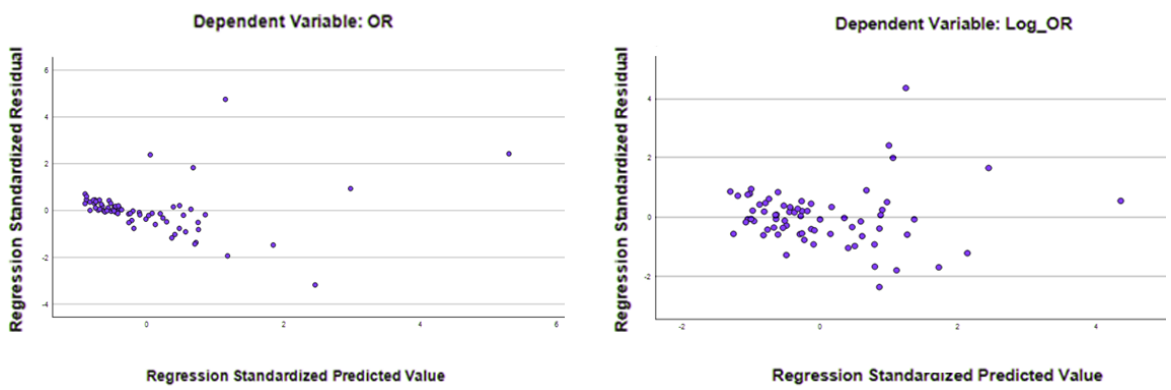


Figure 7.6 Comparison for residual vs. fitted plots for models using raw ORs (right) and log-transformed ORs (right).

In conclusion, using log-transformed ORs to improve conformity to the assumptions of linear regression supports the findings from the original models for the majority of factors examined. One exception is cycling modal shares, for which the association with the impact of darkness is no longer supported and may therefore warrant re-examination. By contrast, the number of cyclists is now supported at the microscale, following the use of log-transformed ORs. Thus, the comparison of the models suggests that only limited revision to the interpretation of original findings is needed.

7.5. Implications

7.5.1. Contribution

The work in this thesis offers methodological and empirical contributions to the understanding of how darkness affects the number of cyclists.

First, in methodological contributions, a revision was introduced to improve the robustness of the case-control method typically used to quantify the impact of darkness on cyclists. This revision addressed the limitation of previous work in which selective case and control hours were used. Findings of this thesis (chapter **3**) demonstrate that the choice of case and control hour influences the conclusions drawn about the effect of darkness on cycling. For example, choosing a later evening case hour has a high probability to result in a larger OR compared to earlier case hours, as shown in the majority of the 15 cities (see **Figure 7.1** earlier in this chapter). Therefore, a method that combines all possible case and control hours to produce a weighted OR was introduced. This aimed to provide a more robust assessment of the overall impact of darkness on cycling counts. Additionally, the thesis proposed further refinements to enhance study design. This included applying a strict definition of darkness periods, to ensure that the transitional light conditions during twilight periods do not obscure any impact of darkness.

Second, in empirical contributions, this thesis adds to the exiting knowledge in the following ways:

1) Expanding the geographical scope of research into the deterrent effect of darkness beyond that established in previous studies, confirming that darkness reduces the number of cyclists in 12 new cities not analysed before.

2) Exploring variation in the impact of darkness. This thesis reported that for the 15 cities analysed, ORs varied. In exploring possible factors behind this variation, several macroscale and microscale factors were associated with variation in ORs. These are latitude, modal shares, bicycle-sharing (as a reported score evaluating its quality), journey type, and distance from city centre. These factors require further research beyond a simple association assessment.

7.5.2. Exploring five additional cities

The stepwise regression analysis carried out in the previous chapter (see section **6.7**) explored the influence of four microscale factors (*Journey type, distance to city centre, presence of street lighting, latitude, and the number of cyclists*) on the variation in ORs across individual counting sites in five cities: Auckland, Edinburgh, Münster, Oslo, and Seattle. The findings first confirmed an association between the weighted ORs and the five factors using linear regression analysis, although for *latitude* and *number of cyclists* this association was very weak. This was followed by a stepwise regression analysis, where the resulting models indicated that ORs may be best predicted by network *distance to city centre*, which can be improved further when adding *Journey type* as a second predictor. However, *the presence of street lighting, latitude,* and the *number of cyclists* failed to be included in the models, which may suggest a reduced influence within the five cities.

There was considerable variation in the influence of the microscale factors within cities; for example, the network distance between counting sites and the city centre in Aukland can explain 58% of variation in ORs, while in Oslo the variation explained is only 1%. For the same two cities, Journey type can explain 42% and 2%, respectively. This suggests the choice of individual cities may have influenced the overall results and the stepwise regression model that was developed to predict variation in the ORs. Had another five cities been used, it is possible the conclusions from the analysis could have been different (e.g. the presence of road lighting may have had more of a significant influence). Related to this, one limitation with the work in this thesis is that one city in particular, Auckland, may have had an especially strong influence on the overall results. This is because Auckland contributed 37 of the 74 counters that were included in the overall results across the five cities.

To assess the impact of the choice of five cities for the microscale analysis in this thesis, the results are compared with parallel work that has been undertaken as part of the EPSRC-funded SATURN (Supporting Active Travel Using Road-Lighting at Night) project [Yesiltepe et al., under review]. This work extends the exploration of association between four of the variables I have used (*Journey type, distance to city centre, number of cyclists, and presence of street lighting*) and the variation in ORs in individual

counting sites in five more cities. This includes four more cities from the list of 15 in this thesis: Arlington, Berlin, Birmingham, Leeds, and one new city added to the list, which is Bergen, Norway. The following describes findings from the study and compares it to findings from the thesis, showing how the models established for both can perform when combining all 10 cities in one analysis.

While Yesiltepe et al. [under review] uses four variables included in this thesis (*Journey type, distance to city centre, number of cyclists, and presence of street lighting*) and establishes them the same way (e.g. assessment of Google street views), a few differences exist:

i) Latitude was only considered a variable in this thesis. This came as a further exploration of its influence after an association was found between it and the impact of darkness in on a macroscale in chapter 4.

ii) Yesiltepe et al. [under review] considered only euclidean distance as the main measure to the city centre. They did not include network distance in their analysis, nor did they compare both approaches. Additionally, they weighted their Euclidean distance by city area to account for urban density and different city sizes.

iii) The number of cyclists variable was normalized by city population in Yesiltepe et al., while in this thesis, raw cyclist counts were used as a direct representation of cycling in each individual site.

Therefore, to enable a comparison between both models, the three differences were addressed here to match Yesiltepe et al.'s analysis. First, the latitude variable was removed. This should not impact the results as it was not retained in the initial run in this thesis. Next, network distance was replaced with euclidean distance, which was then weighted by city area (established through Google searches). Lastly, weighting by city population was introduced to the number of cyclists. The stepwise regression was then repeated and a comparison between both findings is presented in **Table 7.4**.

Table 7.6 Comparison of findings of the stepwise regression analyses reported in this thesis and in the expanded study.

	Reported in this thesis	**Reported in Yesiltepe et al.** [under review]
Cities	Auckland, NZ. Edinburgh, SCT, UK. Münster, DE. Oslo, NO. Seattle, WA, USA.	Arlington, VA, USA. Bergen, NO Berlin, DE. Birmingham, UK. Leeds, UK.
Total number of counting locations	74	117
Predictors	(constant). Proportion of leisure journeys, Weighted Euclidean Distance to city centre.	(constant), Presence of lighting, Proportion of leisure journeys, Number of cyclists.
Excluded variables	Presence of lighting, Number of cyclists.	Weighted Euclidean Distance to city centre.
Adjusted R^2	0.67	0.64
Equation to predict ORs	$R_{odds,p}$ = -0.837 + 5.544 *proportion of leisure journey + 13.653 weighted Euclidean distance*	$R_{odds,p}$ = 0.84 + 0.87 *presence of lighting* + 3.89 *proportion of leisure journey* – 0.22 *number of cyclists*

Comparing the two R^2 values in the table shows that the thesis model performs slightly better. However, these are values established for the respective data of each study. To compare how these models perform outside of their respective datasets, their equations are applied on the other's datasets first to see if R^2 values improve, and are then applied again on the combined datasets of both studies (n = 191 counting sites).

The results of this comparison are shown in **Table 7.7**, which indicated that models perform better on their own data sets. Cross application leads to a deteriorated performance, which suggests the low generalizability of the models, though statistically significant. When evaluating models on the combined datasets, the model developed in the thesis performs better across all evaluation metrics. This suggests that the thesis model can be generalized more effectively across different datasets. This means that its equation may provide a better prediction of ORs for locations beyond the 191 sites used.

Table 7.7 Comparison of errors and coefficients when applying both models on thesis dataset (n = 74 locations), paper dataset (n = 117 locations), and combined datasets (n = 191 locations).

Evaluation metric	Applied on thesis data	Applied on paper data.	Applied on combined data
Thesis MAE*	0.52	1.20	0.48
Paper MAE*	1.59	0.26	1.18
Thesis RMSE**	0.90	1.33	0.74
Paper RMSE**	1.72	0.39	1.32
Thesis R^2	0.45 ($p<0.001$)	0.36 ($p<0.001$)	0.38 ($p<0.001$)
Paper R^2	0.12 ($p=0.002$)	0.65 ($p<0.001$)	0.25 ($p<0.001$)

* MAE: Mean Absolute Error. Calculated as the mean average of individual MAE, where each error is the absolute difference between actual and predicted ORs -lower values indicate better performance.

** RMSE: Root Mean Squared Error. Calculated as the square root of the mean average of individual squared errors -lower values indicate better performance.

7.6. Summary

Chapter **7** discussed the results of the analyses conducted in previous chapters and concluded that the findings support all 7 hypotheses with some limitations. This is described below.

H1: the findings support that the choice of case and control impacts the ORs produced.

H2: the findings support the hypothesis that darkness reduces the number of cyclists. However, Oslo was an exception to this, as the findings reported an increase in cycling after dark. A few possible reasons were given, with a recommendation to explore this further in future research.

H3: The findings support the hypothesis that locations with higher latitude may show a smaller deterrent effect from darkness on cyclists. This is more applicable across cities (where substantial latitude differences can have an impact on weather and the amount of daylight received) rather than within cities.

H4: The findings support the hypothesis that locations with greater cycling culture may show a smaller deterrent effect from darkness on cyclists. However, this is only valid

when using modal share as a proxy for cycling culture. An additional unintentional proxy was also revealed here, where using bicycle-sharing metrics might provide a valid proxy for cycling culture in future research.

H5-H7: the findings support the hypothesis that locations with higher proportion of utilitarian cycling, closer to the city centre, and with street lighting installed will show a smaller deterrent effect from darkness on cyclists to varying degrees.

The chapter then discussed limitations of the analyses including sample size issues, reliability of data collected, and further unexplored macro and microscale factors. To address some limitations, an exploration of five additional cities was introduced through a parallel coauthored study.

The conclusion for this thesis is discussed in chapter **8**.

Chapter 8. Conclusion

8.1. The impact of darkness across different influences

The main aim of this thesis was to investigate the effect of darkness on the number of people cycling. The reviewed literature revealed a methodological limitation in previous studies investigating the effect of darkness using a case-control method, which is the choice of case and control hours. Previous studies used only a small selection of the multiple combinations of case and control hours that were possible. To assess what impact the selective use of case and control hours has on conclusions about the effect of darkness on cycling, this thesis analysed automated cycling counter data from 15 cities using the case-control method to establish an odds ratio (OR) for every possible combination of case and control hour, producing an average of approximately 55 ORs per city. These OR arrays showed significant variation across different choices of case and control hours in each city, confirming the impact of hour selection on ORs produced. Thus, a revised method was introduced to calculate a single OR that considers all combinations of case and control hours.

The revised case-control method produced one summary OR per city. These weighted ORs confirmed that darkness significantly reduces the number of people cycling, with weighted ORs significantly greater than 1.0 in 14 out of the 15 cities, suggesting the effect of darkness may be mediated by a range of possible factors.

To explore causes of this variation at a city (macro) scale, two factors were identified: latitude and cycling culture. The association between the weighted ORs and each factor was assessed using linear regression. While this initially indicated statistically significant associations with latitude and cycling modal share (as a proxy for cycling culture), re-estimation using log-transformed ORs shows that only the association with latitude remained supported. ORs tend to decrease in locations higher in latitude, suggesting that such locations are more resilient to the deterrent effect of darkness. ORs may also decrease in locations with greater cycling culture (proxied by modal share), although the association is no longer statistically supported following re-estimation and may therefore require further investigation.

To explore causes of variation at the journey (micro) scale, five microscale factors were identified: journey type, distance to city centre, presence of lighting, latitude, and the number of cyclists. To assess their influence within cities, weighted ORs were established for 74 counting sites within five cities. The association between these ORs and each factor was assessed using linear regression, followed by a stepwise regression analysis where all factors were added to one model. The results confirmed an association, indicating that ORs tend to decrease in locations that are dominated by utilitarian cycling and closer to the city centres, and to a lesser extent in locations that are higher in latitude, experience higher cycling volumes, and are lit after dark. Distance to city centre was shown to have the strongest influence on OR variation, followed by journey type. The presence of lighting, counter latitude, and number of cyclists showed weaker associations. A re-estimation using log-transformed ORs improved the performance for several of the models and remained statistically significant.

While these findings support all seven hypotheses made in this thesis, the analysis is subject to several limitations that highlight the need for further investigation. Three categories of limitations were identified: limited sample size and representation, reliability of supporting data, and further unexplored macro and microscale factors. To address these limitations, the following section introduces recommendations for consideration in future work.

8.2. Recommendations for future research

The research reported in this thesis and the limitations identified in it highlight two areas that may be suitable for future research.

First, while the thesis expanded the geographical scope of previous work investigating the impact of darkness on cycling by analysing 15 cities with varying latitudes and cycling cultures, it lacked representation from counties with harsher climates (e.g. arid or tropical) and lower socioeconomics (e.g. Sub-Saharan Africa). Including such countries in future research may reveal how factors like very high temperatures, lower income – and by extension less car ownership– and limited lighting infrastructure could

influence the impact of darkness on cycling. One possible limitation to overcome here is the scarcity of cycling data from developing countries.

Second, Using Luko's cycling-friendliness index (see chapter **4**), the final score established for the 12 cities analysed showed little to no association with the ORs established for them. However, using Luko's bicycle-sharing score tentatively suggested that better bicycle sharing programs can reduce the impact of darkness on cycling. There is some support for this in previous research by Zacharias and Meng [2021], but it may suggest a mutually reinforcing relationship, as their findings report that the presence of lighting is one reason for uptake of shared dockless bicycles. Thus, it may be useful for future research to investigate this relationship. This may also offer support for the recommendation made the end of chapter **4**, where bicycle sharing performance was proposed as a suitable proxy for cycling culture to be used to understand the impact of darkness in future studies (see section **4.3**).

Appendices

Appendix A. Automated counter locations

Table A.1. A list of counting locations in **Antwerp**, Belgium, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Eilandje (Fietsmeetnet 09 TOT)	51°13'52.99"N	4°24'20.34"E
2	Oosterweelsteenweg (HAV02)	51°14'59.01"N	4°23'16.67"E
3	Noorderlaanbrug (HAV01)	51°14'32.99"N	4°25'12.17"E
4	Fietsbrug Ijzerenlaan (FMN 10)	51°14'9.03"N	4°25'52.19"E
5	Schijnpoortweg (FMN 08)	51°13'45.09"N	4°26'30.66"E
6	Tussen Turnhoutsebaan en Schijnpoort (ANTS6)	51°13'29.17"N	4°26'40.74"E
7	Statielei (FMN 12)	51°12'57.51"N	4°26'44.87"E
8	Tussen Plantin (ants5)	51°12'34.08"N	4°26'29.08"E
9	Zurenborgbrug Ringfietspad (FMN 6 B)	51°12'11.85"N	4°26'23.62"E
10	Zurenborgbrug (FMN 06 A)	51°12'11.34"N	4°26'22.29"E
11	Borsbeekbrug richting Antwerpen (AFP01)	51°12'2.25"N	4°26'17.33"E
12	Posthofbrug 5366 (FMN GV 16 Berchem TOT)	51°11'51.77"N	4°25'59.68"E
13	Posthofbrug richting Mortsel (AFP04)	51°11'52.87"N	4°25'55.22"E
14	Tussen N1 en Posthofbrug (ANTS3)	51°11'45.46"N	4°25'44.71"E
15	Posthofbrug richting Antwerpen (AFP03)	51°11'41.60"N	4°26'5.21"E
16	Fietsbrug Berchem (AFP06)	51°11'30.64"N	4°25'47.21"E
17	Grotesteenweg richting Mortsel (AFP08)	51°11'30.41"N	4°25'20.95"E
18	Tussen E19 en Grotesteenweg (N1) (ANTS2)	51°11'32.05"N	4°25'15.18"E
19	Gerard Le Grellelaan (FMN 05)	51°11'25.66"N	4°24'21.91"E
20	Ringfietspad onder Jan Van Rijswijcklaan (FMN 11 A)	51°11'32.16"N	4°24'3.73"E
21	Jan Van Rijswijcklaan (FMN 04)	51°11'33.23"N	4°24'1.70"E
22	Desguinlei 25 (ANTB1)	51°11'38.35"N	4°24'12.65"E
23	Desguinlei 94 (AFP13)	51°11'39.07"N	4°24'19.80"E
24	Kolonel Silvertopstraat (FMN 03)	51°11'47.93"N	4°23'21.33"E
25	Mercatorstraat (FMN Antwerpen 02 TOT)	51°12'32.37"N	4°25'22.84"E
26	Tussen Wapenstilstandlaan en Plantin en Moret (ANTS4)	51°12'24.45"N	4°26'22.61"E
27	Antwerpsebaan (HAV03)	51°19'26.92"N	4°20'47.64"E
28	Noordlandbrug (HAV01)	51°22'6.70"N	4°17'55.77"E
29	Steenplein (FMN 01)	51°13'9.07"N	4°23'44.20"E
30	FoS Kapellen-Ekeren Oude Landen (EKE20)	51°16'36.43"N	4°25'57.12"E

Table A.2. A list of counting locations in **Arlington**, VA, USA, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Military SB bike lane 1	38° 54' 20.61" N	77° 6' 35" W
2	Military SB bike lane 2	38° 54' 19.98" N	77° 6' 33.74" W
3	key bridge west	38° 54' 2" N	77° 4' 15.13" W
4	key bridge east	38° 54' 1.63" N	77° 4' 14.28" W
5	Rosslyn barometer	38° 53' 56.75" N	77° 4' 15.79" W
6	TR Island bridge	38° 53' 52.67" N	77° 4' 3.72" W
7	Custice Rosslyn	38° 53' 49.58" N	77° 5' 0.59" W
8	Roosevelt bridge	38° 53' 38.51" N	77° 3' 56.83" W
9	Wilon WB bike lane	38° 53' 23.58" N	77° 5' 24.65" W
10	Clarendon EB bike lane	38° 53' 19.65" N	77° 5' 25.49" W
11	Fairfax WB	38° 53' 0.02" N	77° 6' 13.61" W
12	Fairfax EB	38° 52' 57.96" N	77° 6' 16.58" W
13	Quincy NB	38° 53' 7.68" N	77° 6' 29.1" W
14	Quincy SB	38° 53' 5.56" N	77° 6' 29.22" W
15	Bluemont connector	38° 52' 49.66" N	77° 7' 9.54" W
16	Ballston connector	38° 52' 58.64" N	77° 7' 16.34" W
17	W&OD bon air west	38° 52' 45.73" N	77° 8' 21.4" W
18	custis bon air park	38° 52' 45.2" N	77° 8' 18.46" W
19	W&OD bon air park	38° 52' 44.35" N	77° 8' 18.83" W
20	14th street bridge	38° 52' 27.34" N	77° 2' 40.57" W
21	Joyce street NB	38° 52' 2.25" N	77° 3' 46.22" W
22	Joyce street SB	38° 52' 2.24" N	77° 3' 46.95" W
23	W&OD columbia pike	38° 51' 25.58" N	77° 6' 38.85" W
24	cc connector	38° 51' 27.25" N	77° 2' 49.89" W
25	crystal NB bike lane	38° 51' 26.45" N	77° 2' 57.02" W
26	Eads NB	38° 51' 28.76" N	77° 3' 11.18" W
27	Eads SB	38° 51' 34.28" N	77° 3' 12.67" W
28	Arlington mill trail	38° 50' 44.26" N	77° 5' 45.87" W

Table A.3. A list of counting locations in **Auckland**, New Zealand, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Beach Road	36°50'57.79"S	174°46'27.93"E
2	Carlton Gore Road	36°51'51.60"S	174°46'21.18"E
3	Curran Street	36°50'21.90"S	174°44'21.77"E
4	Dominion Road	36°52'13.40"S	174°45'10.59"E
5	East Coast Road	36°44'30.35"S	174°44'28.67"E
6	Glenn Innes to Tamaki Drive Section	36°52'25.11"S	174°51'2.61"E
7	Grafton Bridge	6°51'36.32"S	174°45'59.39"E
8	Grafton Gully	36°51'19.90"S	174°46'6.89"E
9	Great North Road	36°51'53.83"S	174°44'43.91"E
10	Great South Road Manukau	36°59'13.68"S	174°52'54.47"E
11	Hopetoun Street	36°51'21.96"S	174°45'27.09"E
12	Lagoon Drive	36°54'25.71"S	174°51'27.23"E
13	Lake road	36°48'9.54"S	174°47'14.81"E
14	Leigh Road	36°21'6.96"S	174°43'6.36"E
15	Lightpath 2	36°51'12.54"S	174°45'27.39"E
16	Mangere Bridge	36°55'56.46"S	174°47'10.64"E
17	Mangere Safe Routes	36°58'20.35"S	174°47'58.40"E
18	Nelson Street	36°50'59.61"S	174°45'32.50"E
19	Nw Cycleway Kingsland	36°52'8.88"S	174°44'38.47"E
20	Nw Cycleway Teatatu	36°51'30.33"S	174°39'13.46"E
21	Oceanview Road	36°47'1.35"S	175° 0'41.43"E
22	Orewa Path	36°35'46.89"S	174°41'38.59"E
23	Ormiston Road	36°57'54.64"S	174°54'33.45"E
24	Quay Street Eco Display Classic	36°50'34.26"S	174°45'53.43"E
25	Quay Street Spark Arena	36°50'47.40"S	174°46'40.31"E
26	Queen Street Pukekohe	37°12'13.13"S	174°54'3.49"E
27	Rankin Avenue	36°54'43.45"S	174°40'55.59"E
28	Saint Lukes Road	36°52'16.17"S	174°43'32.74"E
29	SH18 Upper Harbour Drive	36°46'56.22"S	174°40'31.17"E
30	SH20A	36°58'40.14"S	174°47'11.40"E
31	SW SH20	36°54'43.52"S	174°44'24.33"E
32	Symonds Street	36°51'35.16"S	174°45'45.61"E
33	Tamaki Drive Wb	36°50'52.59"S	174°47'20.56"E
34	Teatatu Peninsula	36°50'59.60"S	174°39'5.03"E
35	Twin Streams	36°52'43.69"S	174°37'26.82"E
36	Upper Queen Street	36°51'33.42"S	174°45'38.34"E
37	Waterview Unitec	36°52'57.98"S	174°42'16.87"E

Table A.4. A list of counting locations in **Berlin**, Germany, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Paul-und-Paula-Uferweg	52°30'0.89"N	13°28'27.78"E
2	Schwedter Steg	52°32'55.81"N	13°24'1.32"E
3	Maybachufer	52°29'35.43"N	13°25'44.95"
4	Jannowitzbrücke Nord	52°30'50.16"N	13°25'4.20"E
5	Jannowitzbrücke Süd	52°30'50.20"N	13°25'3.40"E
6	Prinzregentenstraße	52°29'17.31"N	13°19'59.21"E
7	Yorckstraße Ost	52°29'32.21"N	13°22'23.53"E
8	Monumentenstraße	52°29'17.23"N	13°22'11.24"E
9	Markstraße	52°33'29.48"N	13°21'53.71"E
10	Invalidenstraße Ost	52°31'37.83"N	13°22'19.27"E
11	Invalidenstraße West	52°31'39.69"N	13°22'23.16"E
12	Oberbaumbrücke Ost	52°30'4.32"N	13°26'42.21"E
13	Oberbaumbrücke West	52°30'4.60"N	13°26'41.51"E
14	Alberichstraße	52°29'33.01"N	13°33'30.58"E
15	Berliner Straße Nord	52°34'0.94"N	13°24'44.96"E
16	Berliner Straße Süd	52°34'0.53"N	13°24'43.78"E
17	Klosterstraße Süd	52°31'59.90"N	13°11'54.50"E
18	Klosterstraße Nord	52°32'0.53"N	13°11'56.85"E
19	Breitenbachplatz Ost	52°28'0.29"N	13°18'33.11"E
20	Breitenbachplatz West	52°28'2.01"N	13°18'30.08"E
21	Mariendorfer Damm Nord	52°26'16.41"N	13°23'16.30"E
22	Mariendorfer Damm Süd	52°26'17.53"N	13°23'16.99"E
23	Kaisersteg	52°27'26.11"N	13°31'7.54"E
24	Frankfurter Allee Ost	52°30'49.05"N	13°28'27.18"E
25	Frankfurter Allee West	52°30'49.84"N	13°28'27.76"E
26	Straße des 17. Juni Ost	52°30'45.63"N	13°19'35.86"E
27	Straße des 17. Juni West	52°30'47.29"N	13°19'36.66"E
28	Karl-Marx-Allee	52°31'18.81"N	13°25'3.12"E

Table A.5. A list of counting locations in **Birmingham**, UK, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Pershore road	52° 27' 39.04" N	1° 54' 8.61" W
2	Birmingham and Fazeley Canal	52° 29' 49.04" N	1° 52' 45.6" W
3	Rea valley cycleway	52° 26' 48.25" N	1° 54' 37.85" W
4	Elmstead avenue	52° 27' 49.22" N	1° 46' 8.63" W
5	Ebrook road 1	52° 33' 23.07" N	1° 48' 48.14" W
6	Hazel well road	52° 25' 36.81" N	1° 55' 4.84" W

ID	Counter location	Coordinates (DMS)	
7	Wylde green road	52° 32' 33.47" N	1° 48' 26.01" W
8	Birmingham and Warwick canal	52° 29' 11.35" N	1° 51' 48.3" W
9	Worcester and Birmingham Canal 1	52° 28' 20.88" N	1° 54' 41.48" W
10	Birmingham Canal 1	52° 28' 52.37" N	1° 55' 26.9" W
11	Birmingham Canal 2	52° 28' 44.89" N	1° 55' 11.54" W
12	Harborne road	52° 28' 20.84" N	1° 55' 8.4" W
13	Ulwine drive 1	52° 24' 53.76" N	1° 58' 23.45" W
14	Ulwine drive 2	52° 24' 53.47" N	1° 58' 22.24" W
15	Deykin Avenue	52° 30' 56.19" N	1° 52' 10.46" W
16	Marsh hill	52° 31' 27.78" N	1° 52' 17.1" W
17	Icknield port road	52° 29' 5.47" N	1° 56' 11.51" W
18	Pershore road south	52° 24' 37.39" N	1° 55' 44.64" W
19	Penns lane	52° 32' 5.39" N	1° 48' 38.39" W
20	Longmore street	52° 27' 47.01" N	1° 53' 37.44" W
21	Clifton road	52° 33' 42.88" N	1° 49' 55.66" W
22	Orphanage road	52° 31' 33.03" N	1° 50' 12.76" W
23	Moseley road	52° 27' 22.1" N	1° 53' 10" W
24	Valentine road	52° 26' 17.16" N	1° 53' 26.16" W
25	High street	52° 26' 1.92" N	1° 53' 34.67" W
26	Bordesley Green east	52° 28' 46.9" N	1° 49' 22.65" W
27	Hurst street	52° 28' 22.78" N	1° 53' 43.34" W
28	Gooch street	52° 28' 1.18" N	1° 53' 35.49" W
29	Bristol Road 1	52° 26' 48.72" N	1° 55' 45.38" W
30	Severn street	52° 28' 34.87" N	1° 54' 11.93" W
31	Newhall street	52° 28' 59.38" N	1° 54' 19.19" W
32	New Town Row	52° 29' 25.14" N	1° 53' 42.29" W
33	Fazeley Street	52° 28' 47.64" N	1° 53' 12.69" W
34	Wellhead Lane	52° 30' 57.54" N	1° 53' 46.37" W
35	Ebrook Road 2	52° 33' 34.23" N	1° 49' 4.5" W
36	Park Road	52° 33' 50.59" N	1° 49' 36.67" W
37	Sherlock street	52° 28' 3.11" N	1° 53' 49.69" W
38	Bristol Road 2	52° 26' 30.38" N	1° 56' 16.71" W
39	Worcester and Birmingham Canal 2	52° 26' 27.17" N	1° 56' 9.38" W
40	Grand Union Canal 1	52° 27' 37.62" N	1° 50' 16.49" W
41	Hagley Road	52° 28' 18.6" N	1° 55' 45.4" W
42	Grand Union Canal 2	52° 28' 22.91" N	1° 52' 35.08" W
43	Colehall Lane	52° 29' 41.37" N	1° 47' 25.56" W
44	Fort Parkway	52° 30' 45.12" N	1° 48' 16.88" W
45	Small Heath Highway	52° 27' 41.8" N	1° 50' 39.05" W
46	Manor Farm Roa	52° 27' 16.56" N	1° 51' 6.95" W
47	Bordesley Middleway	52° 28' 13.42" N	1° 52' 34.89" W
48	Soho Road	52° 30' 15.55" N	1° 56' 23.29" W

Table A.6. A list of counting locations in **Dublin**, Ireland, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Grove road totem	53° 19' 46.57" N	6° 16' 12.6" W
2	Northern strand road SB	53° 21' 26.75" N	6° 14' 45.79" W
3	Northern strand road NB	53° 21' 26.05" N	6° 14' 42.61" W
4	Guild street	53° 20' 53.53" N	6° 14' 27.52" W
5	Charvelle mall	53° 21' 24.21" N	6° 14' 41.12" W

Table A.7. A list of counting locations in **Edinburgh**, Scotland, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Silverknowes	55°58'44.19"N	3°17'18.64"W
2	RBS Gogar	55°56'11.83"N	3°20'13.13"W
3	Cultins Road	55°55'44.31"N	3°18'23.49"W
4	North Edinburgh Access Road	55°58'6.10"N	3°14'21.09"W
5	Middle Meadow Walk	55°56'33.72"N	3°11'28.90"W
6	Spylaw Park	55°54'23.70"N	3°15'41.76"W
7	Portobello Prom	55°57'24.10"N	3° 6'56.24"W

Table A.8. A list of counting locations in **Helsinki**, Finland, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Kaisaniemi	60°10'41.51"N	24°56'25.75"E
2	Eteläesplanadi	60°10'1.96"N	24°56'41.01"E
3	Baana	60°10'11.43"N	24°55'41.71"E
4	Lauttasaaren silta eteläpuoli	60° 9'41.10"N	24°53'38.20"E
5	Lauttasaaren silta pohjoispuoli	60° 9'46.00"N	24°54'1.29"E
6	Kulosaaren silta et. sisältää myös pohjoispuolen	60°11'7.53"N	24°59'34.61"E
7	Kuusisaarentie	60°11'15.25"N	24°52'21.11"E
8	Munkkiniemi silta pohjoispuoli	60°11'45.49"N	24°53'17.16"E
9	Munkkiniemen silta eteläpuoli	60°11'44.48"N	24°53'16.09"E
10	Heperian puisto (Ooppera)	60°10'51.54"N	24°55'51.91"E
11	Pitkäsilta länsipuoli	60°10'33.83"N	24°57'0.01"E
12	Pitkäsilta itäpuoli	60°10'36.18"N	24°57'1.21"E
13	Merikannontie	60°10'36.01"N	24°54'49.87"E
14	Kulosaaren silta po. suljettu	60°11'10.32"N	24°59'34.11"E
15	Ratapihantie	60°12'2.39"N	24°56'0.09"E
16	Kaivokatu	60°10'13.92"N	24°56'30.24"E

ID	Counter location	Coordinates (DMS)	
17	Käpylä	60°13'7.55"N	24°56'37.80"E
18	Viikintie	60°13'28.80"N	24°59'47.80"E
19	Auroransilta	60°11'28.40"N	24°55'29.69"E

Table A.9 A list of counting locations in **Leeds**, UK, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	A647 Bradford Road Cycle Superhighway (EB)	53° 48' 10.44" N	1° 41' 57.91" W
2	A647 Bradford Road Cycle Superhighway (WB)	53° 48' 10.94" N	1° 41' 51" W
3	Kirkstall Forge Canal Towpath Cycle Counter	53° 49' 22.98" N	1° 37' 21.43" W
4	Cardigan Lane Cycle Counter	53° 48' 47.09" N	1° 34' 22.04" W
5	Stanningley Road Cycle Superhighway (eastbound)	53° 48' 20.56" N	1° 37' 43.46" W
6	Stanningley Road Cycle Superhighway (westbound)	53° 48' 20.16" N	1° 37' 43.03" W
7	Canal Tow Path Armley Mills	53° 48' 7.02" N	1° 34' 43.46" W
8	Wellington Road Cycle Path	53° 47' 44.59" N	1° 33' 49.1" W
9	Armley Road Cycle Superhighway	53° 47' 50.64" N	1° 34' 22.48" W
10	Wellington Street Eastbound Cycle Lane	53° 47' 48.62" N	1° 33' 21.46" W
11	Wellington Street Westbound Cycle Lane	53° 47' 48.23" N	1° 33' 22.25" W
12	Meanwood Road Cycle Path	53° 48' 54.68" N	1° 32' 44.48" W
13	Meanwood Road Cycle Counter Sheepscar	53° 48' 28.73" N	1° 32' 11.51" W
14	Ring Road Cycle Superhighway (e of king lane)	53° 50' 52.22" N	1° 32' 34.22" W
15	Ring Road Cycle Superhighway (w of birchwood hill)	53° 50' 58.38" N	1° 30' 52.02" W
16	Ring Road Cycle Superhighway (e of roundhay park)	53° 50' 53.2" N	1° 29' 52.44" W
17	Wykebeck Woods Cycle Path	53° 49' 45.19" N	1° 29' 18.31" W
18	York Road Cycle Superhighway (killingbeck EB)	53° 48' 24.59" N	1° 28' 21.83" W
19	York Road Cycle Superhighway (killingbeck WB)	53° 48' 24.98" N	1° 28' 13.4" W
20	Grape Street Cycle Counter	53° 47' 7.69" N	1° 31' 58.73" W
21	Hunslet Road Cycle Counter	53° 47' 8.66" N	1° 31' 57.54" W
22	Regent Street Cycle Counter (s of gower street)	53° 48' 2.02" N	1° 32' 1.57" W
23	Regent Street Cycle Counter (s of hope road)	53° 48' 4.5" N	1° 31' 59.59" W
24	York Road Cycle Superhighway (burmantofts WB)	53° 47' 50.82" N	1° 30' 56.99" W
25	St Peters Street Cycle Lane	53° 47' 50.57" N	1° 32' 4.56" W
26	Marsh Lane Cycle Route	53° 47' 50.64" N	1° 31' 45.05" W
27	A647 Bradford Road Cycle Superhighway (eastbound)	53° 48' 10.44" N	1° 41' 57.91" W

Table A.10. A list of counting locations in **Münster**, Germany, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Kanalpromenade	51°55'2.52"N	7°38'57.00"E
2	Neutor	51°58'1.15"N	7°36'55.58"E
3	Warendorfer Straße	51°57'42.73"N	7°38'15.14"E
4	Hüfferstraße	51°57'42.73"N	7°36'39.23"E
5	Weseler Straße	51°57'2.06"N	7°37'3.75"E
6	Hammer Straße	51°57'16.24"N	7°37'34.61"E
7	Gartenstraße	51°58'17.48"N	7°38'8.12"E
8	Promenade	51°57'38.15"N	7°38'2.54"E

Table A.11. A list of counting locations in **Montreal**, Canada, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Maisonneuve / Peel	45°30'1.79"N	73°34'29.85"W
2	Rachel / Papineau	45°31'49.62"N	73°34'10.41"W
3	Berri1	45°30'58.33"N	73°33'46.59"W
4	Parc Stanley	45°33'27.34"N	73°40'23.52"W
5	Pont Jacques-Cartier	45°31'31.80"N	73°33'15.85"W
6	Pierre-Dupuy	45°30'4.58"N	73°32'39.73"W
7	Côte Sainte-Catherine / Stuart	45°30'53.61"N	73°36'26.94"W
8	Parc / Duluth	45°30'50.17"N	73°34'52.92"W
9	Brébeuf / Rachel	45°31'38.93"N	73°34'27.33"W
10	Métro Laurier	45°31'40.11"N	73°35'19.71"W
11	Saint-Antoine	45°30'22.55"N	73°33'27.91"W
12	René-Lévesque / Wolfe	45°31'1.16"N	73°33'14.45"W
13	Maisonneuve / Marcil	45°28'13.82"N	73°36'34.40"W
14	Rachel / Hôtel-de-Ville	45°31'10.73"N	73°34'48.79"W
15	Boyer / Rosemont	45°32'1.14"N	73°35'40.41"W
16	University / Milton	45°30'22.05"N	73°34'33.00"W
17	Saint-Urbain	45°31'9.75"N	73°35'19.02"W
18	Saint-Laurent/Bellechasse	45°31'40.14"N	73°36'11.17"W
19	Gouin / Lajeunesse	45°33'27.56"N	73°40'24.29"W
20	Boyer / Everett	45°32'36.42"N	73°37'0.00"W
21	Christophe-Colomb/Louvain	45°33'27.85"N	73°38'47.90"W
22	Edmond Valade	45°32'30.04"N	73°41'4.06"W
23	Notre-Dame	45°31'48.77"N	73°32'39.87"W
24	Viger / Saint-Urbain	45°30'21.59"N	73°33'34.51"W
25	Rachel 3 (Angus)	45°32'35.80"N	73°33'42.83"W
26	Pont Ile Bizard	45°29'10.39"N	73°51'57.82"W
27	Pont Le Gardeur	45°42'3.21"N	73°28'59.69"W

ID	Counter location	Coordinates (DMS)	
28	Piste Des Carriéres	45°32'2.96"N	73°35'29.21"W
29	Estacade	45°28'0.32"N	73°32'1.85"W
30	Notre-Dame Est / Bellerive	45°35'30.95"N	73°30'36.04"W
31	Bennett / Ontario	45°33'18.32"N	73°32'19.67"W
32	Sainte-Croix / Du Collége Sainte-Croix	45°30'42.28"N	73°40'21.14"W
33	Bord-du-Lac vers est	45°26'48.92"N	73°46'58.02"W
34	Bord-du-Lac vers ouest	45°26'49.20"N	73°46'57.45"W
35	Valois / la Fontaine	45°32'48.63"N	73°32'32.56"W
36	Souligny / Saint-Émile	45°35'43.92"N	73°31'13.58"W
37	16e Avenue / Bélanger	45°33'38.57"N	73°35'26.35"W
38	Maisonneuve / Plessis	45°31'16.81"N	73°33'19.75"W
39	Maurice-Duplessis	45°39'32.91"N	73°32'32.91"W
40	Maisonneuve / Berri	45°30'53.72"N	73°33'40.96"W

Table A.12. A list of counting locations in **New York**, NY, USA, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Staten Island Ferry	40° 38' 36.19" N	74° 4' 19.47" W
2	2nd Avenue - 26th St S	40° 44' 22.96" N	73° 58' 46.34" W
3	Forsyth Plaza	40° 42' 56.24" N	73° 59' 41.08" W
4	Manhattan Bridge	40° 41' 59.16" N	73° 59' 8.95" W
5	Williamsburg Bridge Bike Path	40° 42' 37.91" N	73° 57' 41.22" W
6	1st Avenue - 26th St N - Interference testing	40° 44' 19.79" N	73° 58' 37.79" W
7	Ed Koch Queensboro Bridge Shared Path	40° 45' 3.64" N	73° 56' 25.62" W

Table A.13. A list of 12 counting locations in **Oslo**, Norway, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Dr Eufemias vest	59°54'31.47"N	10°45'17.27"E
2	Dr Eufemias ost	59°54'31.18"N	10°45'14.35"E
3	lysaker	59°54'48.10"N	10°38'32.41"E
4	frognerst	59°54'40.26"N	10°42'14.26"E
5	Skullerod	59°52'9.11"N	10°49'46.91"E
6	Bryn	59°54'7.42"N	10°49'10.01"E
7	Breivol	59°55'23.02"N	10°49'52.95"E
8	Smestad	59°56'19.56"N	10°41'13.92"E
9	Gaustad	59°56'44.78"N	10°42'48.22"E
10	Munkedamsvein	59°54'40.38"N	10°43'32.44"E
11	Grorud	59°57'1.94"N	10°53'46.14"E
12	Akkersyke	59°56'24.48"N	10°47'31.32"E

Table A.14. A list of counting locations in **Paris**, France, arranged by order of appearance in source data.

ID	Counter location	Coordinates (DMS)	
1	Avenue Denfert Rochereau SO-NE	48° 50' 4.9" N	2° 19' 58.68" E
2	Avenue Denfert Rochereau NE-SO	48° 50' 6.51" N	2° 19' 58.91" E
3	Boulevard Voltaire SE-NO	48° 51' 41.36" N	2° 22' 25.54" E
4	Boulevard Voltaire NO-SE	48° 51' 41.58" N	2° 22' 26.65" E
5	Avenue de la Grande Armée SE-NO	48° 52' 28.98" N	2° 17' 32.78" E
6	Rue La Fayette E-O	48° 52' 39.6" N	2° 21' 2" E
7	Rue La Fayette O-E	48° 52' 38.86" N	2° 21' 0.29" E
8	Avenue Daumesnil SE-NO	48° 50' 36.37" N	2° 23' 0.16" E
9	Boulevard Diderot	48° 50' 45.7" N	2° 22' 31.54" E
10	Boulevard Diderot E-O	48° 50' 45.96" N	2° 22' 31.64" E
11	Quai François Mauriac	48° 50' 3.85" N	2° 22' 36.99" E
12	Quai de l'Hôtel de ville	48° 51' 13.39" N	2° 21' 25.27" E
13	Oie Georges Pompidou	48° 50' 54.24" N	2° 16' 33.36" E
14	Avenue de la Grande Armée NO-SE	48° 52' 28.24" N	2° 17' 31.74" E
15	Avenue de la Porte des Ternes E-O	48° 52' 54.52" N	2° 16' 53.57" E
16	Pont du Garigliano NO-SE	48° 50' 23.74" N	2° 16' 1.74" E
17	Ace au 16 Avenue de la Porte des Ternes O-E	48° 52' 53.85" N	2° 16' 52.33" E
18	Avenue de la Porte des Ternes E-O	48° 52' 54.52" N	2° 16' 53.57" E
19	Boulevard Auguste Blanqui SO-NE	48° 49' 49.62" N	2° 21' 11.52" E
20	Bd Richard Lenoir S-N	48° 51' 38.77" N	2° 22' 21.87" E
21	Face au 70 Quai de Bercy	48° 49' 46.28" N	2° 23' 13.16" E
22	Rue Julia Bartet	48° 49' 35.33" N	2° 18' 11.34" E
23	Face au 25 quai de l'Oise	48° 53' 29.09" N	2° 23' 5.83" E
24	Boulevard du Montparnasse	48° 50' 26.88" N	2° 19' 59.64" E
25	Bd Auguste Blanqui NE-SO	48° 49' 51.24" N	2° 21' 11.65" E
26	Rue de Rivoli	48° 51' 26.46" N	2° 21' 7.6" E
27	Avenue Flandre SO-NE	48° 53' 20.57" N	2° 22' 29.54" E
28	Avenue de Flandre NE-SO	48° 53' 21.34" N	2° 22' 28.99" E
29	Rue Lecourbe SO-NE	48° 50' 31.53" N	2° 18' 3.6" E
30	avenue d'Italie S-N	48° 49' 12.94" N	2° 21' 33.12" E
31	Avenue d'Italie N-S	48° 49' 12.86" N	2° 21' 32.47" E
32	Boulevard Saint Germain NO-SE	48° 51' 42.44" N	2° 19' 12.5" E
33	Avenue des Champs Elysées SE-NO	48° 52' 11.54" N	2° 18' 26.71" E
34	Avenue de la Porte de Bagnolet O-E	48° 51' 52.24" N	2° 24' 33.55" E
35	Avenue des Champs Elysées NO-SE	48° 52' 11.39" N	2° 18' 25.47" E
36	Boulevard de Magenta NO-SE	48° 52' 39.67" N	2° 21' 16.1" E
37	Boulevard de Ménilmontant SE-NO	48° 51' 38.24" N	2° 23' 19.41" E
38	Face au 48 quai de la marne	48° 53' 28.37" N	2° 23' 8.63" E
39	Richard linor opposite	48° 51' 39.07" N	2° 22' 20.2" E
40	Rue d'Aubervilliers	48° 53' 25.65" N	2° 22' 7.87" E
41	Pont du Garigliano SE-NO	48° 50' 23.58" N	2° 16' 1.56" E

ID	Counter location	Coordinates (DMS)	
42	Boulevard de Menilmontant NO-SE	48° 51' 37.9" N	2° 23' 18.11" E
43	Bd magenta SE-NO	48° 52' 39.81" N	2° 21' 17.73" E
44	Pont National SO-N	48° 49' 35.41" N	2° 23' 3.62" E
45	Pont National NE-SO	48° 49' 36.55" N	2° 23' 4.74" E
46	Pont de la Concorde N-S	48° 51' 50.11" N	2° 19' 11.57" E
47	Totem Cours la Reine	48° 51' 52.63" N	2° 18' 51.98" E
48	Totem 85 quai d'Austerlitz	48° 50' 31.24" N	2° 22' 2.24" E
49	Rue Lecourbe NE-SO	48° 50' 31.78" N	2° 18' 4.14" E
50	avenue de la Porte d'Orléans S-N	48° 49' 19.31" N	2° 19' 31.62" E
51	ace au 8 avenue de la porte de Charenton	48° 49' 49.19" N	2° 24' 1.98" E
52	Quai de la Tournelle	48° 51' 0.47" N	2° 21' 15.23" E
53	Totem 73 boulevard de Sébastopol	48° 51' 49.57" N	2° 21' 3.46" E
54	pont des Invalides S-N	48° 51' 46.15" N	2° 18' 38.2" E
55	avenue des Champs Elysées NO-SE	48° 52' 11.39" N	2° 18' 25.47" E

Table A.15. A list of counting locations in **Seattle**, WA, USA, arranged by order of appearance in source data.

ID	Counter location	Data range	Coordinates (DMS)	
1	Fremont Bridge	2014-2019	47°38'52.98"N	122°20'59.57"W
2	26th Ave – Delridge greenway	2014-2019	47°33'46.14"N	122°21'55.62"W
3	39th Ave	2014-2019	47°40'26.10"N	122°17'9.30"W
4	BGT North	2014-2019	47°40'45.99"N	122°15'55.27"W
5	Broadway	2014-2019	47°36'48.67"N	122°19'14.45"W
6	Elliot Bay	2014-2019	47°37'5.89"N	122°21'34.31"W
7	2nd Ave	2015-2019	47°36'18.44"N	122°20'5.99"W
8	MTS Trail (I-90)	2014-2019	47°35'25.83"N	122°17'11.67"W
9	NW 58TH St Greenway	2014-2019	47°40'15.62"N	122°23'5.50"W
10	Spokane St. bridge	2014-2019	47°34'17.90"N	122°20'42.29"W

Appendix B. Normalized number of cyclists

Table B.1. The number of cyclists calculated per 1000 inhabitants in **Antwerp**, Belgium.

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Total cyclists	129209	221643	2160968	2357221	2479294	2596343	10641126	11048115
No. of counters	2	2	2	10	9	10	14	13
Cyclists per location per year	64604.5	110821.5	1080484	235722.1	275477.1	259634.3	760080.4	849855
Average cyclist per location	454584.9							
City population	517042							
cyclists per 1000 inhabitants	879.203							

Table B.2. The number of cyclists calculated per 1000 inhabitants in **Arlington**, VA, USA.

	2012	**2013**	**2014**	**2015**
Total cyclists	2416757	2725701	3312526	4226429
No. of counters	18	22	23	25
Cyclists per location per year	134264.3	123895.5	144022.9	169057.2
Average cyclist per location	142810			
City population	238642			
cyclists per 1000 inhabitants	598.4276			

Table B.3. The number of cyclists calculated per 1000 inhabitants in **Auckland**, New Zealand.

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Total cyclists	458710	1199848	1145838	1530221	2453978	2869533	3487201	4075783
No. of counters	5	12	12	15	22	26	34	38
Cyclists per location per year	91742	99987.33	95486.5	102014.7	111544.5	110366.7	102564.7	107257.4
Average cyclist per location	102620.5							
City population	1654800							
cyclists per 1000 inhabitants	62.01383							

Table B.4. The number of cyclists calculated per 1000 inhabitants in **Berlin,** Germany.

	2016	**2017**	**2018**	**2019**
Total cyclists	13187649	19631392	21369545	18024377
No. of counters	26	26	26	26
Cyclists per location per year	507217.3	755053.5	821905.6	693245.3
Average cyclist per location	694355.4			
City population	3596999			
cyclists per 1000 inhabitants	193.0374			

Table B.5. The number of cyclists calculated per 1000 inhabitants in **Birmingham**, UK**.**

	2012	**2013**	**2014**	**2015**
Total cyclists	988846	1754167	1804232	1816478
No. of counters	43	43	43	48
Cyclists per location per year	22996.42	40794.58	41958.88	37843.29
Average cyclist per location	35898.29			
City population	1074283			
cyclists per 1000 inhabitants	33.41605			

Table B.6. The number of cyclists calculated per 1000 inhabitants in **Dublin**, Ireland.

	2019
Total cyclists	2635419
No. of counters	5
Cyclists per location per year	527083.8
Average cyclist per location	527083.8
City population	1263219
cyclists per 1000 inhabitants	417.2545

Table B.7. The number of cyclists calculated per 1000 inhabitants in **Edinburgh**, SCT, UK.

	2019
Total cyclists	1220556
No. of counters	7
Cyclists per location per year	174365.1
Average cyclist per location	174365.1
City population	529580
cyclists per 1000 inhabitants	329.2518

Table B.8. The number of cyclists calculated per 1000 inhabitants in **Helsinki**, Finland.

	2014	**2015**	**2016**	**2017**	**2018**	**2019**
Total cyclists	3501828	7500404	7662596	7690951	10431060	9544501
No. of counters	11	15	15	19	18	19
Cyclists per location per year	318348	500026.9	510839.7	404786.9	579503.3	502342.2
Average cyclist per location	469307.8					
City population	635181					
cyclists per 1000 inhabitants	738.8569					

Table B.9. The number of cyclists calculated per 1000 inhabitants in **Leeds**, UK.

	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Total cyclists	547	72302	177999	277327	301012	437696	874961	1098894	1220267	1618198
No. of counters	1	3	7	7	7	10	21	23	23	35
Cyclists per location per year	547	24100.67	25428.43	39618.14	43001.71	43769.6	41664.81	47778	53055.09	46234.23
Average cyclist per location	36519.77									
City population	809479									
cyclists per 1000 inhabitants	45.11515									

Table B.10. The number of cyclists calculated per 1000 inhabitants in **Münster**, Germany.

	2019
Total cyclists	18928099
No. of counters	9
Cyclists per location per year	2103122
Average cyclist per location	2103122
City population	303,772
cyclists per 1000 inhabitants	6923.36

Table B.11. The number of cyclists calculated per 1000 inhabitants in **Montreal**, Canada.

	2019
Total cyclists	10894250
No. of counters	42
Cyclists per location per year	259386.9
Average cyclist per location	259386.9
City population	1743687
cyclists per 1000 inhabitants	148.7577

Table B.12. The number of cyclists calculated per 1000 inhabitants in **New York**, NY,USA.

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Total cyclists	88283	140510	3988678	4950072	5565337	5162170	3771614	2901343
No. of counters	1	4	3	4	5	5	5	4
Cyclists per location per year	88283	35127.5	1329559	1237518	1113067	1032434	754322.8	725335.8
Average cyclist per location	789456							
City population	8804199							
cyclists per 1000 inhabitants	89.66812							

Table B.13. The number of cyclists calculated per 1000 inhabitants in **Oslo**, Norway.

	2018	2019
Total cyclists	2646417	2933624
No. of counters	12	12
Cyclists per location per year	220534.8	244468.7
Average cyclist per location	232501.7	
City population	693,494	
cyclists per 1000 inhabitants	335.26	

Table B.14. The number of cyclists calculated per 1000 inhabitants in **Paris**, France.

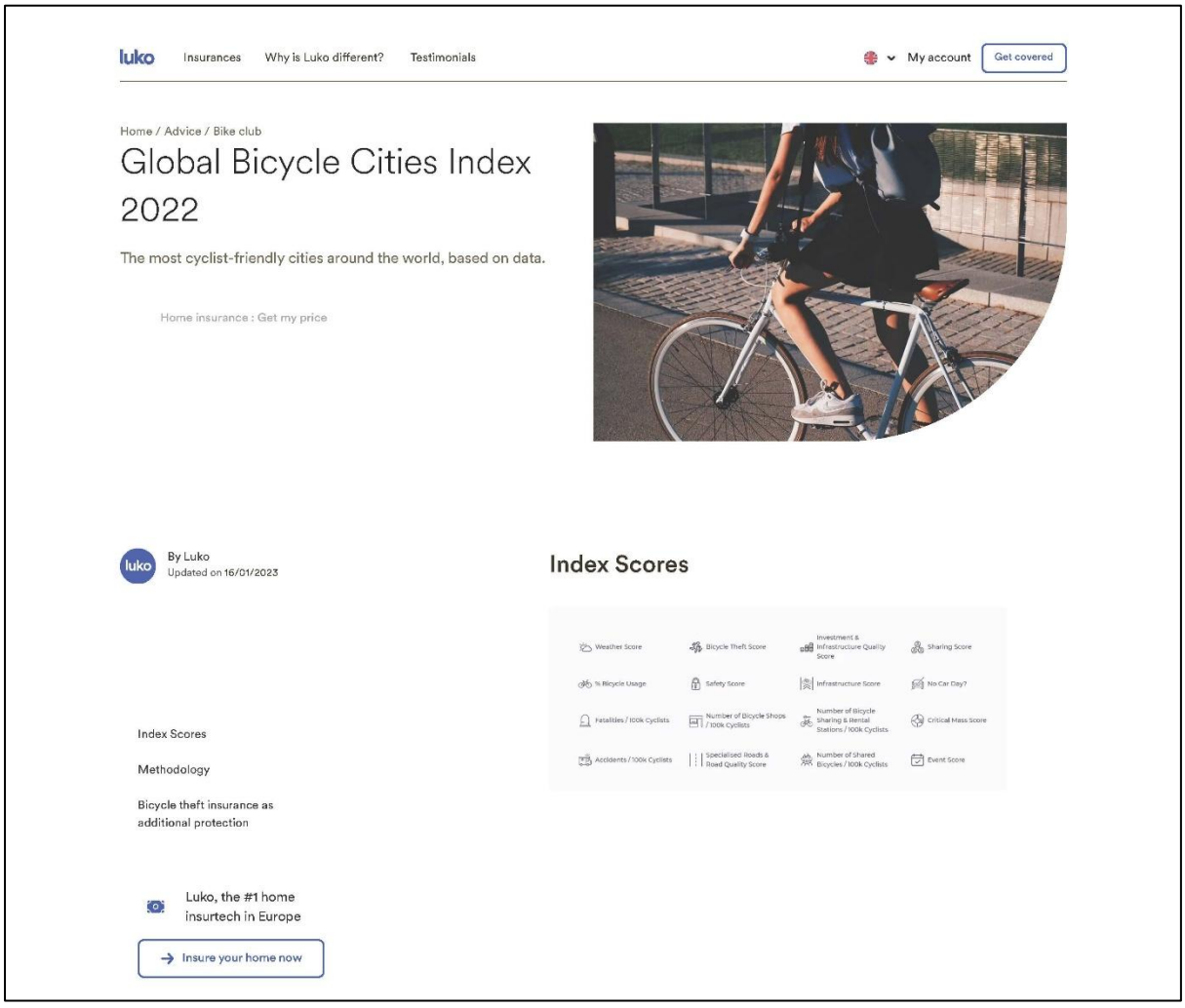
	2018	2019
Total cyclists	4383338	18924626
No. of counters	35	59
Cyclists per location per year	125238.2	320756.4
Average cyclist per location	222997.3	
City population	2113705	
cyclists per 1000 inhabitants	105.5007	

Table B.15. The number of cyclists calculated per 1000 inhabitants in **Seattle**, WA, USA.

	2014	2015	2016	2017	2018	2019
Total cyclists	4039310	3889249	3944226	3921853	4247714	4689654
No. of counters	9	10	10	10	10	10
Cyclists per location per year	448812.2	388924.9	394422.6	392185.3	424771.4	468965.4
Average cyclist per location	419680.3					
City population	737018					
cyclists per 1000 inhabitants	569.4302					

Appendix C. Luko's Global Bicycle Index – Saved website pages used for the analysis

The following webpages from Luko's 2022 Global Bicycle Cities Index were captured in 2023 while still publicly available on Luko's website (https://de.luko.eu/en/advice/guide/bike-index/). The Luko platform and its website are no longer accessible and now redirect visitors to *Getsafe*, a German digital insurance company, which has acquired Luko in October of 2023. These pages are included here solely for academic and non-commercial purposes to document the data source used in this research and to support reproducibility.



				Crime & Safety						Infrastructure				Dining				Events			
#	City	Country	Rev																		Total
1	Utrecht	Netherlands	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2	Munster	Germany	M	69.94	83.12%	0.83	446.33	83.94	66.40	28.13	50.25	66.34	51.13	28.62	25	31	X	12.64	440.58		66.33
3	Anywers	Belgium	S	63.07	89.99%	1.00	460.31	84.68	77.05	73.67	63.37	75.31	34.86	23.07	100	89	✓	14.10	462.61		68.01
4	Copenhagen	Denmark	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	✓	[illegible]	[illegible]		[illegible]
5	Amsterdam	Netherlands	M	62.42	82.58%	1.77	439.18	84.49	77.78	48.72	61.71	25.07	68.0	22.56	33.78	23	X	23.51	432.18		69.04
6	Malmö	Sweden	S	28.96	92.80%	4.27	453.8	86.37	61.69	55.32	53.4	91.65	42.55	90.8	94.92	90	X	7	453.31		62.68
7	Hangzhou	China	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
8	Bern	Switzerland	S	53.27	85.07%	3.63	432.36	75.75	84.00	46.96	65.46	33.73	85.1	71.15	32.52	64	✓	4.22	452.38		48.75
9	Bremen	Germany	M	[illegible]	[illegible]	1.78	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
10	Hannover	Germany	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	✓	[illegible]	[illegible]		[illegible]
11	Strasbourg	France	S	61.12	46.20%	3.63	422.37	69.23	62.73	43.31	56.32	31.81	32.44	62.77	8.73	11	✓	8.02	387.37		45.45
12	Montpellier	France	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	27	✓	[illegible]	[illegible]		[illegible]
13	Hamburg	Germany	L	[illegible]	[illegible]	0.84	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	37	X	9.11	[illegible]		44.97
14	Leipzig	Germany	M	56.37	7.20%	0.71	325.89	73.11	55.21	11.03	11.03	35.4	41.49	25.2	26.34	27	✓	9.13	325.23		44.23
15	Bristol	United Kingdom	M	55.33	14.82%	0.55	384.26	92.11	80.23	22.67	66.17	79.04	43.61	21.4	8.93	6	✓	6.7	384.08		43.76
16	Montreal	Canada	L	42.66	12.80%	3.42	332.17	84.76	53.39	69.03	41.12	73.72	41.9	7.12	5.27	3	✓	3.82	366.47		42.68
17	Nuremberg	Germany	M	[illegible]	[illegible]	0.84	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
18	Hobart	Australia	S	55.14	10.00%	2.75	352.04	55.76	72.87	23.52	50.13	24.06	56.31	20.79	20.37	23	X	2.12	352.96		48.12
19	Berlin	Germany	L	37.09	65.07%	3.08	412.50	66.11	33.66	16.32	33.79	32.0	18.71	13.32	34.43	17	X	19.79	427.12		42.09
20	Middlesbrough	Australia	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
21	Cologne	Germany	L	37.98	12.80%	0.40	372.23	37.79	21.28	18.19	53.24	37.43	42.8	15.54	23.12	21	✓	22.78	372.23		42.07
22	Dresden	Germany	M	37.36	10.00%	0.39	422.21	30.79	21.98	20.21	24.27	34.13	38.41	13.69	26.79	23	✓	10.12	433.21		41.82
23	Frankfurt	Germany	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
24	Tokyo	Japan	L	66.32	13.90%	1.44	422.4	97.6	61.42	10.6	32.68	90	53.61	37	5.17	3	X	2.66	320.64		49.23
25	Düsseldorf	Germany	M	23.72	10.10%	0.19	379.22	89.12	34.13	12.12	28.27	46.31	33.99	13.26	35.21	11	X	9.44	379.13		40.36
26	Rouen	Germany	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
27	Nice	France	S	23.50	0.29%	0.32	359.41	32.49	69.22	23.24	55.04	34.21	33.32	25.33	33.21	27	X	2.26	360.11		36.37
28	Nantes	France	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
29	Geneva	Switzerland	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
30	Wellington	New Zealand	S	72.41	10.70%	0.52	317.31	35.01	34.66	49.60	72.60	31.11	39.77	14.96	6.37	11	X	4.71	318.31		33.69
31	Seattle	Spain	M	70.42	7.50%	0.83	342.39	57.98	34.06	48.53	32.18	72.21	44.84	36.32	32.26	68	✓	2.41	342.53		37.68
32	Paris	France	L	26.31	5.50%	3.72	316.41	68.24	64.12	28.31	36.31	34.21	33.45	68.24	12.33	61	✓	22.27	318.41		37.33
33	Vienna	Austria	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	✓	[illegible]	[illegible]		[illegible]
34	Munich	Germany	L	59.32	10.70%	0.50	371.52	52.23	32.12	17.30	32.96	35.1	46.76	24.12	23.10	27	X	14.31	37.62		35.94
35	Helsinki	Finland	M	47.40	10.20%	1.42	332.26	68.73	46.18	25.37	31.32	36.21	41.31	32.37	43.13	43	X	12.49	332.26		36.33
36	Tel Aviv	Israel	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
37	Vancouver	Canada	M	63.39	2.00%	0.44	466.27	38.37	23.2	42.96	41.11	72.78	33	42.72	23.70	23	✓	2.96	463.37		36.54
38	Beijing	China	L	56.74	11.00%	1.41	324.95	65.32	47.66	3.3	32.11	43.11	30.79	3.7	8.1	11	X	45.32	324.95		35.31
39	San Francisco	United States	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
40	Norway	Australia	L	71.66	11.10%	0.16	312.34	33.14	16.41	3.34	28.3	72.1	38.31	1.13	8.81	9	X	9.34	313.31		32.27
41	Portland	United States	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
42	Casablanca	Morocco	L	58.42	12.20%	4.3	303.83	84.23	70.7	3.77	21.3	28.73	39.26	13	1.29	1	✓	4.72	323.83		33.07
43	Uppsala	Sweden	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	32	✓	18.41	[illegible]		34.23
44	Madrid	Spain	L	53.44	9.10%	0.61	384.31	51.21	64.55	31.42	44.5	73.21	44	12.14	7.44	11	✓	23.44	384.12		34.49
45	Dortmund	Germany	M	43.31	8.60%	0.79	317.05	32.46	45.29	11.27	14.71	37.43	43.7	12.44	33.24	24	X	9.60	317.05		34.25
46	Barcelona	Spain	L	51.04	2.50%	0.50	326.7	59.17	57.42	34.53	54.13	73.21	45.46	23.56	55.12	52	✓	22.15	326.71		33.7
47	Stuttgart	Germany	M	36.31	5.00%	0.60	312.86	41.44	37.21	11.32	43.86	33.43	41.71	36.81	37.12	27	X	28.12	315.01		33.42
48	Reykjavik	Iceland	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
49	Auckland	New Zealand	L	74.84	3.60%	0.29	403.72	32.81	34.34	18.2	36.12	79.26	33.79	1.12	1.87	1	X	1.43	403.72		33.04
50	Seattle	United States	M	75.12	3.00%	0.17	406.31	30.91	75.3	23.12	32.73	36.1	56.11	11.61	4.62	8	✓	1.63	420.13		33.03
51	Shanghai	China	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
52	Singapore	Singapore	L	56.32	10.2%	2.32	332.26	90.30	30.26	23.17	36.79	37.24	56.32	27.32	34.12	31	Y	15.1	332.26		31.42
53	Washington	United States	M	68.42	4.60%	0.17	334.21	31.24	76.7	3.74	43.33	46.1	47.7	5.13	7.12	7	Y	3.6	334.21		31.42
54	Edinburgh	United Kingdom	S	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	11	Y	[illegible]	[illegible]		[illegible]
55	Oslo	Norway	M	47.45	7.90%	0.23	326.42	32.63	34.79	20.07	36.33	71.12	32.31	42.66	46.13	45	X	6.13	326.43		31.31
56	Brussels	Belgium	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Y	[illegible]	[illegible]		[illegible]
57	Los Angeles	United States	L	38.62	1.10%	0.15	268.15	34.21	31.62	16.57	18.53	18.4	40.68	7.41	3.87	5	Y	10.31	268.15		30.53
58	Santiago	Chile	L	3.03	3.00%	2.31	260.72	32.70	32.87	12.07	34.31	32.03	46.41	3.06	2.55	4	Y	4.22	260.72		29.35
59	Vienna	Poland	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Y	[illegible]	[illegible]		[illegible]
60	Dublin	Ireland	M	50.72	3.30%	0.55	317.26	31.96	28.32	46.73	42.66	43.21	28.31	47.37	37.14	42	N	2.44	317.26		27.37
61	Boston	United States	M	53.44	2.40%	0.42	315.27	32.61	23.9	23.46	34.2	31.4	30.1	38	39.03	31	Y	16.01	315.27		23.81
62	London	United Kingdom	L	34.69	2.80%	0.63	323.03	34.36	31.83	12.62	42.61	23.34	32.6	6.33	4.32	11	Y	44.67	323.03		23.72
63	Lisbon	Portugal	M	31.23	1.80%	1.16	347.31	37.12	23.64	21.16	41.34	23.12	32.23	13.43	1.24	3	Y	23.33	347.31		23.21
64	Stockholm	Sweden	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	16	Y	[illegible]	[illegible]		[illegible]
65	Milan	Italy	L	53.21	0.30%	1.9	342.21	23.34	23.33	15.12	33.23	43.78	30.13	22.34	23.1	31	N	6.4	342.71		22.34
66	Athens	Greece	M	31.23	0.30%	0.73	321.33	32.12	32.08	33.17	36.42	41.2	33.12	3.12	1.23	3	Y	4.17	321.33		20.12
67	New York	United States	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	31	Y	[illegible]	[illegible]		[illegible]
68	Helsinki	Finland	M	50.24	1.29%	2.18	312.42	36.73	37	42.89	33.23	44.31	28.23	43.2	18.42	22	Y	17.22	312.42		27.23
69	Cape Town	South Africa	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Y	[illegible]	[illegible]		[illegible]
70	Rome	Italy	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Y	[illegible]	[illegible]		[illegible]
71	Chicago	United States	L	50.68	17.71%	0.62	277.03	33.31	71.64	12.03	43.23	32.4	43.66	16.12	2.29	9	Y	23.43	277.03		23.73
72	Detroit	United States	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	6	N	[illegible]	[illegible]		[illegible]
73	Prague	Czech Republic	L	51.00	1.20%	1.16	303.27	31.61	33.13	43.73	37.34	34.31	34.34	7.56	2.53	5	Y	13.73	303.27		21.37
74	Istanbul	Turkey	L	72.00	0.82%	3.41	402.11	33.42	77.23	2.33	33.71	34.61	37.52	3.41	1.43	2	Y	12.2	402.11		23.43
75	Cairo	Egypt	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1	N	[illegible]	[illegible]		[illegible]
76	Sao Paulo	Brazil	L	66.32	3.10%	1.71	420.44	32.56	32.72	6.12	12.04	23.12	3.04	2.1	1.2	2	Y	43.37	420.44		24.23
77	Johannesburg	South Africa	M	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	5	N	[illegible]	[illegible]		[illegible]
78	Nairobi	Kenya	L	73.53	2.10%	1.12	403.27	33.12	33.53	23.1	23.04	23.27	1.73	1.14	1	N	16.2	403.27		24.12
79	New Delhi	India	L	52.34	4.20%	1.36	411.43	33.96	23.61	3.43	23.33	21.27	23.23	1.23	1.21	1	N	23.27	411.43		23.42
80	Mexico City	Mexico	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Y	[illegible]	[illegible]		[illegible]
81	Bogota	Colombia	L	70.16	4.50%	3.21	387.44	23.31	33.22	2.23	17.3	14.6	23.16	1	1	1	Y	21.27	387.44		23.42
82	Cali	Colombia	L	71.00	1.20%	3.13	388.11	23.33	22.61	23.61	13.07	11.2	6.33	3.11	1.19	1	Y	1.61	388.11		22.34
83	Buenos Aires	Argentina	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	X	[illegible]	[illegible]		[illegible]
84	Hong Kong	SAR China	L	53.13	0.82%	1.12	17.22	33.12	23.33	2.33	34.12	33.73	21.31	13.73	2.27	14	N	7.41	317.33		22.34
85	Jakarta	Indonesia	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1	Y	[illegible]	[illegible]		[illegible]
86	Moscow	Russia	L	45.49	3.20%	1.32	303.27	33.24	73.33	6.4	3.34	23.12	6.33	4.13	3.21	4	Y	4.31	303.27		21.23
87	Tbilisi	Georgia	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	3	Y	[illegible]	[illegible]		[illegible]
88	Bangkok	Thailand	L	23.12	3.30%	4.23	344.42	31.12	33.12	1.62	24.13	43.13	22.23	13.44	4.31	6	Y	2.03	344.42		18.3
89	Medellín	Colombia	L	70.21	2.30%	3.39	388.12	23.12	43.34	3.31	3.27	11.6	6.33	3.34	3.71	3	Y	31.12	388.12		18.63
90	Lagos	Nigeria	L	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1	N	[illegible]	[illegible]		[illegible]

At Luko, cycling is in our DNA. As digital insurance specialists and committed bikers ourselves, we firmly believe that cyclists should be free to get from A to B, without having to worry about road quality, safety or bicycle theft. To delve into the topic further, we decided to investigate which cities around the world are improving their overall cycling conditions, as well as encouraging bicycle-usage as a healthy, sustainable mode of transport. We then ranked each location's efforts to determine the best cycling cities, as, after all, we believe that the road to future mobility is on two wheels.

To conduct the study, we first selected cities from around the world including traditional cycling cities, as well as some lesser-known locations improving their bicycle infrastructure. Then, we analysed each location for several factors which determine if a city is good for cycling or not. To begin, we looked at the percentage of bicycle users, as this is a huge indication of the overall cycling conditions, but also basic requirements such as safety, bicycle-related crime and road infrastructure. This research included the number of stolen bicycles, cycling fatalities and accidents, length of specialised cycling roads, road quality investments and more.

Next, since many casual cyclists are impacted by weather conditions, we determined the average hours of sunshine, millimetres of rainfall and number of extreme weather days to paint an overall picture of the climate in each city. Considering that the sharing economy is a billion-dollar industry, we wanted to include information about the boom in bike-sharing by looking into the volume of shared bicycles, as well as the number of sharing and rental stations in each city. Finally, to determine which locations go the extra mile for cyclists and their community, we included the popularity of special cycling-related events such as No Car Day and Critical Mass. We then ranked all factors to determine the best cycling cities overall.

The table above reveals the best cities for cycling, where the higher the total score, the better the results. The legend below describes each of the factors within each category. You can filter each factor from highest to lowest and vice versa by clicking on the icon above each column. For a full explanation of how each factor was calculated, please see the methodology at the bottom of the page.

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Methodology

The Bicycle Cities Index analyses the conditions for cycling in 90 cities across the globe to determine if they are good for cyclists.

CITY SELECTION

90 cities were selected for their willingness to invest and work on initiatives to improve cycling infrastructure and safety. The study does not reflect the best and worst cities for cycling, but rather evaluates the cycling climate for these 90 cities based on factors related to bike-users.

City Size: S stands for cities with less than 500,000 inhabitants, M for cities with between 500,000 and 999,999 inhabitants and L for cities with 1 million inhabitants and above.

THE STUDY FOCUSES ON SIX MAIN CATEGORIES WITH THE FOLLOWING FACTORS THAT MAKE A CITY CYCLING-FRIENDLY:

- **Weather**
- **Percentage Bicycle Usage.**
- **Crime & Safety:** Fatalities / 100,000 Cyclists, Accidents / 100,000 Cyclists, Bicycle Theft Score.
- **Infrastructure:** Number of Bicycle Shops / 100,000 Cyclists, Specialised Roads & Road Quality Score, Investment & Infrastructure Quality Score.
- **Sharing:** Number of Bicycle Sharing & Rental Stations / 100,000 Score, # Shared Bicycles / 100,000 Score.

- **Events:** No Car Day, Critical Mass Score.

A weighted average was used for all of the factors in order to create the final scores for each category, for example the Weather Score was generated by analysing and aggregating the Hours of Sunshine, Rainfall and Extreme Weather Days of each city.

All of the information collected is based on the latest data available.

SCORING

Scores are normalized such that 1 represents the lowest and 100 the highest value in the dataset, meaning that the higher the score, the better. However, for the factors Fatalities and Accidents / 100,00 cyclists, a lower value is better as it represents a higher safety rating for each city.

The equation for normalization is as follows: score = 10 * [x - min(X)] / [max(X) - min(X)]; or score inverted = 10 -10 * [x - min(X)] / [max(X) - min(X)] for inverted scores

The formula used for the weighted average, where n is the number of categories, and i is the i-th factor, is as follows: weighted_average: sum_(i=1)^n w_i*x_i, there w_i is the weight of column i, n - total number of columns used for the weighted average, x_i : i-th column.

WEATHER

The Weather Score was calculated using an aggregated score, taking into account the total annual hours of sunshine, average annual precipitation in millimetres, and the number of weather days below 0 °C and over 30 °C in a city.
Sources: World Weather Online, Weather Base, Deutscher Wetter Dienst, other websites.

BICYCLE USAGE

Percentage of people using bicycles in everyday life in each city.
Sources: Local statistical departments, Greenpeace, UN, Eco Mobility, The League of American Cyclists, and others.

CRIME & SAFETY

FATALITIES / 100,000 CYCLISTS

Deaths in bicycle accidents (includes deaths related to bicycle theft) per 100,000 cyclists in cities. Total number of cyclists estimated from bicycle usage rates as well as bicycle ownership rates.
Sources: OECD, local statistical departments. Bicycle ownership rate source: Oke, O., et al., Tracking global bicycle ownership patterns. Journal of Transport & Health (2015).

ACCIDENTS / 100,000 CYCLISTS

An estimate of bicycle-related accidents that resulted in at least light injuries, per 100,000 cyclists. Total number of cyclists estimated from bicycle usage rates as well as bicycle ownership rates.
Sources: OECD, local statistical departments. Bicycle ownership rate source: Oke, O., et al., Tracking global bicycle ownership patterns. Journal of Transport & Health (2015).

BICYCLE THEFT SCORE

A weighted average of the following subcategories collected in order to offset the low crime report rates in countries where crime is prevalent but underreported.

- Stolen bicycles / 100,000 cyclists
- An estimate of stolen bicycle rate per 100,000 cyclists. Total number of cyclists estimated from bicycle usage rates as well as bicycle ownership rates. Sources:

local statistical departments. Bicycle ownership rate source: Oke, O., et al., Tracking global bicycle ownership patterns. Journal of Transport & Health (2015).

- Homicide Rate
- In order to account for low report rates of bicycle theft in some countries, the homicide rate was added as it is the most reported crime.
  Source: World Bank.

INFRASTRUCTURE

NUMBER OF BICYCLE SHOPS / 100,000 CYCLISTS

Total number of bicycle shops within the city. Total number of cyclists estimated from bicycle usage rates as well as bicycle ownership rates.
Sources: the yellow pages, Google search engine result pages, Open Street Maps Overpass API responses. Bicycle ownership rate source: Oke, O., et al., Tracking global bicycle ownership patterns. Journal of Transport & Health (2015).

SPECIALISED ROADS AND ROAD QUALITY

Bicycle roads length per population.
Sources: Open Street Maps Overpass API responses: km of ways (highways) tagged for bicycle usage (allowed and specific). Road Quality score. Source: World Economic Forum.

INVESTMENT AND INFRASTRUCTURE QUALITY

An average of the scored subcategories (country-level for international; investment and infrastructure: city level for German cities):

- Infrastructure Investment Score.
  Sources: World Bank LPI infrastructure score, German Institute of Economy (DIW): investment in infrastructure, Bertelsmann Stiftung.
- Infrastructure Quality Score.
  Sources: World Economic Forum Global Competitiveness Index Quality of Overall Infrastructure.

SHARING

NUMBER OF BICYCLE SHARING AND RENTAL STATIONS / 100,000

An estimate of bicycle sharing and rental stations per 100,000 of population.
Sources: The yellow pages, google search engine result pages, Open Street Maps Overpass API responses.

NUMBER OF SHARED BICYCLES / 100,000

An estimate of shared bicycle fleet per 100,000 of population.
Sources: Local statistical departments, local bicycle sharing company websites, bicycle share map (http://bikes.oobrien.com).

EVENTS

NO CAR DAY

Score dependant on the existence of a car-free day, where motorists are encouraged to give up their car for one day. 1 - Has No Car Day. 0 - Does not have a No Car Day.

CRITICAL MASS SCORE

Average of the subcategories: Size of Critical Mass events attendees.

- Sources: local statistical departments, local websites, social media group pages (e.g. Facebook). Latest available event.
- Size of local Critical Mass communities.
  Sources: local Critical Mass event social media group size (e.g. Facebook).

Bicycle theft insurance as additional protection

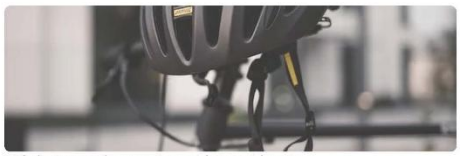
Don't make it easier for thieves! A bicycle should be secured with at least one independent, high-quality lock and connected to a fixed object. Thieves are more likely to shy away if the lock can't be cracked without great effort. In the event of theft, bicycle theft insurance helps. Luko Home Contents Insurance will insure bicycles up to 5,000 euros replacement value. We'll cover your bike 24/7, worldwide, indoors and outdoors.

Linked articles

The advantages of an electric bike at a glance

What are electric bikes? What makes these bikes so popular? Find everything you need to know for your e-bike decision.

By Luko



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Useful bicycle accessories that provide greater safety

What makes your bike really safe? With these accessories, you are well prepared for the traffic!

By Luko

Appendix D. Odds ratio arrays – detailed calculations for Seattle

Table D.1. Detailed OR calculations for **Fremont Bridge** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	84,172	33,531	160,128	76,261	**1.196**	1.177 - 1.214
18:00:00	09:00:00	407,733	102,854	276,687	85,144	**1.220**	1.207 - 1.232
19:00:00	09:00:00	155,294	70,849	197,184	134,880	**1.499**	1.483 - 1.516
20:00:00	09:00:00	36,195	56,735	70,294	190,172	**1.726**	1.699 - 1.753
06:00:00	10:00:00	84,172	33,531	86,637	37,903	**1.098**	1.079 - 1.118
18:00:00	10:00:00	407,733	102,854	147,373	43,059	**1.158**	1.144 - 1.173
19:00:00	10:00:00	155,294	70,849	106,436	67,169	**1.383**	1.365 - 1.402
20:00:00	10:00:00	36,195	56,735	38,993	94,831	**1.552**	1.524 - 1.579
06:00:00	11:00:00	84,172	33,531	79,620	31,576	**0.996**	0.978 - 1.014
18:00:00	11:00:00	407,471	102,854	133,426	35,709	**1.060**	1.046 - 1.075
19:00:00	11:00:00	155,157	70,849	97,427	55,923	**1.257**	1.240 - 1.274
20:00:00	11:00:00	36,195	56,735	35,694	79,980	**1.429**	1.404 - 1.456
06:00:00	12:00:00	84,172	33,531	83,715	32,850	**0.985**	0.967 - 1.003
18:00:00	12:00:00	407,471	102,854	141,521	37,337	**1.045**	1.031 - 1.059
19:00:00	12:00:00	155,157	70,849	103,078	58,192	**1.236**	1.220 - 1.253
20:00:00	12:00:00	36,195	56,735	37,172	83,970	**1.441**	1.415 - 1.467
06:00:00	13:00:00	84,172	33,531	87,670	35,362	**1.013**	0.995 - 1.031
18:00:00	13:00:00	407,733	102,854	148,326	40,756	**1.089**	1.075 - 1.103
19:00:00	13:00:00	155,294	70,849	107,682	63,596	**1.295**	1.278 - 1.312
20:00:00	13:00:00	36,195	56,735	38,811	90,777	**1.492**	1.466 - 1.519
06:00:00	14:00:00	84,172	33,531	94,248	39,466	**1.051**	1.033 - 1.069
18:00:00	14:00:00	407,733	102,854	159,758	44,956	**1.116**	1.102 - 1.130
19:00:00	14:00:00	155,294	70,849	115,023	70,180	**1.337**	1.320 - 1.355
20:00:00	14:00:00	36,195	56,735	41,384	100,586	**1.551**	1.524 - 1.578
06:00:00	15:00:00	84,172	33,531	120,396	51,500	**1.074**	1.056 - 1.091
18:00:00	15:00:00	407,733	102,854	205,272	57,634	**1.113**	1.100 - 1.126
19:00:00	15:00:00	155,294	70,849	147,045	91,197	**1.359**	1.343 - 1.376
20:00:00	15:00:00	36,195	56,735	52,658	130,947	**1.586**	1.560 - 1.613
06:00:00	22:00:00	84,172	33,531	31,881	9,692	**0.763**	0.744 - 0.783
18:00:00	22:00:00	407,733	102,854	50,092	10,946	**0.866**	0.848 - 0.885
19:00:00	22:00:00	155,294	70,849	38,073	17,597	**1.013**	0.993 - 1.033
20:00:00	22:00:00	36,195	56,735	14,845	25,627	**1.101**	1.075 - 1.128
06:00:00	23:00:00	84,172	33,531	20,267	6,615	**0.819**	0.795 - 0.845
18:00:00	23:00:00	407,733	102,854	32,185	7,368	**0.908**	0.884 - 0.932
19:00:00	23:00:00	155,294	70,849	24,123	11,804	**1.073**	1.047 - 1.098
20:00:00	23:00:00	36,195	56,735	9,993	17,115	**1.093**	1.062 - 1.124
06:00:00	00:00:00	84,172	33,531	10,417	3,947	**0.951**	0.915 - 0.989
18:00:00	00:00:00	407,733	102,854	16,980	4,320	**1.009**	1.004 - 0.975
19:00:00	00:00:00	155,294	70,849	12,664	6,865	**1.188**	1.152 - 1.225
20:00:00	00:00:00	36,195	56,735	4,853	9,857	**1.296**	1.249 - 1.344
06:00:00	01:00:00	84,172	33,531	5,445	2,206	**1.017**	0.966 - 1.070
18:00:00	01:00:00	407,733	102,854	8,911	2,350	**1.045**	0.998 - 1.095
19:00:00	01:00:00	155,294	70,849	6,660	3,694	**1.216**	1.167 - 1.267
20:00:00	01:00:00	36,195	56,735	2,477	5,281	**1.360**	1.294 - 1.429
06:00:00	02:00:00	84,172	33,531	3,176	1,356	**1.072**	1.004 - 1.144
18:00:00	02:00:00	407,733	102,854	5,480	1,430	**1.034**	0.976 - 1.097
19:00:00	02:00:00	155,294	70,849	3,993	2,382	**1.308**	1.242 - 1.377
20:00:00	02:00:00	36,195	56,735	1,430	3,391	**1.513**	1.420 - 1.612
06:00:00	03:00:00	84,172	33,531	2,473	1,111	**1.128**	1.049 - 1.212
18:00:00	03:00:00	407,733	102,854	4,431	1,231	**1.101**	1.034 - 1.174
19:00:00	03:00:00	155,294	70,849	3,239	1,925	**1.303**	1.230 - 1.379
20:00:00	03:00:00	36,195	56,735	1,135	2,738	**1.539**	1.434 - 1.651
06:00:00	04:00:00	84,172	33,531	5,724	2,660	**1.167**	1.112 - 1.224
18:00:00	04:00:00	407,733	102,854	9,579	2,905	**1.202**	1.153 - 1.254
19:00:00	04:00:00	155,294	70,849	7,016	4,698	**1.468**	1.413 - 1.525
20:00:00	04:00:00	36,195	56,735	2,578	6,548	**1.620**	1.545 - 1.699

Table D.2. Detailed OR calculations for **26th Ave** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	4,436	2,230	5,061	3,422	**1.345**	1.258 - 1.438
18:00:00	09:00:00	18,927	6,112	9,513	4,140	**1.348**	1.286 - 1.412
19:00:00	09:00:00	8,458	6,032	6,284	6,381	**1.424**	1.357 - 1.494
20:00:00	09:00:00	2,219	6,331	2,110	8,999	**1.495**	1.397 - 1.600
06:00:00	10:00:00	4,434	2,230	4,319	3,058	**1.408**	1.314 - 1.508
18:00:00	10:00:00	18,929	6,112	8,093	3,670	**1.404**	1.338 - 1.474
19:00:00	10:00:00	8,464	6,032	5,396	5,587	**1.453**	1.382 - 1.527
20:00:00	10:00:00	2,221	6,331	1,902	7,674	**1.415**	1.320 - 1.518
06:00:00	11:00:00	4,440	2,230	4,933	3,410	**1.376**	1.287 - 1.472
18:00:00	11:00:00	18,930	6,112	9,199	4,072	**1.371**	1.308 - 1.437
19:00:00	11:00:00	8,465	6,032	6,217	6,236	**1.408**	1.477 - 1.341
20:00:00	11:00:00	2,221	6,331	2,141	8,572	**1.405**	1.313 - 1.503
06:00:00	12:00:00	4,440	2,230	5,469	3,837	**1.397**	1.308 - 1.491
18:00:00	12:00:00	18,930	6,112	10,235	4,692	**1.420**	1.357 - 1.485
19:00:00	12:00:00	8,465	6,032	6,821	7,128	**1.467**	1.399 - 1.537
20:00:00	12:00:00	2,221	6,331	2,355	9,805	**1.461**	1.367 - 1.560
06:00:00	13:00:00	4,440	2,230	5,554	4,340	**1.556**	1.459 - 1.660
18:00:00	13:00:00	18,930	6,112	10,781	5,040	**1.448**	1.385 - 1.513
19:00:00	13:00:00	8,465	6,032	7,033	7,646	**1.526**	1.457 - 1.598
20:00:00	13:00:00	2,221	6,331	2,490	10,665	**1.503**	1.408 - 1.604
06:00:00	14:00:00	4,440	2,230	6,116	4,823	**1.570**	1.474 - 1.673
18:00:00	14:00:00	18,930	6,112	11,797	5,689	**1.494**	1.431 - 1.559
19:00:00	14:00:00	8,465	6,032	7,681	8,362	**1.528**	1.460 - 1.599
20:00:00	14:00:00	2,221	6,331	2,833	11,465	**1.420**	1.332 - 1.513
06:00:00	15:00:00	4,440	2,230	7,431	5,554	**1.488**	1.399 - 1.583
18:00:00	15:00:00	18,930	6,112	13,802	6,322	**1.419**	1.361 - 1.479
19:00:00	15:00:00	8,465	6,032	9,005	9,643	**1.503**	1.438 - 1.570
20:00:00	15:00:00	2,221	6,331	3,303	13,535	**1.438**	1.352 - 1.529
06:00:00	22:00:00	4,440	2,230	2,002	1,262	**1.255**	1.151 - 1.369
18:00:00	22:00:00	18,930	6,112	3,383	1,376	**1.260**	1.176 - 1.350
19:00:00	22:00:00	8,465	6,032	2,467	2,052	**1.167**	1.091 - 1.248
20:00:00	22:00:00	2,221	6,331	932	2,841	**1.069**	0.979 - 1.168
06:00:00	23:00:00	4,440	2,230	1,174	700	**1.187**	1.067 - 1.321
18:00:00	23:00:00	18,930	6,112	2,071	848	**1.268**	1.165 - 1.381
19:00:00	23:00:00	8,465	6,032	1,449	1,256	**1.216**	1.120 - 1.321
20:00:00	23:00:00	2,221	6,331	527	1,749	**1.164**	1.044 - 1.298
06:00:00	00:00:00	4,440	2,230	650	512	**1.568**	1.382 - 1.780
18:00:00	00:00:00	18,930	6,112	1,137	556	**1.515**	1.363 - 1.683
19:00:00	00:00:00	8,465	6,032	802	822	**1.438**	1.298 - 1.594
20:00:00	00:00:00	2,221	6,331	291	1,101	**1.327**	1.156 - 1.524
06:00:00	01:00:00	4,440	2,230	398	355	**1.776**	1.526 - 2.067
18:00:00	01:00:00	18,930	6,112	724	409	**1.750**	1.545 - 1.982
19:00:00	01:00:00	8,465	6,032	499	557	**1.566**	1.382 - 1.775
20:00:00	01:00:00	2,221	6,331	190	721	**1.331**	1.127 - 1.573
06:00:00	02:00:00	4,440	2,230	290	236	**1.620**	1.354 - 1.938
18:00:00	02:00:00	18,930	6,112	503	249	**1.533**	1.314 - 1.790
19:00:00	02:00:00	8,465	6,032	356	391	**1.541**	1.330 - 1.786
20:00:00	02:00:00	2,221	6,331	131	497	**1.331**	1.091 - 1.623
06:00:00	03:00:00	4,440	2,230	208	153	**1.465**	1.181 - 1.816
18:00:00	03:00:00	18,930	6,112	370	187	**1.565**	1.310 - 1.871
19:00:00	03:00:00	8,465	6,032	266	251	**1.324**	1.111 - 1.578
20:00:00	03:00:00	2,221	6,331	86	333	**1.358**	1.066 - 1.730
06:00:00	04:00:00	4,440	2,230	436	253	**1.155**	0.982 - 1.360
18:00:00	04:00:00	18,930	6,112	813	281	**1.070**	0.932 - 1.230
19:00:00	04:00:00	8,465	6,032	547	439	**1.126**	0.989 - 1.282
20:00:00	04:00:00	2,221	6,331	211	636	**1.057**	0.898 - 1.245

Table D.3. Detailed OR calculations for **39th Ave** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	5,167	2,017	8,493	4,177	**1.260**	1.182 - 1.342
18:00:00	09:00:00	20,995	5,302	14,967	4,851	**1.283**	1.228 - 1.341
19:00:00	09:00:00	8,405	4,479	10,358	7,720	**1.399**	1.335 - 1.466
20:00:00	09:00:00	1,746	3,607	3,498	10,946	**1.515**	1.414 - 1.622
06:00:00	10:00:00	5,167	2,017	5,988	2,727	**1.167**	1.089 - 1.249
18:00:00	10:00:00	21,017	5,302	10,850	3,156	**1.153**	1.097 - 1.212
19:00:00	10:00:00	8,413	4,479	7,467	5,042	**1.268**	1.205 - 1.335
20:00:00	10:00:00	1,746	3,607	2,478	7,290	**1.424**	1.324 - 1.532
06:00:00	11:00:00	5,167	2,017	5,362	2,392	**1.143**	1.065 - 1.226
18:00:00	11:00:00	21,017	5,302	9,521	2,908	**1.211**	1.150 - 1.274
19:00:00	11:00:00	8,413	4,479	6,691	4,504	**1.264**	1.200 - 1.332
20:00:00	11:00:00	1,746	3,607	2,359	6,299	**1.293**	1.200 - 1.392
06:00:00	12:00:00	5,167	2,017	5,396	2,640	**1.253**	1.169 - 1.343
18:00:00	12:00:00	21,017	5,302	9,857	3,026	**1.217**	1.157 - 1.280
19:00:00	12:00:00	8,413	4,479	6,701	4,723	**1.324**	1.257 - 1.395
20:00:00	12:00:00	1,746	3,607	2,313	6,659	**1.394**	1.294 - 1.501
06:00:00	13:00:00	5,167	2,017	5,612	2,824	**1.289**	1.204 - 1.380
18:00:00	13:00:00	21,017	5,302	10,078	3,357	**1.320**	1.257 - 1.387
19:00:00	13:00:00	8,413	4,479	6,898	5,202	**1.417**	1.346 - 1.491
20:00:00	13:00:00	1,746	3,607	2,373	7,187	**1.466**	1.362 - 1.578
06:00:00	14:00:00	5,167	2,017	6,054	2,928	**1.239**	1.158 - 1.326
18:00:00	14:00:00	21,017	5,302	10,861	3,461	**1.263**	1.203 - 1.326
19:00:00	14:00:00	8,413	4,479	7,410	5,377	**1.363**	1.296 - 1.434
20:00:00	14:00:00	1,746	3,607	2,591	7,548	**1.410**	1.312 - 1.516
06:00:00	15:00:00	5,167	2,017	7,287	3,685	**1.295**	1.214 - 1.382
18:00:00	15:00:00	21,017	5,302	12,743	4,307	**1.340**	1.280 - 1.403
19:00:00	15:00:00	8,413	4,479	8,769	6,646	**1.424**	1.356 - 1.494
20:00:00	15:00:00	1,746	3,607	2,912	9,244	**1.537**	1.432 - 1.649
06:00:00	22:00:00	5,167	2,017	1,225	681	**1.424**	1.280 - 1.585
18:00:00	22:00:00	21,017	5,302	2,130	748	**1.392**	1.274 - 1.521
19:00:00	22:00:00	8,413	4,479	1,503	1,154	**1.442**	1.325 - 1.570
20:00:00	22:00:00	1,746	3,607	519	1,605	**1.497**	1.335 - 1.678
06:00:00	23:00:00	5,167	2,017	776	326	**1.076**	0.936 - 1.237
18:00:00	23:00:00	21,017	5,302	1,266	399	**1.249**	1.112 - 1.404
19:00:00	23:00:00	8,413	4,479	911	589	**1.214**	1.088 - 1.355
20:00:00	23:00:00	1,746	3,607	372	810	**1.054**	0.921 - 1.207
06:00:00	00:00:00	5,167	2,017	566	280	**1.267**	1.088 - 1.476
18:00:00	00:00:00	21,017	5,302	931	361	**1.537**	1.356 - 1.742
19:00:00	00:00:00	8,413	4,479	674	503	**1.402**	1.242 - 1.586
20:00:00	00:00:00	1,746	3,607	254	664	**1.265**	1.083 - 1.478
06:00:00	01:00:00	5,167	2,017	181	149	**2.109**	1.688 - 2.635
18:00:00	01:00:00	21,017	5,302	352	176	**1.982**	1.650 - 2.381
19:00:00	01:00:00	8,413	4,479	222	250	**2.115**	1.759 - 2.543
20:00:00	01:00:00	1,746	3,607	75	321	**2.072**	1.601 - 2.681
06:00:00	02:00:00	5,167	2,017	67	71	**2.715**	1.937 - 3.805
18:00:00	02:00:00	21,017	5,302	147	77	**2.076**	1.573 - 2.740
19:00:00	02:00:00	8,413	4,479	91	109	**2.250**	1.699 - 2.979
20:00:00	02:00:00	1,746	3,607	75	321	**2.072**	1.601 - 2.681
06:00:00	03:00:00	5,167	2,017	52	34	**1.675**	1.084 - 2.589
18:00:00	03:00:00	21,017	5,302	103	41	**1.578**	1.097 - 2.269
19:00:00	03:00:00	8,413	4,479	76	60	**1.483**	1.055 - 2.084
20:00:00	03:00:00	1,746	3,607	36	137	**1.842**	1.270 - 2.671
06:00:00	04:00:00	5,167	2,017	179	66	**0.945**	0.709 - 1.258
18:00:00	04:00:00	21,017	5,302	264	97	**1.456**	1.152 - 1.842
19:00:00	04:00:00	8,413	4,479	198	148	**1.404**	1.131 - 1.743
20:00:00	04:00:00	1,746	3,607	35	79	**1.093**	0.731 - 1.633

Table D.4. Detailed OR calculations for **BGT North** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	71,469	13,526	99,353	37,161	**1.976**	1.933 - 2.020
18:00:00	09:00:00	184,506	17,706	154,137	38,236	**2.585**	2.536 - 2.635
19:00:00	09:00:00	97,458	17,652	116,600	64,196	**3.040**	2.983 - 3.097
20:00:00	09:00:00	16,904	17,178	36,393	88,612	**2.396**	2.338 - 2.455
06:00:00	10:00:00	71,469	13,668	113,236	36,693	**1.694**	1.658 - 1.732
18:00:00	10:00:00	184,699	17,706	171,962	35,700	**2.166**	2.124 - 2.208
19:00:00	10:00:00	97,581	17,652	132,049	61,608	**2.579**	2.531 - 2.628
20:00:00	10:00:00	16,904	17,159	41,672	86,922	**2.055**	2.006 - 2.105
06:00:00	11:00:00	71,469	13,615	118,568	35,625	**1.577**	1.543 - 1.612
18:00:00	11:00:00	184,699	17,642	183,700	35,558	**2.026**	1.988 - 2.066
19:00:00	11:00:00	97,581	17,619	140,796	60,217	**2.369**	2.325 - 2.413
20:00:00	11:00:00	16,904	17,159	44,382	86,316	**1.916**	1.870 - 1.963
06:00:00	12:00:00	71,469	13,668	115,245	37,890	**1.719**	1.682 - 1.757
18:00:00	12:00:00	184,699	17,706	178,721	37,229	**2.173**	2.132 - 2.215
19:00:00	12:00:00	97,581	17,652	135,689	63,683	**2.594**	2.547 - 2.643
20:00:00	12:00:00	16,904	17,178	40,020	91,474	**2.249**	2.195 - 2.304
06:00:00	13:00:00	71,469	13,668	115,727	40,512	**1.830**	1.792 - 1.870
18:00:00	13:00:00	184,699	17,706	180,035	38,172	**2.212**	2.170 - 2.254
19:00:00	13:00:00	97,581	17,652	135,895	66,957	**2.724**	2.674 - 2.775
20:00:00	13:00:00	16,904	17,178	37,919	94,838	**2.461**	2.402 - 2.522
06:00:00	14:00:00	71,469	13,668	114,650	42,425	**1.935**	1.158 - 1.326
18:00:00	14:00:00	184,699	17,706	181,127	39,683	**2.285**	2.243 - 2.329
19:00:00	14:00:00	97,581	17,652	134,468	69,653	**2.863**	2.811 - 2.917
20:00:00	14:00:00	16,904	17,178	37,844	100,589	**2.616**	2.553 - 2.680
06:00:00	15:00:00	71,469	13,668	113,375	45,195	**2.084**	2.040 - 2.129
18:00:00	15:00:00	184,699	17,706	181,153	41,654	**2.399**	2.354 - 2.444
19:00:00	15:00:00	97,581	17,652	132,946	74,244	**3.087**	3.031 - 3.144
20:00:00	15:00:00	16,904	17,178	39,555	106,343	**2.646**	2.583 - 2.710
06:00:00	22:00:00	71,469	13,668	25,410	5,268	**1.084**	1.047 - 1.123
18:00:00	22:00:00	184,699	17,706	32,022	2,792	**0.910**	0.872 - 0.948
19:00:00	22:00:00	97,581	17,652	26,191	7,640	**1.613**	1.565 - 1.662
20:00:00	22:00:00	16,904	17,178	2,226	9,260	**4.094**	3.890 - 4.307
06:00:00	23:00:00	71,469	13,668	22,630	4,772	**1.103**	1.063 - 1.143
18:00:00	23:00:00	184,699	17,706	28,738	2,035	**0.739**	0.704 - 0.775
19:00:00	23:00:00	97,581	17,652	22,995	6,587	**1.584**	1.534 - 1.635
20:00:00	23:00:00	16,904	17,178	1,020	7,942	**7.662**	7.154 - 8.206
06:00:00	00:00:00	71,469	13,668	26,326	5,470	**1.086**	1.050 - 1.124
18:00:00	00:00:00	184,699	17,706	30,947	1,891	**0.637**	0.607 - 0.669
19:00:00	00:00:00	97,581	17,652	26,527	7,165	**1.493**	1.448 - 1.540
20:00:00	00:00:00	16,904	17,178	493	8,038	**16.044**	4.614 - 17.615
06:00:00	01:00:00	71,469	13,668	19,621	4,139	**1.103**	1.062 - 1.146
18:00:00	01:00:00	184,699	17,706	23,842	1,175	**0.514**	0.484 - 0.546
19:00:00	01:00:00	97,581	17,652	19,699	5,190	**1.456**	1.407 - 1.508
20:00:00	01:00:00	16,904	17,178	214	5,571	**25.617**	2.311 - 29.413
06:00:00	02:00:00	71,469	13,668	21,329	3,336	**0.818**	0.785 - 0.852
18:00:00	02:00:00	184,699	17,706	22,522	476	**0.220**	0.201 - 0.242
19:00:00	02:00:00	97,581	17,652	21,426	3,641	**0.939**	0.904 - 0.976
20:00:00	02:00:00	16,904	17,178	185	3,950	**21.011**	8.103 - 24.386
06:00:00	03:00:00	71,469	13,668	33,527	3,519	**0.549**	0.528 - 0.571
18:00:00	03:00:00	184,699	17,706	33,953	680	**0.209**	0.193 - 0.226
19:00:00	03:00:00	97,581	17,652	33,617	4,042	**0.665**	0.641 - 0.689
20:00:00	03:00:00	16,904	17,178	219	4,325	**19.434**	6.939 - 22.296
06:00:00	04:00:00	71,469	13,668	38,520	4,494	**0.610**	0.589 - 0.632
18:00:00	04:00:00	184,699	17,706	40,222	1,602	**0.415**	0.394 - 0.438
19:00:00	04:00:00	97,581	17,652	39,010	5,518	**0.782**	0.757 - 0.808
20:00:00	04:00:00	16,904	17,178	1,209	6,446	**5.247**	4.916 - 5.599

Table D.5. Detailed OR calculations for **Broadway** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclist	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	7,668	3,903	10,187	6,081	**1.173**	1.116 - 1.233
18:00:00	09:00:00	34,999	11,867	18,612	6,775	**1.074**	1.037 - 1.112
19:00:00	09:00:00	18,089	12,463	12,790	10,635	**1.207**	1.166 - 1.249
20:00:00	09:00:00	4,972	13,262	4,660	15,020	**1.208**	1.154 - 1.266
06:00:00	10:00:00	7,668	3,905	8,008	4,928	**1.208**	1.147 - 1.273
18:00:00	10:00:00	34,999	11,877	14,625	5,631	**1.135**	1.093 - 1.177
19:00:00	10:00:00	18,089	12,465	10,068	8,800	**1.268**	1.223 - 1.316
20:00:00	10:00:00	4,972	13,264	3,583	12,154	**1.272**	1.210 - 1.336
06:00:00	11:00:00	7,668	3,905	9,182	5,089	**1.088**	1.034 - 1.146
18:00:00	11:00:00	34,999	11,877	16,272	5,834	**1.057**	1.019 - 1.096
19:00:00	11:00:00	18,089	12,465	11,530	8,955	**1.127**	1.087 - 1.168
20:00:00	11:00:00	4,972	13,264	4,335	12,545	**1.085**	1.034 - 1.138
06:00:00	12:00:00	7,668	3,905	11,153	6,067	**1.068**	1.016 - 1.123
18:00:00	12:00:00	34,999	11,877	19,384	7,127	**1.083**	1.047 - 1.121
19:00:00	12:00:00	18,089	12,465	13,800	10,875	**1.144**	1.105 - 1.183
20:00:00	12:00:00	4,972	13,264	5,273	14,943	**1.062**	1.015 - 1.111
06:00:00	13:00:00	7,668	3,905	10,801	6,167	**1.121**	1.067 - 1.178
18:00:00	13:00:00	34,999	11,877	19,420	7,074	**1.073**	1.037 - 1.111
19:00:00	13:00:00	18,089	12,465	13,609	11,055	**1.179**	1.140 - 1.220
20:00:00	13:00:00	4,972	13,264	5,226	15,369	**1.102**	1.054 - 1.153
06:00:00	14:00:00	7,668	3,905	11,380	6,554	**1.131**	1.077 - 1.188
18:00:00	14:00:00	34,999	11,877	20,312	7,567	**1.098**	1.062 - 1.135
19:00:00	14:00:00	18,089	12,465	14,218	11,683	**1.192**	1.153 - 1.233
20:00:00	14:00:00	4,972	13,264	5,239	16,269	**1.164**	1.113 - 1.218
06:00:00	15:00:00	7,668	3,905	12,481	7,151	**1.125**	1.072 - 1.181
18:00:00	15:00:00	34,999	11,877	22,663	8,404	**1.093**	1.058 - 1.129
19:00:00	15:00:00	18,089	12,465	15,635	12,974	**1.204**	1.166 - 1.244
20:00:00	15:00:00	4,972	13,264	5,750	18,194	**1.186**	1.135 - 1.240
06:00:00	22:00:00	7,668	3,905	5,853	2,762	**0.927**	0.873 - 0.983
18:00:00	22:00:00	34,999	11,877	10,233	3,048	**0.878**	0.839 - 0.919
19:00:00	22:00:00	18,089	12,465	7,301	4,750	**0.944**	0.904 - 0.986
20:00:00	22:00:00	4,972	13,264	2,739	6,842	**0.936**	0.886 - 0.989
06:00:00	23:00:00	7,668	3,905	4,949	2,492	**0.989**	0.930 - 1.052
18:00:00	23:00:00	34,999	11,877	8,633	2,594	**0.885**	0.843 - 0.930
19:00:00	23:00:00	18,089	12,465	6,173	4,236	**0.996**	0.952 - 1.042
20:00:00	23:00:00	4,972	13,264	2,355	5,996	**0.954**	0.901 - 1.011
06:00:00	00:00:00	7,668	3,905	3,224	1,477	**0.900**	0.837 - 0.967
18:00:00	00:00:00	34,999	11,877	5,663	1,596	**0.830**	0.783 - 0.881
19:00:00	00:00:00	18,089	12,465	4,076	2,526	**0.899**	0.852 - 0.950
20:00:00	00:00:00	4,972	13,264	1,502	3,610	**0.901**	0.841 - 0.965
06:00:00	01:00:00	7,668	3,905	2,438	1,025	**0.826**	0.760 - 0.897
18:00:00	01:00:00	34,999	11,877	4,255	1,142	**0.791**	0.738 - 0.847
19:00:00	01:00:00	18,089	12,465	3,107	1,810	**0.845**	0.794 - 0.900
20:00:00	01:00:00	4,972	13,264	1,168	2,569	**0.824**	0.764 - 0.890
06:00:00	02:00:00	7,668	3,905	1,862	820	**0.865**	0.790 - 0.947
18:00:00	02:00:00	34,999	11,877	3,258	828	**0.749**	0.692 - 0.811
19:00:00	02:00:00	18,089	12,465	2,329	1,374	**0.856**	0.798 - 0.919
20:00:00	02:00:00	4,972	13,264	914	2,033	**0.834**	0.766 - 0.907
06:00:00	03:00:00	7,668	3,905	506	288	**1.118**	0.962 - 1.298
18:00:00	03:00:00	34,999	11,877	937	312	**0.981**	0.862 - 1.117
19:00:00	03:00:00	18,089	12,465	633	468	**1.073**	0.950 - 1.212
20:00:00	03:00:00	4,972	13,264	233	706	**1.136**	0.976 - 1.322
06:00:00	04:00:00	7,668	3,905	805	515	**1.256**	1.117 - 1.412
18:00:00	04:00:00	34,999	11,877	1,473	618	**1.236**	1.123 - 1.361
19:00:00	04:00:00	18,089	12,465	1,031	939	**1.322**	1.206 - 1.448
20:00:00	04:00:00	4,972	13,264	400	1,319	**1.236**	1.100 - 1.389

Table D.6. Detailed OR calculations for **Elliot Bay** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	107,242	33,898	162,720	68,644	**1.335**	1.315 - 1.355
18:00:00	09:00:00	509,402	49,682	273,449	81,018	**3.038**	3.001 - 3.075
19:00:00	09:00:00	289,226	37,940	199,851	124,825	**4.761**	4.701 - 4.823
20:00:00	09:00:00	75,558	31,315	73,770	173,731	**5.682**	5.594 - 5.772
06:00:00	10:00:00	107,242	33,898	146,345	62,036	**1.341**	1.321 - 1.362
18:00:00	10:00:00	509,402	49,682	249,836	74,236	**3.047**	3.009 - 3.084
19:00:00	10:00:00	289,226	37,940	184,538	111,550	**4.608**	4,548 - 4.669
20:00:00	10:00:00	75,558	31,315	65,787	153,139	**5.617**	5.527 - 5.707
06:00:00	11:00:00	107,242	33,898	167,873	78,546	**1.480**	1.458 - 1.502
18:00:00	11:00:00	509,402	49,682	293,916	92,722	**3.235**	3.197 - 3.273
19:00:00	11:00:00	289,226	37,940	214,394	137,541	**4.891**	4.829 - 4.953
20:00:00	11:00:00	75,558	31,315	73,511	188,463	**6.186**	6.090 - 6.284
06:00:00	12:00:00	106,789	33,898	230,070	109,862	**1.504**	1.483 - 1.526
18:00:00	12:00:00	508,792	49,682	406,055	130,629	**3.295**	3.258 - 3.331
19:00:00	12:00:00	288,748	37,940	295,686	197,857	**5.093**	5.031 - 5.155
20:00:00	12:00:00	75,558	31,315	101,488	272,188	**6.471**	6.375 - 6.569
06:00:00	13:00:00	107,242	33,765	200,084	93,343	**1.482**	1.460 - 1.503
18:00:00	13:00:00	509,402	49,583	355,177	111,715	**3.231**	3.195 - 3.269
19:00:00	13:00:00	289,226	37,891	262,535	169,237	**4.921**	4.860 - 4.982
20:00:00	13:00:00	75,558	31,303	88,242	229,244	**6.271**	6.176 - 6.367
06:00:00	14:00:00	107,242	33,898	193,318	92,228	**1.509**	1.488 - 1.531
18:00:00	14:00:00	509,402	49,682	352,994	109,126	**3.170**	3.134 - 3.206
19:00:00	14:00:00	289,226	37,940	259,707	166,042	**4.874**	4.814 - 4.934
20:00:00	14:00:00	75,558	31,315	83,458	226,098	**6.537**	6.437 - 6.638
06:00:00	15:00:00	107,242	33,898	231,484	104,928	**1.434**	1.414 - 1.455
18:00:00	15:00:00	509,402	49,682	415,765	125,411	**3.093**	3.058 - 3.128
19:00:00	15:00:00	289,226	37,940	308,185	189,498	**4.687**	4.631 - 4.745
20:00:00	15:00:00	75,558	31,315	97,148	257,192	**6.388**	6.292 - 6.485
06:00:00	22:00:00	107,242	33,898	28,668	5,053	**0.558**	0.540 - 0.576
18:00:00	22:00:00	509,402	49,682	40,697	5,689	**1.433**	1.392 - 1.476
19:00:00	22:00:00	289,226	37,940	33,974	8,844	**1.984**	1.934 - 2.036
20:00:00	22:00:00	75,558	31,315	15,273	12,970	**2.049**	1.995 - 2.105
06:00:00	23:00:00	107,242	33,898	12,309	3,223	**0.828**	0.795 - 0.863
18:00:00	23:00:00	509,402	49,682	19,276	3,477	**1.849**	1.782 - 1.920
19:00:00	23:00:00	289,226	37,940	15,257	5,544	**2.770**	2.681 - 2.862
20:00:00	23:00:00	75,558	31,315	5,922	8,227	**3.352**	3.234 - 3.475
06:00:00	00:00:00	107,242	33,898	7,916	2,365	**0.945**	0.901 - 0.991
18:00:00	00:00:00	509,402	49,682	12,137	2,727	**2.304**	2.208 - 2.404
19:00:00	00:00:00	289,226	37,940	9,497	4,534	**3.639**	3.507 - 3.776
20:00:00	00:00:00	75,558	31,315	3,358	6,284	**4.515**	4.321 - 4.718
06:00:00	01:00:00	107,242	33,898	4,994	1,346	**0.853**	0.802 - 907
18:00:00	01:00:00	509,402	49,682	7,865	2,077	**2.708**	2.578 - 2.844
19:00:00	01:00:00	289,226	37,940	5,982	2,932	**3.736**	3.570 - 3.910
20:00:00	01:00:00	75,558	31,315	2,181	4,188	**4.633**	4.392 - 4.887
06:00:00	02:00:00	107,242	33,898	3,182	1,510	**1.501**	1.410 - 1.598
18:00:00	02:00:00	509,402	49,682	5,311	1,325	**2.558**	2.407 - 2.719
19:00:00	02:00:00	289,226	37,940	4,018	2,482	**4.709**	4.474 - 4.956
20:00:00	02:00:00	75,558	31,315	1,234	3,253	**6.361**	5.949 - 6.800
06:00:00	03:00:00	107,242	33,898	2,697	1,914	**2.245**	2.115 - 2.384
18:00:00	03:00:00	509,402	49,682	4,582	1,456	**3.258**	3.069 - 3.458
19:00:00	03:00:00	289,226	37,940	3,380	2,904	**6.550**	6.226 - 6.891
20:00:00	03:00:00	75,558	31,315	967	3,733	**9.315**	8.668 - 10.009
06:00:00	04:00:00	107,242	33,898	3,745	3,445	**2.910**	2.774 - 3.053
18:00:00	04:00:00	509,402	49,682	6,868	2,430	**3.628**	3.461 - 3.803
19:00:00	04:00:00	289,226	37,940	4,865	4,622	**7.242**	6.947 - 7.551
20:00:00	04:00:00	75,558	31,315	1,431	5,827	**9.825**	9.259 - 10.425

Table D.7. Detailed OR calculations for **2nd Ave** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	19,957	7,790	39,294	16,931	**1.104**	1.069 - 1.140
18:00:00	09:00:00	86,181	19,639	65,648	17,999	**1.203**	1.176 - 1.231
19:00:00	09:00:00	27,283	13,300	47,647	29,660	**1.277**	1.245 - 1.310
20:00:00	09:00:00	5,818	11,299	16,689	42,960	**1.325**	1.278 - 1.375
06:00:00	10:00:00	19,957	7,790	20,550	9,057	**1.129**	1.089 - 1.170
18:00:00	10:00:00	86,181	19,639	34,770	10,174	**1.284**	1.250 - 1.319
19:00:00	10:00:00	27,283	13,300	24,838	16,366	**1.352**	1.314 - 1.391
20:00:00	10:00:00	5,818	11,299	9,043	23,205	**1.321**	1.270 - 1.375
06:00:00	11:00:00	19,957	7,790	22,326	9,483	**1.088**	1.050 - 1.128
18:00:00	11:00:00	86,181	19,639	37,370	10,601	**1.245**	1.212 - 1.278
19:00:00	11:00:00	27,283	13,300	27,042	16,884	**1.281**	1.245 - 1.318
20:00:00	11:00:00	5,818	11,299	9,989	24,321	**1.254**	1.205 - 1.304
06:00:00	12:00:00	19,957	7,790	26,665	10,302	**0.990**	0.956 - 1.025
18:00:00	12:00:00	86,181	19,639	43,797	11,532	**1.155**	1.126 - 1.186
19:00:00	12:00:00	27,283	13,300	32,130	18,431	**1.177**	1.145 - 1.210
20:00:00	12:00:00	5,818	11,299	11,669	26,627	**1.175**	1.131 - 1.221
06:00:00	13:00:00	19,957	7,790	25,093	10,468	**1.069**	1.032 - 1.106
18:00:00	13:00:00	86,181	19,639	41,739	11,358	**1.194**	1.164 - 1.225
19:00:00	13:00:00	27,283	13,300	30,286	18,357	**1.243**	1.209 - 1.278
20:00:00	13:00:00	5,818	11,299	11,025	26,540	**1.240**	1.193 - 1.288
06:00:00	14:00:00	19,957	7,790	27,498	11,255	**1.049**	1.013 - 1.085
18:00:00	14:00:00	86,181	19,639	45,771	12,324	**1.182**	1.152 - 1.212
19:00:00	14:00:00	27,283	13,300	33,263	19,906	**1.228**	1.195 - 1.261
20:00:00	14:00:00	5,818	11,299	12,180	28,785	**1.217**	1.171 - 1.264
06:00:00	15:00:00	19,957	7,790	41,697	16,514	**1.015**	0.983 - 1.047
18:00:00	15:00:00	86,181	19,639	68,649	17,664	**1.129**	1.104 - 1.155
19:00:00	15:00:00	27,283	13,300	50,262	28,776	**1.174**	1.145 - 1.205
20:00:00	15:00:00	5,818	11,299	18,097	42,231	**1.202**	1.159 - 1.246
06:00:00	22:00:00	19,957	7,790	7,962	2,335	**0.751**	0.713 - 0.792
18:00:00	22:00:00	86,181	19,639	12,955	2,444	**0.828**	0.791 - 0.867
19:00:00	22:00:00	27,283	13,300	9,680	3,957	**0.839**	0.804 - 0.875
20:00:00	22:00:00	5,818	11,299	3,391	6,273	**0.953**	0.904 - 1.004
06:00:00	23:00:00	19,957	7,790	4,495	1,492	**0.850**	0.798 - 0.907
18:00:00	23:00:00	86,181	19,639	7,573	1,476	**0.855**	0.807 - 0.906
19:00:00	23:00:00	27,283	13,300	5,610	2,498	**0.913**	0.868 - 0.962
20:00:00	23:00:00	5,818	11,299	1,929	3,786	**1.011**	0.949 - 1.077
06:00:00	00:00:00	19,957	7,790	2,843	1,172	**1.056**	0.982 - 1.136
18:00:00	00:00:00	86,181	19,639	4,663	1,209	**1.138**	1.066 - 1.214
19:00:00	00:00:00	27,283	13,300	3,463	1,900	**1.125**	1.060 - 1.195
20:00:00	00:00:00	5,818	11,299	1,223	2,751	**1.158**	1.075 - 1.248
06:00:00	01:00:00	19,957	7,790	1,388	661	**1.220**	1.108 - 1.343
18:00:00	01:00:00	86,181	19,639	2,307	690	**1.312**	1.204 - 1.431
19:00:00	01:00:00	27,283	13,300	1,659	1,107	**1.369**	1.265 - 1.481
20:00:00	01:00:00	5,818	11,299	605	1,586	**1.350**	1.223 - 1.490
06:00:00	02:00:00	19,957	7,790	1,024	572	**1.431**	1.288 - 1.590
18:00:00	02:00:00	86,181	19,639	1,768	584	**1.450**	1.318 - 1.594
19:00:00	02:00:00	27,283	13,300	1,299	987	**1.559**	1.431 - 1.697
20:00:00	02:00:00	5,818	11,299	426	1,340	**1.620**	1.446 - 1.814
06:00:00	03:00:00	19,957	7,790	671	373	**1.424**	1.251 - 1.621
18:00:00	03:00:00	86,181	19,639	1,216	359	**1.296**	1.150 - 1.459
19:00:00	03:00:00	27,283	13,300	847	592	**1.434**	1.288 - 1.596
20:00:00	03:00:00	5,818	11,299	277	854	**1.587**	1.381 - 1.825
06:00:00	04:00:00	19,957	7,790	866	491	**1.453**	1.296 - 1.628
18:00:00	04:00:00	86,181	19,639	1,526	526	**1.513**	1.368 - 1.672
19:00:00	04:00:00	27,283	13,300	1,051	861	**1.681**	1.532 - 1.843
20:00:00	04:00:00	5,818	11,299	387	1,220	**1.623**	1.442 - 1.828

Table D.8. Detailed OR calculations for **MTS Trail** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclists	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclist	OR	95% CI
06:00:00	09:00:00	24,750	7,052	47,937	15,898	**1.164**	1.127 - 1.202
18:00:00	09:00:00	107,257	12,349	80,550	18,064	**1.948**	1.900 - 1.996
19:00:00	09:00:00	50,740	8,783	58,176	28,497	**2.830**	2.755 - 2.906
20:00:00	09:00:00	11,828	5,868	21,687	43,207	**4.016**	3.877 - 4.160
06:00:00	10:00:00	24,750	7,008	49,712	15,492	**1.101**	1.066 - 1.136
18:00:00	10:00:00	107,257	12,236	80,870	17,536	**1.901**	1.854 - 1.949
19:00:00	10:00:00	50,740	8,724	60,393	27,297	**2.629**	2.559 - 2.700
20:00:00	10:00:00	11,828	5,853	22,178	39,635	**3.612**	3.486 - 3.742
06:00:00	11:00:00	24,750	7,052	53,545	17,393	**1.140**	1.105 - 1.177
18:00:00	11:00:00	107,257	12,349	88,456	19,273	**1.892**	1.847 - 1.939
19:00:00	11:00:00	50,740	8,783	65,491	30,075	**2.653**	2.584 - 2.724
20:00:00	11:00:00	11,828	5,868	22,612	44,257	**3.945**	3.809 - 4.086
06:00:00	12:00:00	24,750	7,052	57,072	16,865	**1.037**	1.005 - 1.070
18:00:00	12:00:00	107,257	12,349	88,744	18,987	**1.858**	1.814 - 1.904
19:00:00	12:00:00	50,740	8,783	67,804	29,196	**2.488**	2.423 - 2.554
20:00:00	12:00:00	11,828	5,868	20,886	41,997	**4.053**	3.912 - 4.199
06:00:00	13:00:00	24,750	7,052	58,512	16,636	**0.998**	0.967 - 1.030
18:00:00	13:00:00	107,257	12,349	88,117	18,553	**1.829**	1.785 - 1.874
19:00:00	13:00:00	50,740	8,783	68,033	28,673	**2.435**	2.371 - 2.500
20:00:00	13:00:00	11,828	5,868	19,695	40,675	**4.163**	4.017 - 3.415
06:00:00	14:00:00	24,750	7,052	57,371	16,968	**1.038**	1.006 - 1.071
18:00:00	14:00:00	107,257	12,349	87,264	18,714	**1.863**	1.818 - 1.909
19:00:00	14:00:00	50,740	8,783	66,913	28,986	**2.503**	2.437 - 2.570
20:00:00	14:00:00	11,828	5,868	19,680	41,915	**4.293**	4.143 - 4.449
06:00:00	15:00:00	24,750	7,052	49,204	17,071	**1.218**	1.180 - 1.257
18:00:00	15:00:00	107,257	12,349	83,074	18,405	**1.924**	1.878 - 1.972
19:00:00	15:00:00	50,740	8,783	60,056	29,588	**2.846**	2.772 - 2.923
20:00:00	15:00:00	11,828	5,868	20,607	44,165	**4.320**	4.170 - 4.476
06:00:00	22:00:00	24,750	6,986	5,185	811	**0.554**	0.512 - 0.599
18:00:00	22:00:00	107,257	12,233	6,681	986	**1.294**	1.207 - 1.387
19:00:00	22:00:00	50,740	8,735	5,687	1,610	**1.644**	1.549 - 1.746
20:00:00	22:00:00	11,828	5,851	3,751	2,362	**1.273**	1.199 - 1.352
06:00:00	23:00:00	24,750	6,986	4,856	613	**0.447**	0.410 - 0.488
18:00:00	23:00:00	107,257	12,233	5,753	630	**0.960**	0.882 - 1.045
19:00:00	23:00:00	50,740	8,735	5,166	1,071	**1.204**	1.123 - 1.291
20:00:00	23:00:00	11,828	5,851	4,117	1,468	**0.721**	0.672 - 0.771
06:00:00	00:00:00	24,750	6,986	2,781	376	**0.479**	0.479 - 0.535
18:00:00	00:00:00	107,257	12,233	3,368	423	**1.101**	0.994 - 1.220
19:00:00	00:00:00	50,740	8,735	2,985	931	**1.812**	1.677 - 1.957
20:00:00	00:00:00	11,828	5,851	2,247	1,164	**1.047**	0.969 - 1.131
06:00:00	01:00:00	24,750	6,986	1,888	319	**0.599**	0.530 - 0.676
18:00:00	01:00:00	107,257	12,233	2,302	389	**1.482**	1.329 - 1.652
19:00:00	01:00:00	50,740	8,735	2,041	647	**1.841**	1.681 - 2.017
20:00:00	01:00:00	11,828	5,851	1,532	813	**1.073**	0.980 - 1.175
06:00:00	02:00:00	24,750	6,986	1,538	248	**0.571**	0.498 - 0.655
18:00:00	02:00:00	107,257	12,233	1,973	237	**1.053**	0.919 - 1.207
19:00:00	02:00:00	50,740	8,735	1,725	456	**1.536**	1.382 - 1.707
20:00:00	02:00:00	11,828	5,851	1,272	618	**0.982**	0.888 - 1.087
06:00:00	03:00:00	24,750	6,986	1,271	4,402	**12.270**	1.466 - 13.131
18:00:00	03:00:00	107,257	12,233	1,619	4,448	**24.089**	2.688 - 25.575
19:00:00	03:00:00	50,740	8,735	1,401	4,529	**18.778**	7.613 - 20.021
20:00:00	03:00:00	11,828	5,851	1,050	4,686	**9.022**	8.379 - 9.714
06:00:00	04:00:00	24,750	6,986	3,093	1,009	**1.156**	1.071 - 1.247
18:00:00	04:00:00	107,257	12,233	4,691	1,017	**1.901**	1.772 - 2.039
19:00:00	04:00:00	50,740	8,735	3,537	1,674	**2.749**	2.583 - 2.926
20:00:00	04:00:00	11,828	5,851	1,694	2,547	**3.039**	2.837 - 3.257

Table D.9. Detailed OR calculations for **Spokane** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclis	CaseDark cyclists	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	41,799	16,027	37,175	15,953	**1.119**	1.090 - 1.149
18:00:00	09:00:00	104,354	23,632	62,079	17,963	**1.278**	1.250 - 1.306
19:00:00	09:00:00	38,164	14,963	45,182	27,755	**1.567**	1.529 - 1.605
20:00:00	09:00:00	8,205	11,616	16,181	39,153	**1.709**	1.653 - 1.768
06:00:00	10:00:00	41,799	16,027	25,509	9,246	**0.945**	0.917 - 0.974
18:00:00	10:00:00	104,354	23,632	41,701	10,487	**1.110**	1.082 - 1.139
19:00:00	10:00:00	38,164	14,963	30,943	16,414	**1.353**	1.317 - 1.390
20:00:00	10:00:00	8,205	11,616	11,363	23,310	**1.449**	1.398 - 1.502
06:00:00	11:00:00	41,799	16,027	24,787	8,914	**0.938**	0.910 - 0.967
18:00:00	11:00:00	104,354	23,632	40,677	10,254	**1.113**	1.085 - 1.142
19:00:00	11:00:00	38,164	14,963	30,358	15,819	**1.329**	1.294 - 1.365
20:00:00	11:00:00	8,205	11,616	11,090	22,502	**1.433**	1.382 - 1.486
06:00:00	12:00:00	41,799	16,027	26,937	9,670	**0.936**	0.909 - 0.964
18:00:00	12:00:00	104,354	23,632	43,986	11,092	**1.114**	1.086 - 1.142
19:00:00	12:00:00	38,164	14,963	32,656	17,181	**1.342**	1.307 - 1.378
20:00:00	12:00:00	8,205	11,616	11,935	24,502	**1.450**	1.399 - 1.503
06:00:00	13:00:00	41,799	16,027	27,294	10,686	**1.021**	0.992 - 1.051
18:00:00	13:00:00	104,354	23,632	45,092	11,956	**1.171**	1.142 - 1.200
19:00:00	13:00:00	38,164	14,963	33,194	18,472	**1.419**	1.383 - 1.457
20:00:00	13:00:00	8,205	11,616	12,157	26,105	**1.517**	1.464 - 1.572
06:00:00	14:00:00	41,799	16,027	29,850	12,082	**1.056**	1.027 - 1.085
18:00:00	14:00:00	104,354	23,632	49,599	13,594	**1.210**	1.182 - 1.239
19:00:00	14:00:00	38,164	14,963	36,209	20,705	**1.458**	1.422 - 1.496
20:00:00	14:00:00	8,205	11,616	12,994	29,308	**1.593**	1.583 - 1.650
06:00:00	15:00:00	41,799	16,027	39,618	15,737	**1.036**	1.009 - 1.063
18:00:00	15:00:00	104,354	23,632	66,060	17,572	**1.175**	1.149 - 1.201
19:00:00	15:00:00	38,164	14,963	48,085	27,433	**1.455**	1.421 - 1.491
20:00:00	15:00:00	8,205	11,616	17,096	39,535	**1.633**	1.580 - 1.689
06:00:00	22:00:00	41,799	16,027	6,881	2,343	**0.888**	0.844 - 0.934
18:00:00	22:00:00	104,354	23,632	10,945	2,370	**0.956**	0.913 - 1.002
19:00:00	22:00:00	38,164	14,963	8,381	3,659	**1.114**	1.066 - 1.163
20:00:00	22:00:00	8,205	11,616	3,167	5,340	**1.191**	1.130 - 1.255
06:00:00	23:00:00	41,799	16,027	4,163	1,463	**0.917**	0.861 - 0.975
18:00:00	23:00:00	104,354	23,632	7,027	1,554	**0.977**	0.923 - 1.034
19:00:00	23:00:00	38,164	14,963	5,166	2,412	**1.191**	1.131 - 1.254
20:00:00	23:00:00	8,205	11,616	1,877	3,629	**1.366**	1.283 - 1.454
06:00:00	00:00:00	41,799	16,027	2,721	1,032	**0.989**	0.919 - 1.065
18:00:00	00:00:00	104,354	23,632	4,540	1,151	**1.120**	1.048 - 1.196
19:00:00	00:00:00	38,164	14,963	3,359	1,706	**1.295**	1.218 - 1.377
20:00:00	00:00:00	8,205	11,616	1,222	2,488	**1.438**	1.335 - 1.549
06:00:00	01:00:00	41,799	16,027	1,622	885	**1.423**	1.308 - 1.548
18:00:00	01:00:00	104,354	23,632	2,814	971	**1.524**	1.415 - 1.641
19:00:00	01:00:00	38,164	14,963	2,032	1,454	**1.825**	1.702 - 1.957
20:00:00	01:00:00	8,205	11,616	685	2,020	**2.083**	1.901 - 2.282
06:00:00	02:00:00	41,799	16,027	1,389	755	**1.418**	1.295 - 1.552
18:00:00	02:00:00	104,354	23,632	2,440	847	**1.533**	1.416 - 1.660
19:00:00	02:00:00	38,164	14,963	1,769	1,296	**1.869**	1.735 - 2.012
20:00:00	02:00:00	8,205	11,616	597	1,744	**2.063**	1.872 - 2.274
06:00:00	03:00:00	41,799	16,027	1,179	896	**1.982**	1.814 - 2.166
18:00:00	03:00:00	104,354	23,632	2,180	965	**1.955**	1.810 - 2.111
19:00:00	03:00:00	38,164	14,963	1,496	1,455	**2.481**	2.302 - 2.673
20:00:00	03:00:00	8,205	11,616	515	1,969	**2.701**	2.441 - 2.988
06:00:00	04:00:00	41,799	16,027	3,064	1,367	**1.164**	1.089 - 1.243
18:00:00	04:00:00	104,354	23,632	5,161	1,552	**1.328**	1.252 - 1.408
19:00:00	04:00:00	38,164	14,963	3,740	2,432	**1.659**	1.571 - 1.751
20:00:00	04:00:00	8,205	11,616	1,327	3,396	**1.808**	1.686 - 1.938

Table D.10. Detailed OR calculations for **NW 58th** in Seattle, WA, USA.

Case hour	Control hour	CaseDay cyclis	CaseDark cyclis	CtrlDay cyclists	CtrlDark cyclists	OR	95% CI
06:00:00	09:00:00	2,191	1,580	7,779	5,531	**0.986**	0.916 - 1.061
18:00:00	09:00:00	20,876	6,952	13,799	6,105	**1.329**	1.276 - 1.384
19:00:00	09:00:00	11,063	8,214	9,371	9,385	**1.349**	1.295 - 1.405
20:00:00	09:00:00	3,221	7,497	3,929	12,740	**1.393**	1.319 - 1.471
06:00:00	10:00:00	2,198	1,575	7,867	5,322	**0.944**	0.877 - 1.016
18:00:00	10:00:00	20,871	6,942	13,901	5,941	**1.285**	1.234 - 1.338
19:00:00	10:00:00	11,078	8,207	9,525	9,054	**1.283**	1.232 - 1.336
20:00:00	10:00:00	3,227	7,496	3,906	12,430	**1.370**	1.297 - 1.447
06:00:00	11:00:00	2,198	1,580	9,033	6,638	**1.022**	0.951 - 1.099
18:00:00	11:00:00	20,897	6,952	15,985	7,235	**1.361**	1.309 - 1.414
19:00:00	11:00:00	11,078	8,207	10,911	10,914	**1.350**	1.299 - 1.404
20:00:00	11:00:00	3,227	7,497	4,414	14,795	**1.443**	1.368 - 1.522
06:00:00	12:00:00	2,198	1,563	10,025	7,459	**1.046**	0.974 - 1.124
18:00:00	12:00:00	20,897	6,952	18,116	8,195	**1.360**	1.310 - 1.412
19:00:00	12:00:00	11,078	8,207	12,206	12,504	**1.383**	1.331 - 1.436
20:00:00	12:00:00	3,227	7,497	4,928	16,880	**1.474**	1.400 - 1.553
06:00:00	13:00:00	2,198	1,563	9,908	7,793	**1.106**	1.030 - 1.188
18:00:00	13:00:00	20,897	6,952	18,067	8,536	**1.420**	1.368 - 1.474
19:00:00	13:00:00	11,078	8,207	12,094	12,512	**1.396**	1.344 - 1.450
20:00:00	13:00:00	3,227	7,497	4,797	16,924	**1.519**	1.441 - 1.600
06:00:00	14:00:00	2,198	1,563	9,864	7,637	**1.089**	1.014 - 1.169
18:00:00	14:00:00	20,897	6,952	17,872	8,145	**1.370**	1.319 - 1.423
19:00:00	14:00:00	11,078	8,207	12,050	12,224	**1.369**	1.318 - 1.422
20:00:00	14:00:00	3,227	7,497	4,733	16,587	**1.508**	1.431 - 1.590
06:00:00	15:00:00	2,198	1,563	9,912	7,179	**1.019**	0.948 - 1.094
18:00:00	15:00:00	20,897	6,952	17,509	7,810	**1.341**	1.291 - 1.393
19:00:00	15:00:00	11,078	8,207	11,923	11,702	**1.325**	1.275 - 1.377
20:00:00	15:00:00	3,227	7,497	4,754	15,984	**1.447**	1.373 - 1.525
06:00:00	22:00:00	2,198	1,580	2,711	1,593	**0.817**	0.747 - 0.894
18:00:00	22:00:00	20,897	6,968	4,545	1,728	**1.140**	1.072 - 1.213
19:00:00	22:00:00	11,078	8,230	3,286	2,509	**1.028**	0.960 - 1.091
20:00:00	22:00:00	3,227	7,500	1,430	3,373	**1.015**	0.942 - 1.093
06:00:00	23:00:00	2,198	1,580	1,811	1,074	**0.825**	0.747 - 0.911
18:00:00	23:00:00	20,897	6,968	2,952	1,170	**1.189**	1.105 - 1.279
19:00:00	23:00:00	11,078	8,230	2,123	1,682	**1.066**	0.994 - 1.144
20:00:00	23:00:00	3,227	7,500	970	2,295	**1.018**	0.934 - 1.109
06:00:00	00:00:00	2,198	1,580	1,001	660	**0.917**	0.815 - 1.032
18:00:00	00:00:00	20,897	6,968	1,639	725	**1.327**	1.211 - 1.454
19:00:00	00:00:00	11,078	8,230	1,201	1,008	**1.130**	1.034 - 1.234
20:00:00	00:00:00	3,227	7,500	538	1,348	**1.078**	0.968 - 1.201
06:00:00	01:00:00	2,198	1,580	637	451	**0.985**	0.859 - 1.129
18:00:00	01:00:00	20,897	6,968	1,092	505	**1.387**	1.244 - 1.546
19:00:00	01:00:00	11,078	8,230	758	723	**1.284**	1.155 - 1.427
20:00:00	01:00:00	3,227	7,500	319	942	**1.271**	1.112 - 1.452
06:00:00	02:00:00	2,198	1,580	450	314	**0.971**	0.829 - 1.137
18:00:00	02:00:00	20,897	6,968	769	318	**1.240**	1.085 - 1.417
19:00:00	02:00:00	11,078	8,230	549	499	**1.223**	1.080 - 1.386
20:00:00	02:00:00	3,227	7,500	258	658	**1.097**	0.945 - 1.275
06:00:00	03:00:00	2,198	1,580	300	307	**1.424**	1.199 - 1.690
18:00:00	03:00:00	20,897	6,968	506	348	**2.063**	1.795 - 2.371
19:00:00	03:00:00	11,078	8,230	366	439	**1.615**	1.401 - 1.860
20:00:00	03:00:00	3,227	7,500	146	532	**1.568**	1.299 - 1.892
06:00:00	04:00:00	2,198	1,580	335	242	**1.005**	0.841 - 1.200
18:00:00	04:00:00	20,897	6,968	560	268	**1.435**	1.238 - 1.664
19:00:00	04:00:00	11,078	8,230	411	360	**1.179**	1.021 - 1.362
20:00:00	04:00:00	3,227	7,500	195	468	**1.033**	0.869 - 1.227

Appendix E. Visual assessment of journey type

Table E.1. A visual classification for all counting locations in **Auckland,** New Zealand, alongside their corresponding weighted odds ratios (arranged low to high). Locations are classified between utilitarian, mixed, and leisure. A binary value is proposed following the suggestion that U and M locations can be added together after no significant change was revealed in their combined weighted ORs.

Location	Classification	Assigned binary value	Odds ratios
Carlton Gore Road	M	0	1.00
Dominion Road	U	0	1.09
Symonds Street	U	0	1.11
Hopetoun Street	U	0	1.12
Grafton Bridge	U	0	1.14
Nelson Street	U	0	1.14
Upper Queen Street	U	0	1.20
Quay Street Eco Display	U	0	1.22
Beach Road	U	0	1.22
Oceanview Road	U	0	1.24
Grafton Gully	M	0	1.25
Saint Lukes Road	U	0	1.26
Nw Cycleway Kingsland	M	0	1.27
Teatatu Peninsula	M	0	1.30
Lagoon Drive	M	0	1.30
Lightpath 2	M	0	1.31
Great North Road	U	0	1.33
Great South Road	U	0	1.36
Quay Street Spark Arena	U	0	1.37
Ormiston Road	M	0	1.43
East Coast Road	U	0	1.51
SH20A	U	0	1.53
Nw Cycleway Teatatu	M	0	1.54
Lake road	U	0	1.56
Tamaki Drive Wb	M	0	1.59
Rankin Avenue	U	0	1.61
Curran Street	L	1	1.70
Mangere Safe Routes	L	1	1.79
Queen Street Pukekohe	M	0	1.86
SW SH20	L	1	2.00
Waterview Unitec	L	1	2.23
Glenn Innes to Tamaki	L	1	2.29
Mangere Bridge	M	0	2.34
SH18 Upper Harbour	M	0	2.44
Orewa Path	L	1	5.30
Twin Streams	L	1	6.13
Leigh Road	L	1	8.72

Table E.2. A visual classification for all counting locations in **Edinburgh**, Scotland, UK, alongside their corresponding weighted odds ratios (arranged low to high).

Location	Classification	Assigned binary value	Odds ratio
RBS Gogar	U	0	0.96
Middle Meadow Walk	M	0	0.99
Cultins Road	M	0	1.10
North Edinburgh Access Road	U	0	1.24
Portobello Prom	M	0	1.36
Spylaw Park	L	1	1.55
Silverknowes	L	1	3.58

Table E.3. A visual classification for all counting locations in **Münster**, Germany, alongside their corresponding weighted odds ratios (arranged low to high).

Location	Classification	Assigned binary value	Odds ratio
Weseler Straße	M	0	1.04
Hammer Straße	M	0	1.07
Neutor	M	0	1.09
Promenade	L	1	1.09
Hüfferstraße	M	0	1.10
Warendorfer Straße	M	0	1.11
Gartenstraße	M	0	1.11
Kanalpromenade	L	1	1.47

Table E.4. A visual classification for all counting locations in **Oslo**, Norway, alongside their corresponding weighted odds ratios (arranged low to high).

Location	Classification	Assigned binary value	Odds ratio
Lysaker Sykkel	M	0	0.75
Skullerud Sykkel	M	0	0.86
Munkedamsveien Sykkel	M	0	0.88
Frognerst.Sykkel 03	M	0	0.88
Gaustad sykkel	M	0	0.91
Bryn Sykkel	M	0	0.93
Akersyke Sykkel 03	M	0	0.93
Dr. Eufemias gt. Sykkel Vestgående	U	0	0.94
Smestad Sykkel	M	0	1.02
Breivoll Sykkel	U	0	1.03
Dr. Eufemias Gt. Sykkel Østgående	U	0	1.06
Grorud Sykkel	M	0	1.07

Table E.5. A visual classification for all counting locations in **Seattle**, WA, USA, alongside their corresponding weighted odds ratios (arranged low to high).

Location	Classification	Assigned binary value	Odds ratio
Broadway	U	0	1.08
2nd Ave	U	0	1.17
Fremont Bridge	U	0	1.21
Spokane	M	0	1.26
NW 58TH St Greenway	M	0	1.29
39th Ave	M	0	1.32
26th Ave	M	0	1.42
BGT North	L	1	2.00
MTS Trail	L	1	2.10
Elliot Bay	L	1	3.33

Appendix F. Variance Inflation Factor (VIF) results for microscale factors – SPSS output

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.006	.112		8.949	<.001
	Cycling_distance_km	.066	.007	.766	9.907	<.001
2	(Constant)	-.182	.283		-.642	.523
	Cycling_distance_km	.050	.007	.583	7.306	<.001
	Journey_type_A	3.325	.742	.358	4.482	<.001

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics **VIF**
1	(Constant)		
	Cycling_distance_km	1.000	**1.000**
2	(Constant)		
	Cycling_distance_km	.737	**1.358**
	Journey_type_A	.737	**1.358**

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Journey_type_A	.358[b]	4.482	<.001	.478	.737
	Unweighted_total_cyclists	.157[b]	2.036	.046	.240	.961
	Latitude	-.073[b]	-.909	.366	-.110	.920
	Lighting_presence	-.130[b]	-1.626	.109	-.193	.914
2	Unweighted_total_cyclists	.117[c]	1.679	.098	.201	.944
	Latitude	.052[c]	.680	.499	.083	.794
	Lighting_presence	.008[c]	.104	.917	.013	.748

Excluded Variables[a]

Model		Collinearity Statistics **VIF**	Collinearity Statistics Minimum Tolerance
1	Journey_type_A	**1.358**	.737
	Unweighted_total_cyclists	**1.040**	.961
	Latitude	**1.087**	.920
	Lighting_presence	**1.094**	.914
2	Unweighted_total_cyclists	**1.060**	.695
	Latitude	**1.260**	.635
	Lighting_presence	**1.337**	.603

Appendix G. Pilot study: Exploring influence of lighting characteristics on OR variance

The following is a description of a pilot study conducted as a part of my PhD research.

In this thesis, Google street view were used to record whether street lighting was present or absent at cycle counting sites, as a way to assess the influence of lighting on the effect of darkness. This approach was chosen for practical reasons, but it is a crude representation of lighting conditions that disregards the impact of the different characteristics of the lighting provided. Such characteristics were shown to influence the impact of darkness to different degrees in previous work. For example, Uttley et al., [2020] compared ORs from 48 locations in Birmingham, UK, with records of lantern density and relative brightness of street lighting (estimated from aerial images). They reported the effect of darkness on cycling varied depending on how bright a street was and the density of lamps on that street, suggesting the influence of lighting on cycling after dark is nuanced and may not be entirely represented by the simple presence or absence of street lighting.

The pilot study follows the same methodology introduced in Chapters **3** and **4**, where a case-control method establishes ORs for counting sites, which are then compared with collected supporting data to explore their association. Both parts of the study are detailed below.

1. Cycling counts

Cycling counts were collected as part of a study by my colleague Shahab Gorjimahlabani for his PhD research at the University of Sheffield [Gorjimahlabani, 2025]. A total of 20 participants (including myself) carried out observational travel counts of pedestrians and cyclists in 11 locations around the University of Sheffield campus. These daily observations started on 25.3.2024, six days before the spring DST clock change, and ended on 6.4.2024, six days after the spring DST clock change. Counts were carried out twice a day, once from 16:00 to 16:59 to establish a case hour where lighting conditions switch from daylight to darkness before and after the clock change; and once from 19:00 to 19:59, to establish a control hour that's in darkness throughout the two weeks. Participants were also asked to record information about

weather conditions, street lighting conditions (on or off), gender of pedestrians and cyclists, and an estimate of their age range. Further details about the travel count are available in Shahab's PhD thesis, titled "*Road Lighting for Pedestrian Reassurance: An Investigation of Methods and Optimal Illuminance*", submitted February 2025.

Odds ratios for each counting location were established by applying the case-control method: clock-change approach on the collected cyclist counts. These are shown in **Table G.1**.

Table G.1. Odds ratios established for locations around The University of Sheffield campus, using observational counts from Gorjimahlabani [2025].

Location name	coordinates	Case day cyclists	Case dark cyclists	Control day cyclists	Control dark cyclists	OR
S1	53°22'24.0"N 1°29'04.9"W	27	33	111	87	0.64
S2	53°22'27.5"N 1°29'06.5"W	35	38	127	92	0.67
S3	53°22'31.5"N 1°29'08.9"W	2	1	5	6	2.4
S4	53°22'34.1"N 1°29'07.5"W	10	18	10	12	0.67
S5	53°22'33.1"N 1°29'06.7"W	1	0	0	0	N/A
S6	53°22'36.4"N 1°29'03.4"W	54	56	105	107	0.98
S8	53°22'45.4"N 1°29'09.1"W	5	3	3	10	5.56
S11	53°22'41.7"N 1°29'13.4"W	22	16	11	15	1.88
S12	53°22'40.0"N 1°29'14.2"W	24	16	12	20	2.50
S13	53°22'37.0"N 1°29'13.9"W	71	59	145	115	0.95
S14	53°22'38.2"N 1°29'12.7"W	71	86	152	89	0.48

2. Light measurements using a specialised camera, lens, and analysis software.

While illuminance was measured using an illuminance metre in all 11 locations in the study by Gorjimahlabani [2025], The pilot study uses a camera-based analysis to establish illuminance. This experimental method follows a suggestion by Greffier

[2022] in using HDRI (High Dynamic Range Imaging) with a specialised post processing software to capture and analyse road surface luminance. This offers several benefits when compared to using an illuminance metre, such as the ability to analyse an entire field of vision with a single capture rather than the time-consuming point-based measurement of the metre. A comparison of the process of both methods is illustrated in **Figure G.1**.

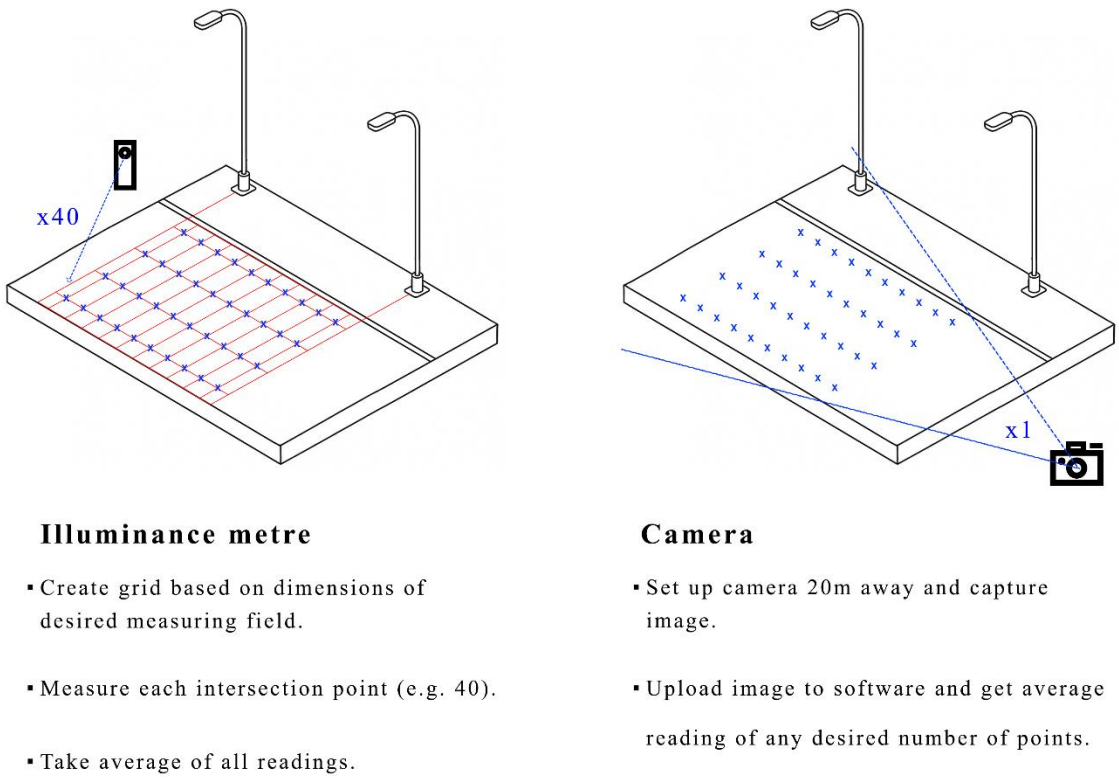

Fig. G.1. A Comparison between the process of using an illuminance metre to measure illuminance vs. using a camera and a post-processing software to measure luminance. Here an example of a 15m x 6m measuring field is given, which generates approx. 40 measuring points. [originally shown in Chapter 7, as **Figure 7.4**]

For this study and future lighting research use, a DSLR camera complete with a specialised lens and luminance distribution analysis software were purchased from LumiDISP (https://lumidisp.eu/). The package was delivered to the University of Sheffield on Friday 22.12.2023. Following this, myself and the research lighting group in the University of Sheffield attended two workshops with the LumiDISP developers

team to understand how to use the camera. Several field tests were conducted following this by myself and my colleagues in the lighting research group (see example of such tests in **Figure G.2**). The initial results for a few sites are shown in **Table G.2**.

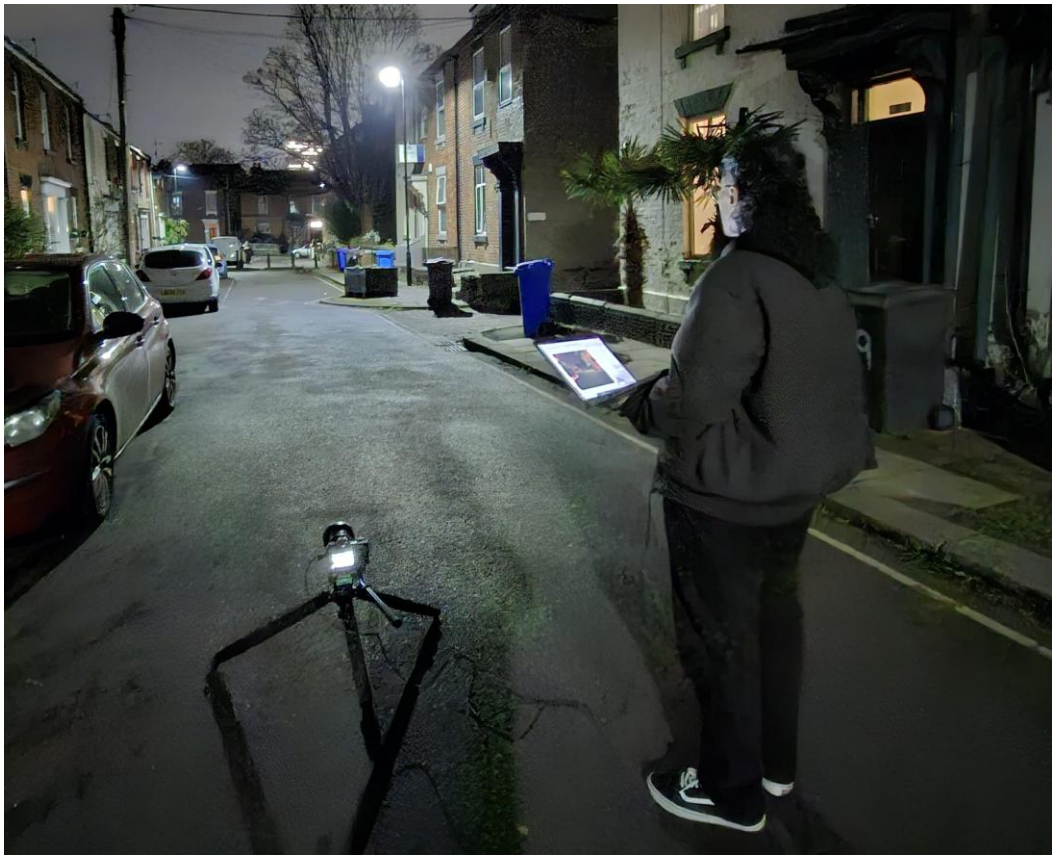

Fig. G.2. An example of a field test carried out in January 2025. The picture shows the author using the camera and software in a street in Sheffield. Photo by Yohanes Satyayoga Raniasta.

Table G.2. Illuminances for locations around the University of Sheffield as measured in Gorjimahlabani [2025] and established later using the camera and LumiDISP analysis.

Location name	Illuminance (lx) measured in Gorjimahlabani [2025]	Illuminance (lx) measured using LumiDISP*
S3	6.79	5.28
S4	2.64	4.05
S5	11.80	14.97
S7	6.92	1.59
S8	6.06	5.72
S10	9.73	3.77

*These illuminance values are converted from luminance measurements captured and analysed using the camera and LumiDISP software. For this, a conversion equation was used (equation 8).

The illuminance values established using the camera and post processing software did not match the ones established using the luminance meter in the same location. This could be for many reasons, as there were many challenges faced when using the camera. One possible reason for this might be that the two measurements were taken more than a year apart. Gorjimahlabani's [2025] measurement were taken in 2023, while the camera measurements were taken at the start of 2025. Thus, to test if this impacted the measurements, a new set of field measurements were carried out using both methods. On Thursday 30.1.2025, colleagues from the Lighting Research group and I conducted field measurements in the car park of the Arts Tower building in the University of Sheffield. We found a difference of 7.7 lx between average readings using the two methods at the same time and location. We speculated that this difference might be the results of using a provisional road reflectance ratio of 0.2 in the equation required to convert luminance values into illuminance (**Equation G.1**). Thus, we attempt to measure road surface reflectance the following day.

$$E = \frac{(L\ x\ \pi)}{0.2} \qquad \text{(G.1)}$$

Where,

E = the illuminance in lux

L = the average luminance in cd/m^2

$\pi \approx 3.14\ 16$

The denominator 0.2 assumes a typical reflection coefficient (or luminance existence factor) of 20%

To measure road surface reflectance, luminance of the road and luminance of a *Reference White* are measured in the same spot. The average reading of five measurements was calculated in the same site used the day before, establishing a ratio of 0.13. Using this ratio on to convert readings of the 6 locations mentioned in **Table**

G.1 resulted in an increase of up to 30 lx between the camera readings and Gorjimahlabani's readings.

Despite these efforts, measurement using the two methods did not align, suggesting a possible problem with the process of using the camera. This and several other challenges faced with the camera (see **Table G.3**) forced us to postpone the experiment. This means that no conclusion can be reached from the pilot study in this thesis, but the documentation of the process should allow for further research to continue in the future.

Table G.3. A list of challenges faced when using the camera to measure illuminance and their outcome.

No.	Challenge faced	Outcome/solution
1	Delay in approval of funding from the University of Sheffield.	Postponing the study to the next winter.
2	Issues with the narrow width of field in the camera meant that images would have to be taken multiple times to cover the entirety of the field. Upon investigating this, it was cleared that the wrong lens was ordered.	A new wide lens was ordered from LumiDISP. This added to the delays.
3	Using the right settings to capture accurate readings.	A second workshop was organized with the developers. Despite this, some problems persisted and took a lot of trial-and-error to solve.
4	When reading luminance maps from the captured images, several options for creating a field/grid are possible. Every change generates a different reading.	An attempt was made to replicate the grid created in Gorjimahlabani [2025]
5	Moving the camera slightly to adjust the field of measurement can lead to a variation of up to 5lx in the reading.	An attempt was made improvise when the manual did not offer answers.
6	A minimum distance of 20m from the measurement field is required. This means that for roads that are not straight or with uneven surfaces, some parts may be obscured.	Currently no solution.
7	In almost all measurement locations, parked cars blocking the measurement field might limit the accuracy of readings.	An attempt was made to measure outside of the shadows cast by cars.
8	To convert luminance to illuminance, the equation needs road surface reflectance. To measure this, a White Block is needed. The team was unable to locate the white block to measure road reflectance.	A piece of white paper was used instead.

Appendix H. Linear regression re-estimates using log-transformed ORs

Chapter 4: Across-cities analysis of the impact of darkness

Latitude:

Table H.1. Latitudes and log-transformed ORs for all 15 cities.

Location	Latitude	log(OR)
Helsinki	60.19	0.076961
Oslo	59.91	-0.13926
Edinburgh	55.95	0.139762
Leeds	53.8	0.165514
Dublin	53.35	0.076961
Berlin	52.52	0.131028
Birmingham	52.48	0.41211
Münster	51.96	0.086178
Antwerp	51.22	0.058269
Paris	48.86	0.076961
Seattle	47.61	0.553885
Montreal	45.5	0.10436
New York	40.73	0.207014
Arlington	38.88	0.565314
Auckland	36.85	0.364643

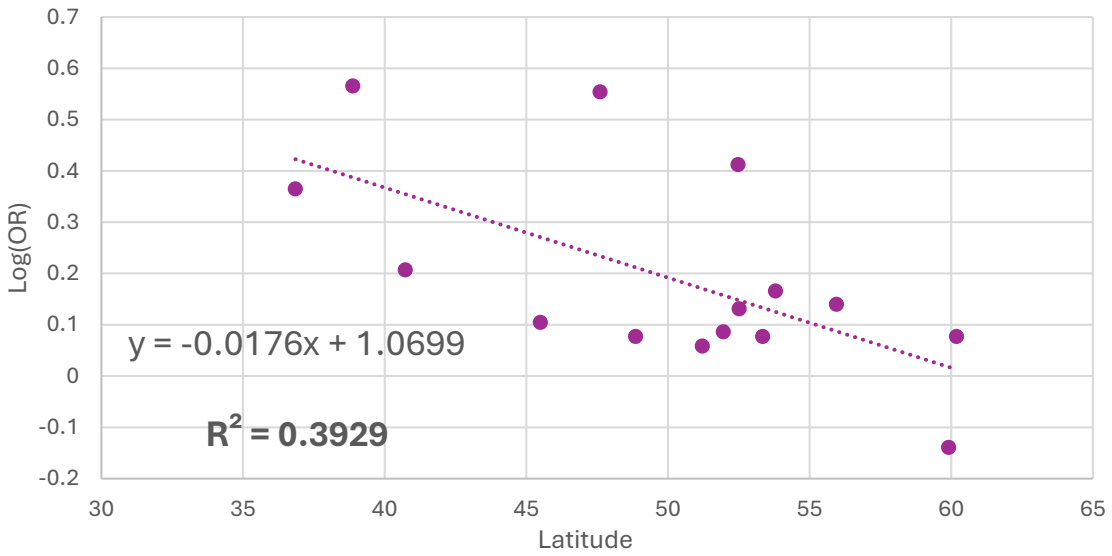

Fig. H.1. The relationship between latitude and log-transformed ORs for all 15 cities.

Cycling culture – cycling modal share:

Table H.2. Cycling modal shares and log-transformed ORs for all 15 cities.

Location	Modal share of cycling	log(or)
Münster	0.47	0.086178
Antwerp	0.42	0.058269
Berlin	0.13	0.131028
Paris	0.112	0.076961
Helsinki	0.09	0.076961
Dublin	0.07	0.076961
Oslo	0.06	-0.13926
Edinburgh	0.04	0.139762
Montreal	0.033	0.10436
Seattle	0.03	0.553885
New York	0.026	0.207014
Arlington	0.02	0.565314
Leeds	0.011	0.165514
Auckland	0.01	0.364643
Birmingham	0.01	0.41211

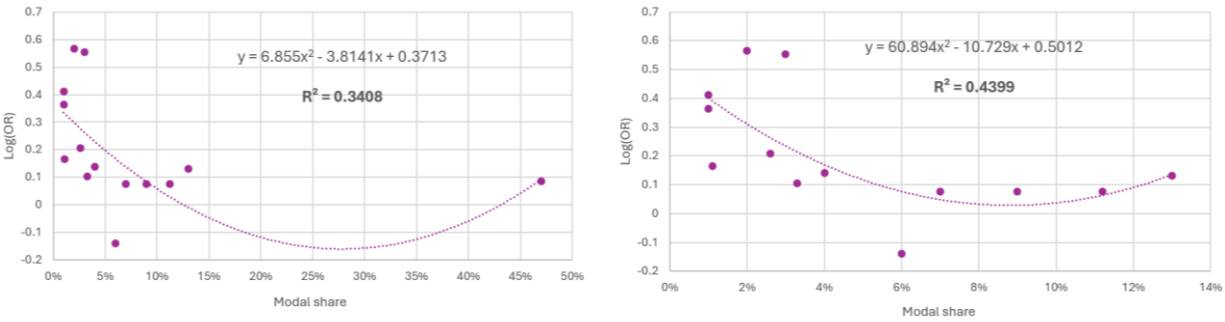

Fig. H.2. The relationship between modal shares and log-transformed ORs for all 15 cities (left) and for 13 cities when excluding Münster and Antwerp as outliers.

Cycling culture – number of cyclists per 1000 inhabitants:

Table H.3. Number of cyclists per 100 inhabitants and log-transformed ORs for all 15 cities.

City	Cyclists per 1k inhabitants	log(OR)
Münster	6923.36	0.086178
Antwerp	879.2	0.058269
Helsinki	738.86	0.076961
Arlington	598.43	0.565314
Seattle	569.43	0.553885
Dublin	417.25	0.076961
Oslo	335.26	-0.13926
Edinburgh	329.25	0.139762
Berlin	193.04	0.131028
Paris	105.5	0.076961
Montreal	148.76	0.10436
New York	89.67	0.207014
Auckland	62.01	0.364643
Leeds	45.12	0.165514
Birmingham	33.42	0.41211

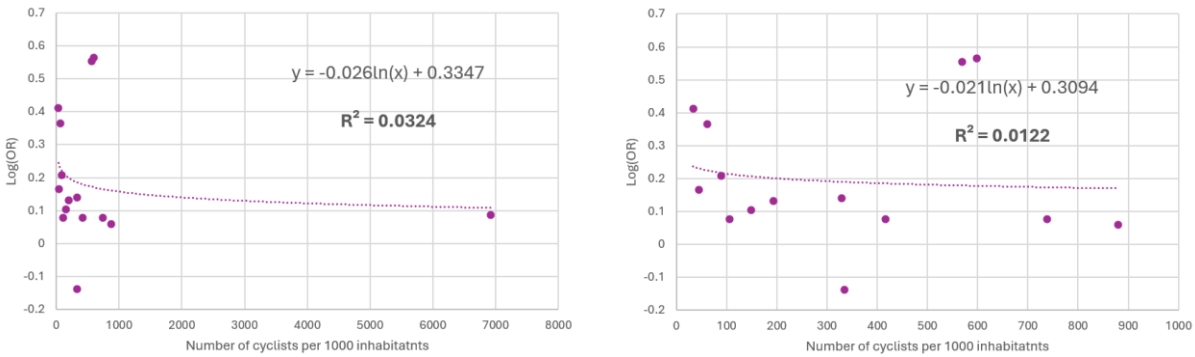

Fig. H.3. The relationship between the number of cyclists per 1000 inhabitants and log-transformed ORs for all 15 cities (left) and for 14 cities when excluding Münster as an outlier.

Cycling culture – cycling friendliness:

Table H.4. Scores for Luko's categories and log-transformed ORs for all 15 cities.

City	Weather score	Bicycle usage	Safety score	infrastructure score	Sharing score	Event score	Total score	log(or)
Münster	58.74	0.39	88.43	51.23	31	445.58	65.93	0.086178
Antwerp	62.67	0.29	77.05	34.28	89	1165.81	60.51	0.058269
Montreal	49.6	0.18	87.51	45.91	6	986.47	43.68	0.10436
Berlin	57.69	0.15	89.86	48.71	17	407.56	42.59	0.131028
Paris	66.31	0.03	84.28	63.15	81	318.14	37.53	0.076961
Helsinki	47.16	0.1	90.19	45.89	40	222.36	36.62	0.076961
Auckland	74.64	0.08	94.54	33.73	1	453.72	33.04	0.364643
Seattle	71.92	0.04	75.3	56.92	8	1688.2	32.93	0.553885
Edinburgh	62.56	0.03	79.84	43.82	11	1175.78	31.32	0.139762
Oslo	47.45	0.07	90.79	30.31	45	226.4	31.31	-0.13926
Dublin	68.72	0.03	86.92	35.91	42	517.05	29.97	0.076961
New York	60.75	0.01	71.76	48.21	20	2157.77	28.1	0.207014

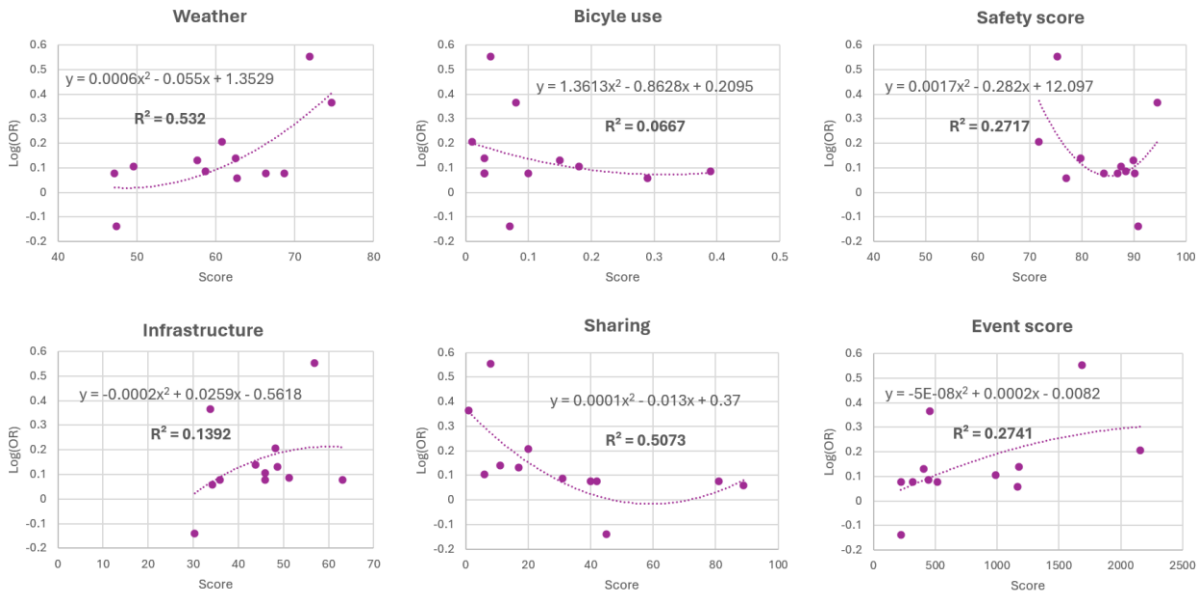

Fig. H.4. The relationship between each of the 6 Luko categories and log-transformed ORs for all 15 cities.

Chapter 5-6: Within-cities analysis of the impact of darkness

Table H.5. Log-transformed ORs for 37 sites in **Auckland**, NZ, arranged low to high, alongside estimates for each microscale factor (shaded columns) as established in chapters 5-6.

Site	Log(OR)	Microscale factors					
		P_L	Euclidean distance (km)	Network distance (km)*	Street lighting presence	Latitude	No. of cyclists
Carlton Gore Road	0.0000	0.25	1.53	1.9	Yes	-36.864	324913
Dominion Road	0.0862	0.27	2.16	2.4	Yes	-36.870	233301
Symonds Street	0.1044	0.28	0.78	0.95	indirect	-36.860	650985
Hopetoun Street	0.1133	0.25	0.63	0.9	Yes	-36.856	218979
Grafton Bridge	0.1310	0.29	0.87	1.1	Yes	-36.860	128643
Nelson Street	0.1310	0.29	0.5	0.8	Yes	-36.850	678620
Upper Queen Street	0.1823	0.31	0.76	0.75	Yes	-36.859	239369
Quay Street Eco Display	0.1989	0.43	1.13	1.5	Yes	-36.843	106134
Beach Road	0.1989	0.36	1.07	1.9	Yes	-36.849	539342
Oceanview Road	0.2151	0.53	23.39	Excluded	Yes	-36.784	99802
Grafton Gully	0.2231	0.38	0.57	0.9	Yes	-36.856	651043
Saint Lukes Road	0.2311	0.38	3.91	5.3	Yes	-36.871	147445
Nw Cycleway Kingsland	0.2390	0.33	2.5	2.8	Yes	-36.869	183547
Teatatu Peninsula	0.2624	0.38	9.98	12.8	indirect	-36.850	66509
Lagoon Drive	0.2624	0.55	10.37	13.3	Yes	-36.907	486423
Lightpath 2	0.2700	0.39	0.51	1.1	Yes	-36.853	591887
Great N. Road	0.2852	0.33	2.07	2.3	Yes	-36.865	121033
Great S. Road Manukau	0.3075	0.45	18.28	20.3	Yes	-36.987	25693
Quay Street Spark Arena	0.3148	0.44	1.48	2.1	Yes	-36.847	123447
Ormiston Road	0.3577	0.49	18.02	27.1	indirect	-36.965	39808
East Coast Road	0.4121	0.55	12.5	Excluded	Yes	-36.742	309523
SH20A	0.4253	0.45	14.06	17.2	indirect	-36.978	12103
Nw Cycleway Teatatu	0.4318	0.50	9.77	12.0	indirect	-36.858	117893
Lake road	0.4447	0.45	5.98	Excluded	Yes	-36.803	414794
Tamaki Drive Wb	0.4637	0.51	2.36	3.2	Yes	-36.848	113050
Rankin Avenue	0.4762	0.44	9.79	11.1	Yes	-36.912	12353
Curran Street	0.5306	0.53	2.59	4.3	indirect	-36.839	120756
Mangere Safe Routes	0.5822	0.50	13.68	17.7	No	-36.839	36400
Queen Street Pukekohe	0.6206	0.49	40.89	53.3	Yes	-37.204	8098
SW SH20	0.6931	0.55	6.91	9.9	indirect	-36.912	339850
Waterview Unitec	0.8020	0.57	6.15	7.4	Yes	-36.883	160174
Glenn Innes to Tamaki	0.8286	0.57	8.13	10.8	No	-36.874	30258
Mangere Bridge	0.8502	0.63	9.59	11.1	No	-36.932	116194
SH18 Upper Harbour	0.8920	0.71	11.08	26.1	indirect	-36.782	392246
Orewa Path	1.6677	0.61	29	29.17	Yes	-36.596	888308
Twin Streams	1.8132	0.62	12.71	17.8	Yes	-36.879	300995
Leigh Road	2.1656	0.73	55.78	95.3	indirect	-36.356	15963

* Some values were excluded because the journey requires a mix of modes (i.e. ferry).

Table H.6. Log-transformed ORs for 7 sites in **Edinburgh**, SCT, UK, arranged low to high, alongside estimates for each microscale factor (shaded columns) as established in chapters 5-6.

Site	Log(OR)	Microscale factors					
		P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
RBS Gogar	-0.0408	0.30	9.26	10.2	Yes	55.937	41784
Middle Meadow Walk	-0.0101	0.34	0.84	1.0	Yes	55.943	497591
Cultins Road	0.0953	0.17	7.62	9.0	Yes	55.929	66731
N. Edinburgh Access Rd.	0.2151	0.35	3.65	4.7	Yes	55.968	300594
Portobello Prom	0.3075	0.42	4.7	5.5	Yes	55.957	191277
Spylaw Park	0.4383	0.50	6.58	8.2	No	55.907	50894
Silverknowes	1.2754	0.61	6.89	8.8	No	55.979	72405

Table H.7. Log-transformed ORs for 8 sites in **Münster**, Germany, arranged low to high, alongside estimates for each microscale factor (shaded columns) as established in chapters 5-6.

Site	Log(OR)	Microscale factors					
		P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
Weseler Straße	0.0392	0.35	1.42	1.6	Yes	51.951	116093
Hammer Straße	0.0677	0.39	0.79	0.9	Yes	51.955	271583
Neutor	0.0862	0.34	1.06	1.3	Yes	51.967	439025
Promenade	0.0862	0.37	0.41	1.1	Yes	51.961	510327
Hüfferstraße	0.0953	0.31	1.19	1.3	Yes	51.962	208906
Warendorfer Straße	0.1044	0.39	0.64	0.85	Yes	51.962	237161
Gartenstraße	0.1044	0.36	1.22	1.5	Yes	51.972	965303
Kanalpromenade	0.3853	0.41	5.46	1.1	Yes	51.918	123761

Table H.8. Log-transformed ORs for 12 sites in **Oslo**, Norway, arranged low to high, alongside estimates for each microscale factor (shaded columns) as established in chapters 5-6.

Site	Log(OR)	Microscale factors					
		P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
Lysaker	-0.2877	0.18	5.11	6.6	Yes	59.913	390753
Skullerud	-0.1508	0.33	7.18	9.7	Yes	59.869	59478
Munkedamsveien	-0.1278	0.24	0.47	1.1	Yes	59.911	116005
Frognerst.Sykkel 03	-0.1278	0.28	1.67	2.4	Yes	59.911	145787
Gaustad	-0.0943	0.23	3.89	4.9	Yes	59.946	684285
Bryn	-0.0726	0.25	4.91	6.4	Yes	59.901	150452
Akersyke l 03	-0.0726	0.24	4.48	5.5	Yes	59.940	500724
Dr. Eufemias Vest	-0.0619	0.32	1.23	1.4	Yes	59.909	424761
Smestad	0.0198	0.18	3.93	5.5	Yes	59.939	263612
Breivoll	0.0296	0.20	5.57	6.5	Yes	59.923	97138
Dr. Eufemias Øst	0.0583	0.31	1.19	1.6	Yes	59.909	341870
Grorud	0.0677	0.28	9.87	12.4	Yes	59.951	49053

Table H.9. Log-transformed ORs for 10 sites in **Seattle**, WA, USA, arranged low to high, alongside estimates for each microscale factor (shaded columns) as established in chapters 5-6.

Site	Log(OR)	Microscale factors					
		P_L	Euclidean distance (km)	Network distance (km)	Street lighting presence	Latitude	No. of cyclists
Broadway	0.0770	0.37	1.28	1.6	Yes	47.614	657868
2nd Ave	0.1570	0.25	0.4	0.45	Yes	47.605	155909
Fremont Bridge	0.1906	0.31	5.13	5.6	Yes	47.648	617738
Spokane	0.2311	0.34	3.76	4.6	Yes	47.572	177089
NW 58TH St Greenway	0.2546	0.51	8.52	10.0	Yes	47.671	429671
39th Ave	0.2776	0.36	8.45	11.3	Yes	47.674	334503
26th Ave	0.3507	0.38	5.32	8.0	Yes	47.563	365493
BGT North	0.6931	0.56	9.49	13.6	No	47.679	371568
MTS Trail	0.7419	0.58	3.58	4.9	No	47.591	175169
Elliot Bay	1.2030	0.50	2.7	3.3	No	47.683	796974

Journey type:

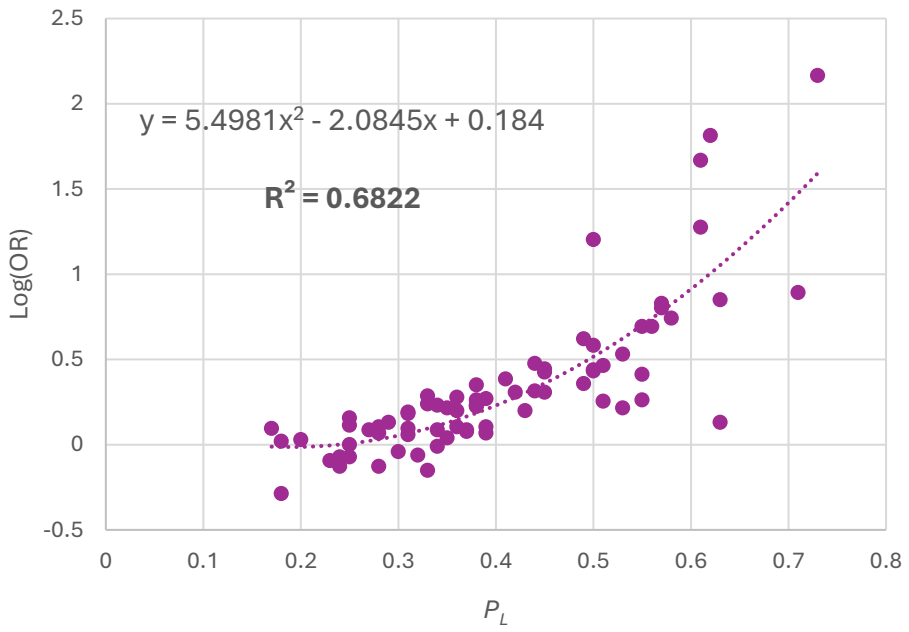

Fig. H.5. The relationship between the proportion of leisure journeys (P_L) and log-transformed ORs for the combined data from cycling sites in the five select cities.

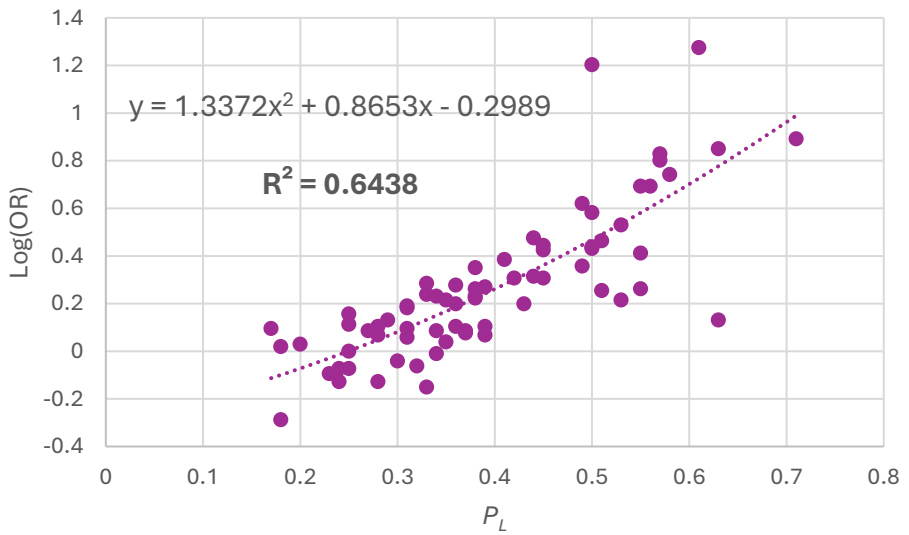

Fig. H.5. The relationship between the proportion of leisure journeys (P_L) and log-transformed ORs for the combined data from cycling sites in the five select cities after excluding ORs>5.00 as outliers.

Distance to city centre – Network distance:

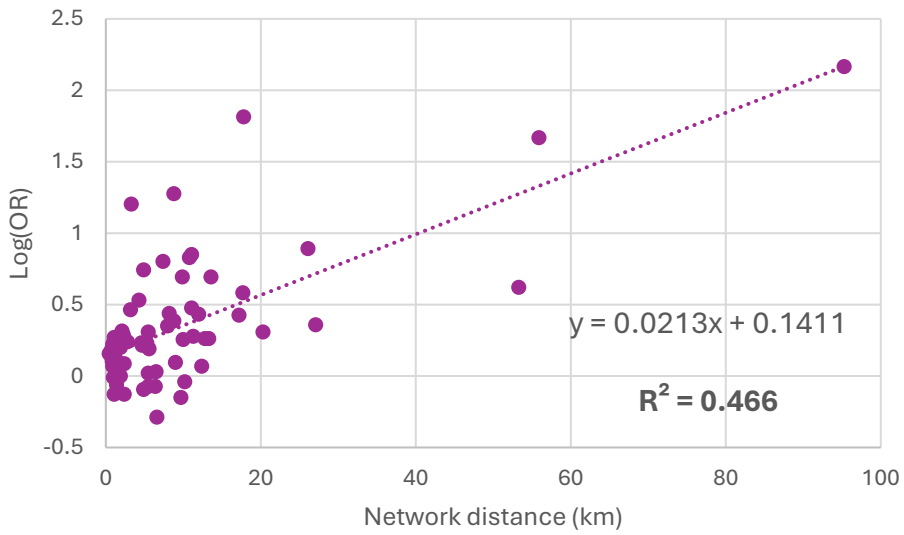

Fig. H.6. The relationship between network distance and log-transformed ORs for the combined data from cycling sites in the five select cities.

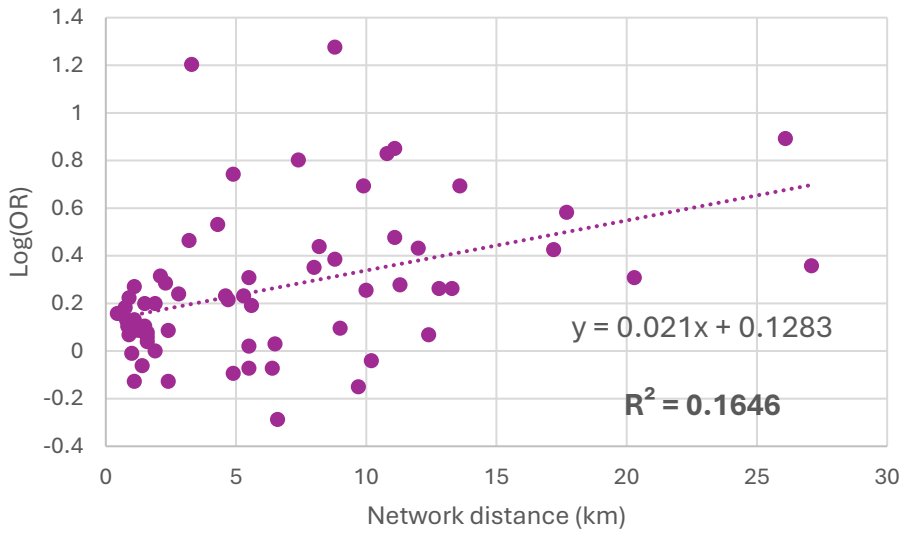

Fig. H.5. The relationship between network distance and log-transformed ORs for the combined data from cycling sites in the five select cities, after excluding outliers (ORs>5.00 and distances>50km).

Number of cyclists:

The raw numbers of cyclists were log-transformed before the regression.

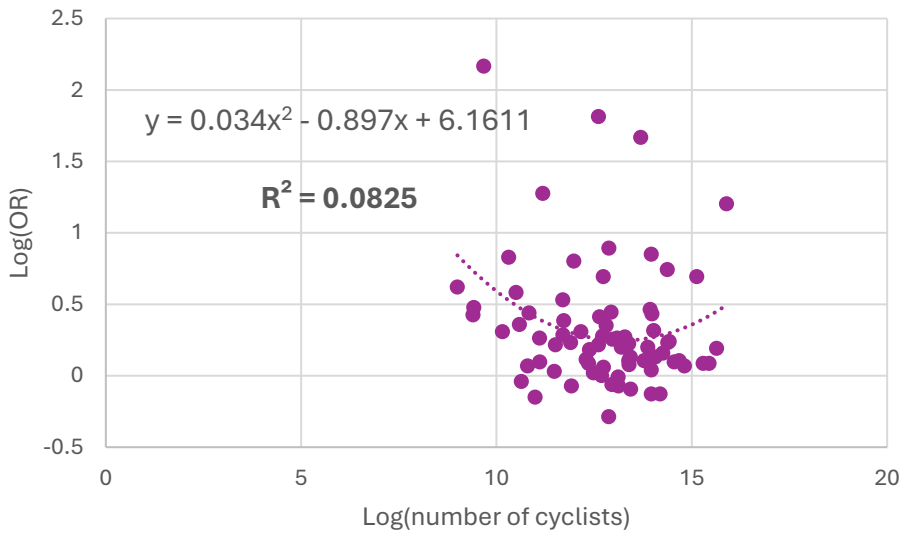

Fig. H.6. The relationship between log-transformed numbers of cyclist and log-transformed ORs for the combined data from cycling sites in the five select cities, after excluding outliers (ORs>5.00 and distances>50km).

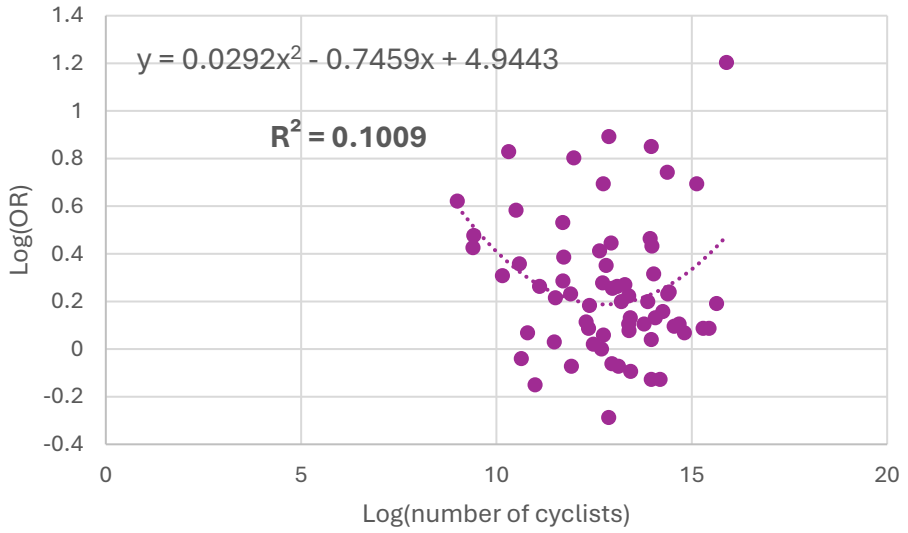

Fig. H.7. The relationship between log-transformed numbers of cyclist and log-transformed ORs for the combined data from cycling sites in the five select cities, after excluding outliers (ORs>3.50).

Stepwise regression analysis with log-transformed ORs – SPSS output:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.802[a]	.644	.639	.26989
2	.862[b]	.743	.736	.23075

a. Predictors: (Constant), Journey_type_A

b. Predictors: (Constant), Journey_type_A, Cycling_distance_km

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.090	1	9.090	124.788	<.001[b]
	Residual	5.026	69	.073		
	Total	14.115	70			
2	Regression	10.495	2	5.247	98.547	<.001[c]
	Residual	3.621	68	.053		
	Total	14.115	70			

a. Dependent Variable: Log_OR

b. Predictors: (Constant), Journey_type_A

c. Predictors: (Constant), Journey_type_A, Cycling_distance_km

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.751	.102		-7.341	<.001
	Journey_type_A	2.713	.243	.802	11.171	<.001
2	(Constant)	-.600	.092		-6.500	<.001
	Journey_type_A	2.075	.242	.614	8.576	<.001
	Cycling_distance_km	.011	.002	.368	5.137	<.001

a. Dependent Variable: Log_OR

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation
1	Cycling_distance_km	.368[b]	5.137	<.001	.529
	Unweighted_total_cyclists	.027[b]	.372	.711	.045
	Latitude	-.028[b]	-.345	.731	-.042
	Lighting_presence	-.099[b]	-1.197	.235	-.144
2	Unweighted_total_cyclists	.108[c]	1.729	.088	.207
	Latitude	-.004[c]	-.062	.950	-.008
	Lighting_presence	-.082[c]	-1.151	.254	-.139

Excluded Variables[a]

Model		Collinearity Statistics Tolerance
1	Cycling_distance_km	.737
	Unweighted_total_cyclists	1.000
	Latitude	.797
	Lighting_presence	.750
2	Unweighted_total_cyclists	.944
	Latitude	.794
	Lighting_presence	.748

a. Dependent Variable: Log_OR

b. Predictors in the Model: (Constant), Journey_type_A

c. Predictors in the Model: (Constant), Journey_type_A, Cycling_distance_km

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