The value of slow travel: An econometric method for valuing the user benefits of active transport infrastructure

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"The idea is to savour time rather than simply to count it."

– Carl Honoré (2004)

ABSTRACT

Transport infrastructure investments are typically justified largely on the basis of their ability to increase travel speeds. However, new bicycle facilities, such as separated cycleways, may result in slower journeys. Economic appraisals of proposed bicycle facilities therefore tend to focus on the social benefits, in particular, improvements in public health resulting from increased physical activity. Yet, some welfare benefit must also accrue to the users of the new facilities, given they willingly choose to use them over faster alternatives.

This thesis explores how discrete choice modelling can be used to analyse the trade-offs people make when choosing how they travel, and thereby (a) forecast changes in travel demand resulting from bicycle network improvements, and (b) quantify and monetise the resulting benefits to users. Despite the theory having been established in the 1970s, there have been few practical applications of this methodology, and it is yet to be used to value the user benefits of new bicycle facilities in a car-centric city. This thesis also assesses the short-term reliability of such assessments, by analysing changes in travel demand and preferences following an actual infrastructure intervention.

It is found that bicycle network improvements offer substantial welfare benefits to users, in terms of improved accessibility, comfort, perceived safety, and transport choice – even though their journeys may end up being slower. Furthermore, these benefits amplify when links are connected into a network. By ignoring such benefits in project appraisal, bicycle facilities may be significantly undervalued, and transport investment decisions inadequately informed.

STATEMENT OF ORIGINALITY

This is to certify that, to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis, and sources, have been acknowledged.

Christopher Standen

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I feel fortunate to have had an opportunity to spend four years researching a subject in which I am deeply interested. I grew up thinking walking and cycling are normal ways to get around, and would like to see more people having the option to do so; for this I blame my parents, Mel and Amanda.

Finally, my deepest appreciation to Dani for your patience and understanding while I completed this research. I dedicate this thesis to our daughter, Hanna, who arrived in our lives midway through Chapter 7, and already loves going for walks and bicycle rides.[1]

[1] I interpret sleep as an indication of positive utility.

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ABBREVIATIONS

ABS	Australian Bureau of Statistics
AOR	Adjusted odds ratio
API	Application programming interface
ARC	Australian Research Council
AUD	Australian dollar (currency)
BC	British Columbia
BCR	Benefit-cost ratio
BKT	Bicycle kilometre(s) travelled
CBD	Central business district
CI	Confidence interval
CW	Cycleway
DCA	Discrete choice analysis
EUR	Euro (currency)
EV	Electric vehicle
FYRR	First year rate of return
GBP	British pound (currency)
GDP	Gross domestic product
GIS	Geographic information system
GPS	Global Positioning System
GRP	Gross regional product
HEV	Heteroskedastic extreme value
HTTP	Hypertext transfer protocol
ICV	Internal combustion vehicle
IIA	Independence of irrelevant alternatives
IID	Independently and identically distributed
IV	Inclusive value

km	Kilometre(s)
km/h	Kilometre(s) per hour
LGA	Local government area
MLHS	Modified Latin hypercube sampling
mm	Millimetre(s)
MNL	Multinomial logit
MRS	Marginal rate of substitution
NPV	Net present value
NPVI	Net present value per unit of capital invested
NSW	New South Wales
OD	Origin-destination
PHP	PHP: Hypertext Preprocessor (programming language)
pp	Percentage point(s)
PSL	Path size logit
PT	Public transport
QALY	Quality adjusted life year
QoL	Quality of life
RDD	Random digit dialling
RP	Revealed preference
SCBA	Social cost benefit analysis
SEK	Swedish krona (currency)
SMS	Short message service
SP	Stated preference
STAHS	Sydney Travel and Health Study
UK	United Kingdom
USA	United States of America
USB	Universal serial bus
USD	United States dollar (currency)

VKT	Vehicle kilometre(s) travelled
VTTS	Value of travel time savings
WEB	Wider economic benefit
WGS	World Geodetic System
Wi-Fi	Wireless fidelity
WTP	Willingness to pay

GLOSSARY OF TERMS

Active transport	Walking and cycling to access activity destinations.
Bicycle lane	A marked lane for the exclusive use of bicycle riders.
Bicycle path	A path for the exclusive use of bicycles that is physically separated from motorised traffic. Can be in a road reserve, or not in a road reserve (e.g., in a park).
Consumer surplus	The difference between the price that consumers are willing and able to pay for a good or service, and the price that they actually do pay for it (i.e., the market price).
Cycleway	A continuous route designated for bicycle use, which is physically separated from motorised traffic. Can include sections of bicycle path and/or shared path.
Project appraisal	Forecasting the impacts and merits of a project proposal, to aid decision making.
Project assessment	Generic term for project appraisal or evaluation.
Project evaluation	Reviewing the outcomes and performance of a project(post-implementation).
Road reserve	The full width of any road, from property line to property line. This includes footpaths, bicycle paths, kerbs, swales, shoulders, verges, etc.
Shared path	A path designated for use by pedestrians, wheelchair users and bicycle riders. Can be in a road reserve, or not in a road reserve (e.g., in a park).
Skim	The modelled shortest network path for an origin-destination pair, estimated using a transport demand model.
Utility	A measure of the relative ability of products or services to satisfy a person’s wants and needs.

PUBLICATIONS

The following are the journal articles, conference papers and conference presentations I authored or co-authored whilst completing this thesis.

2017

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Standen, C., Crane, M., Collins, A., Greaves, S., & Rissel, C. (2017). Determinants of mode and route change following the opening of a new cycleway in Sydney, Australia. *Journal of Transport and Health*, *4*, 255–266. https://doi.org/10.1016/j.jth.2016.10.004

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2016

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2015

Crane, M., Rissel, C., Greaves, S., Standen, C., & Wen, L. M. (2015). Neighbourhood expectations and engagement with new cycling infrastructure in Sydney, Australia: Findings from a mixed method before-and-after study. *Journal of Transport & Health*, *3*(1), 48–60. https://doi.org/10.1016/j.jth.2015.10.003

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2014

Crane, M., Rissel, C., Standen, C., & Greaves, S. (2014). Associations between the frequency of cycling and domains of quality of life. *Health Promotion Journal of Australia*, *25*(3). https://doi.org/10.1071/HE14053

Ellison, A. B., Ellison, R. B., Rance, D., Greaves, S. P., & Standen, C. (2014). Harnessing smartphone sensors for tracking location to support travel data collection. In *10th International Conference on Transport Survey Methods*. Leura, Australia.

Greaves, S., Ellison, A., Ellison, R., Rance, D., Standen, C., Rissel, C., & Crane, M. (2014). A web-based diary and companion smartphone app for travel/activity surveys. In *10th International Conference on Transport Survey Methods*. Leura, Australia.

Greaves, S. P., Ellison, A. B., Ellison, R. B., & Standen, C. (2014). Development of online diary for longitudinal travel and activity surveys. In *Proceedings of The 93rd Annual Meeting of the Transportation Research Board*. Washington, D.C.

2013

Rissel, C., Greaves, S., Wen, L. M. L. M., Capon, A., Crane, M., & Standen, C. (2013). Evaluating the transport, health and economic impacts of new urban cycling infrastructure in Sydney, Australia: Protocol paper. *BMC Public Health*, *13*(1), 963. https://doi.org/10.1186/1471-2458-13-963

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Student name: Christopher Standen

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As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statement above is correct.

Supervisor name: Professor Stephen Greaves

Signature:

Date: 25 October 2017

1 INTRODUCTION

1.1 Why is bicycle use in Australia declining, and what should/can be done about it?

Cycling for transport has clear social, health and environmental benefits (Bauman et al., 2008). It can also be an enjoyable way to travel. However, in Australia, bicycle use has fallen dramatically over the last century (R. Lee, 2010). The 2017 National Cycling Participation Survey (Munro, 2017) shows a statistically significant decline in the proportion of the population who use a bicycle in a typical month – from 27.1 per cent (95% confidence interval (CI) 26.4 to 27.8) in 2011, to 21.8 per cent (95% CI 20.6 to 23.0) in 2017 (see Figure 1.1). Of those who do use a bicycle in a typical month, 80.6 per cent use it for recreation, while only 30.7 per cent use it for transport (i.e., with an activity destination in mind, e.g., work, study or shopping).[2]

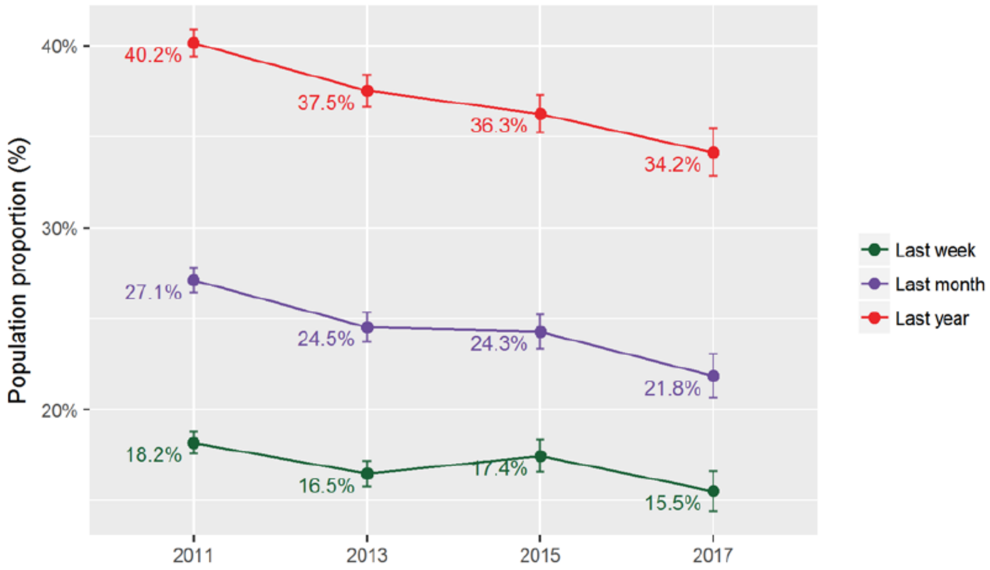

Figure 1.1: Cycling participation in Australia 2011 to 2017 (Munro, 2017)

The declining level of transport cycling could be attributed to a number of factors. Motor vehicle traffic volumes have grown in towns and cities, helped by governments continually trying to optimise the flow of cars, at the expense of

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[2] Some respondents reported using a bicycle for both transport and recreation.

people using other transport modes (R. Lee, 2010). With urban speed limits generally set at 50 or 60 km/h, it is perhaps not surprising that fear of motorised traffic is the most commonly stated reason for not wanting to cycle (Fishman, Washington, & Haworth, 2012). In addition, Australia has laws mandating the use of bicycle helmets, and police actively enforce them, with current fines ranging up to AUD 330 in New South Wales (NSW).[3] Other possible factors include low-density urban sprawl and increasing travel distances, development of retail centres designed to be accessed by car, and the increasing propensity for parents to enrol their children in non-local private schools (Rowe, 2016).

Given the fear of motorised traffic is a major barrier, a proven strategy for giving more people the opportunity to use a bicycle for transport is to provide a network of low-stress bicycle routes – comprising bicycle paths physically or spatially separated from traffic, and low-speed streets (Pucher & Buehler, 2008). Australian state roads authorities are not generally supportive of the latter (Lahausse, Van Nes, Fildes, & Keall, 2010), meaning investment in bicycle paths is the principal built environment intervention available.

1.2 How expenditure on transport projects is prioritised

Although the per-kilometre cost of bicycle infrastructure is low compared to that for public transport or private car infrastructure (Department of Infrastructure and Transport, 2013), government finances are limited and there are many other demands on them. To help government decision makers and other stakeholders decide between, and prioritise, alternative transport project proposals, social cost benefit analysis (SCBA) can be used to assess their net welfare benefits to society (see OECD, 2011).[4] In a SCBA, net welfare benefits over a project's anticipated lifetime are valued in monetary units, and divided by the lifetime project cost to

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[3] These laws may not have had such an impact on sport cycling, because higher risk sport cyclists tend to use helmets regardless of any laws.

[4] In practice, governments announce many projects before they are assessed, and then use SCBA to justify the decision (Terrill, 2016).

give a benefit-cost ratio (BCR). In theory, projects with a BCR above 1.0 are worthwhile, provided there are no better options. Projects with the highest BCRs provide the best value for society, and should be prioritised.

For a road or rail project, the main welfare benefit is usually an increase in travel speed (though the quality of the journey time is starting to be considered, e.g., crowding levels on public transport). This is generally expressed in terms of 'travel time savings', but in practice tends to materialise as an increase in travel distances, while the average daily travel time changes little in the long term (Marchetti, 1994). Thus, individual travellers benefit from greater home location choice (e.g., a larger home in a cheaper suburb farther from work), and being able to access more distant destinations (Metz, 2008; Van Wee & Rietveld, 2008). However, encouraging urban sprawl in this way is not always the most efficient and sustainable way to plan a city (Newman & Kenworthy, 1999). Access to economic and social opportunities (hereafter defined as 'accessibility') can be provided by proximity, as well as "by velocity" (Rode et al., 2014, p. 4).

Assessing bicycle infrastructure proposals using travel speed as the yardstick presents particular difficulties. Although cycling can sometimes be faster than driving or public transport for short trips (R. B. Ellison & Greaves, 2011), it has been found that some people will opt to cycle, even if there are faster options available (Wardman, Tight, & Page, 2007). Additionally, some people will opt for a low-stress cycling route, even if there are more direct options available (Sener, Eluru, & Bhat, 2009). If travel time is used as the only welfare measure, these people would be considered *worse-off*, even though they have willingly chosen the slower option.

Mokhtarian & Salomon (2001) argue time spent travelling for transport is not always just a means to an end (accessing a destination). In some cases, a person can have a positive affinity for travel, because it gives them "a sense of speed, motion, control, enjoyment of beauty" (p.695), and transition time between work and home in which to relax, work, read, etc. In the case of walking and cycling, it is also an opportunity for exercise.

1.3 The slow movement

The notion that speed is all-important is being challenged in other aspects of modern life: the *slow food movement* was founded in 1989, with the aim “to prevent the disappearance of local food cultures and traditions, counteract the rise of fast life and combat people’s dwindling interest in the food they eat” (Slow Food International, 2015). It spawned a broader *slow movement* that, according to Lumsdon and McGrath (2011, p. 266), “rails against structures in western society that encourage fast consumption”. The movement has spread to include *slow television* (Puijk, 2015), *slow journalism* (Ball, 2016), and even *slow fashion* (Pookulangara & Shephard, 2013).

The concept of *slow travel* is not a new one; the desire to wander is part of human nature. The existing literature on *slow travel* focuses on holiday and leisure travel, with Lumsdon and McGrath (2011, p. 265) observing an increasing desire amongst tourists for “slowing down, travelling shorter distances and enriching the travel experience both en route to and at the destination”. Catering to this demand, Affirm Press has published a series of S*low Guide Books*, including the *Slow Guide to Sydney* (Hawkes, 2007) and the *Slow Guide to Melbourne* (Egger & Hughes, 2010).

Some of the notions of *slow tourism* could also apply to utilitarian transport. The journey experience can have intrinsic value, while excessive speed creates a detachment from one's surroundings and community – two neighbours driving along their street in opposite directions at 50 km/h are not likely to stop for a chat (Speakman, 2005). High traffic speeds are also associated with increased crash/injury risk (Aarts & Van Schagen, 2006) and increased traffic noise (Ouis, 2001).

However, any positive affinity that people have for travel time and journey experience is not well captured by existing SCBA approaches. Rather, they discriminate against transport modes that offer a more pleasant journey experience, or an opportunity to be productive while travelling (due to the travel time savings for these modes being valued lower). Should the focus be on the *quality* of time spent travelling, rather than just its *duration*?

1.4 Can social cost benefit analysis be made more suitable for assessing bicycle projects?

Perhaps because bicycle infrastructure projects do not appear to offer significant benefit to users when assessed through a travel speed/time lens, attention has shifted to forecasting and valuing the social benefits of cycling instead. In particular, the health benefits that result from increases in physical activity (see Mulley, Tyson, McCue, Rissel, & Munro, 2013), and anticipated reductions in motor vehicle externalities, due to people switching from driving to cycling. The NSW Government's appraisal guidelines assume the value of travel time savings for bicycle projects to be zero, because "choosing to ride a [bicycle] is aimed at improving health and gaining other social benefits but not to reach a destination faster" (Transport for NSW, 2013a, p. 157). The guidelines value health benefits at AUD 1.11 per additional bicycle kilometre travelled (BKT), and reduced motor vehicle externalities at AUD 0.58 per additional BKT.

However, the low cost of bicycle projects means they are rarely subjected to a SCBA alongside other transport proposals, even though they might offer substantial welfare benefits. (The NSW Treasury recommends SCBA should be carried out for projects with a capital cost of AUD 10 million or more.)

Van Wee & Börjesson (2015) suggest some other reasons why SCBA is rarely used to appraise cycling projects. There are challenges in estimating and valuing the effects of cycling interventions: data on cycling behaviour are scarce, while forecasting and valuing social benefits, such as improved health, is not straightforward. In addition, cycling projects are typically undertaken by local governments, whereas SCBA has traditionally been undertaken at a state or national government level.

Notwithstanding these barriers, van Wee & Börjesson (2015) argue SCBA should be applied more routinely to cycling projects, to help ensure better allocation of public funding. However, they identify a number of research needs to improve the valuation of user and social benefits (capital and operational costs are fairly well known). Among other recommendations, they suggest that:

> Research is needed to improve the possibilities of evaluating all the accessibility-related impacts of cycling policies. Such impacts include travel times, effort, the option value, the impact on social exclusion levels, the appreciation of the 'freedom to move', mode dependent wellbeing, etc. (p. 123).

In addition, they call for improved models for predicting cycling behaviour, as these inform the magnitude of many costs and benefits (e.g., improved accessibility and health).

1.5 Aim and scope

This thesis aims to address the research gaps discussed above, primarily the need for improved methods and models for forecasting and valuing the user/accessibility benefits of new bicycle infrastructure.

It was funded by an Australian Research Council Linkage Project grant (Number LP120200237), with the broader remit of making major contributions to the assessment of the transport, health and economic impacts of bicycle infrastructure (The University of Sydney, 2012). To address the question of assessing accessibility-related impacts, the use of discrete choice analysis (DCA) to forecast and value changes in utility is explored, using a proposed new cycleway in Sydney as a case study. The theory for DCA-based valuation was established in the 1970s (see de Jong, Daly, Pieters, & van der Hoorn, 2007), but there have been few applications to bicycle project appraisal.

To address the question of improved models, DCA-based travel demand forecasts made prior to the cycleway opening are evaluated by assessing changes in actual travel demand. In addition, the hypothesis that cycling preferences remain stable over time – which underpins DCA-based forecasting – is tested using longitudinal travel survey data collected from residents living near the cycleway, and in a separate control area.

The primary data source for this research is The Sydney Travel and Health Study (Rissel et al., 2013), which is described in detail in Chapter 1. Secondary data include a post-intervention survey of users of the new cycleway, and biannual bicycle traffic counts.

1.6 Thesis outline

This thesis is organised as follows. Chapter 2 reviews the literature on the costs and benefits of cycling projects, and existing methods of assessing them.

Chapter 3 outlines the theory of DCA-based demand forecasting and project appraisal. This is followed by a review of the literature on bicycle choice analysis, and preference transferability.

Chapter 1 begins with a statement of key research questions and hypotheses, followed by an outline of the experimental design, and a description of the case study (new cycleway) and data sources.

Chapter 5 describes the analytical approach, while Chapter 6 presents the results. These two chapters follow a similar structure. They begin with the pre-intervention modelling, forecasting and economic valuation (appraisal), then deal with the post-intervention assessment of actual changes, and conclude with the temporal preference transferability tests.

Chapter 7 presents a discussion of the findings in this thesis. This includes: addressing the research questions and hypotheses; detailing contributions to the literature; acknowledging the study limitations; identifying possibilities for future research; and outlining implications for transport policy and practice. This is followed by some concluding remarks.

2 THE WELFARE BENEFITS AND COSTS OF BICYCLE PROJECTS AND POLICIES

This chapter reviews the current state of practice of, and the literature on, assessing bicycle projects and policies – specifically, how the various benefits and costs are estimated, valued and incorporated (or not) during assessment.

It begins with a discussion of bicycle policy objectives, and the various interventions used to achieve them (Section 2.1). The following section (2.2) outlines high-level approaches for assessing the merits of these interventions, both *ex-ante* (appraisal) and *ex-post* (evaluation). The predominant appraisal method used in Australia, social cost benefit analysis (SCBA), is outlined in Section 2.3. Sections 2.4 and 2.5 detail how the social and user benefits and costs of interventions may be quantified and valued in the SCBA framework. Some alternative appraisal methods are reviewed in Section 2.5.5, while post-project evaluation and longitudinal (before-after) assessment are discussed in Sections 2.7 and 2.8 respectively. The chapter concludes with a summary and a discussion of the research gaps (Section 2.9).

For this literature review, Scopus [5] and Google Scholar [6] were searched for publications concerned with the assessment of bicycle projects and policies. Search terms included 'bicycle', 'cycling', 'cost benefit analysis', 'appraisal', 'evaluation', 'safety', 'health', 'equity', 'accessibility', 'longitudinal' and 'natural experiment'.

2.1 Bicycle projects and policies

Given the clear environmental, health and economic benefits of cycling as a mode of transport (Bauman et al., 2008), governments worldwide have outlined policies to make cycling more attractive and accessible. Two common policy objectives are (a) to increase bicycle ridership (usually in terms of mode share), and (b) to improve rider safety (Lumsdona & Tolley, 2001).

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[5] An abstract and citation database (https://www.scopus.com).

[6] A search engine for scholarly literature (https://scholar.google.com.au).

The NSW Government's bicycle strategy (Transport for NSW, 2013b, p. 5) includes an objective to "increase the mode share of cycling", though it gives no target level or timeframe against which to measure progress. It also includes an objective to "increase safety", again with no target level or timeframe (or even a unit of measurement). The City of Sydney's bicycle strategy (City of Sydney, 2007, p. 3) has a well-defined target to "increase the number of bicycle trips made in the City of Sydney, as a percentage of total trips, from less than 2 per cent in 2006 to … 10 per cent by 2016". On the other hand, its safety objective, to "achieve a reduction in the number of incidents", has no target level or timeframe. Some overseas governments have objectives that are more ambitious. In 2007, the City of Copenhagen set goals of increasing the bicycle commuting mode share from 36 per cent to 50 per cent by 2015, and reducing serious crashes involving bicycle riders by 50 per cent (Gössling & Choi, 2015).

Pucher et al. (2010) outline five broad categories of intervention used to achieve bicycle policy objectives: infrastructure; integration with public transport; education and marketing programs; bicycle access programs; and law changes. Some example policies in each category are listed in Table 2.1. To this list could be added financial and tax incentives, such as the United Kingdom government's Cycle to Work scheme (Cycling UK, 2016).

Table 2.1: Examples of bicycle policy interventions

Category	Policy examples
Infrastructure	• Bicycle paths, lanes and bridges • Signage • Bicycle parking
Integration with public transport	• Bicycle storage on trains and buses • Short-term bicycle hire at train stations
Education and marketing programs	• Ride to work days • Bicycle rider training
Bicycle access programs	• Short-term public bicycle hire/share
Laws	• Lower speed limits • Helmet laws • Strict liability laws

2.2 Assessing the costs and benefits of bicycle projects and policies

The assessment of bicycle projects and policies can be performed *ex-ante*, to provide decision makers and stakeholders with information about the relative benefits and costs of alternative project proposals, and to allow projects competing for finite public funding to be prioritised (appraisal). Alternatively, assessment can be performed e*x-post*, to measure the impacts or success of a project (evaluation). Rarely is assessment done both *ex-ante* and e*x-post*.

In his review article on the benefits and costs of investing in non-motorised transport projects, Litman (2014) makes the distinction between those that accrue to users – both existing and potential – and those that accrue to society (externalities). In both cases, he notes that the benefits of non-motorised transport tend to be overlooked or undervalued in conventional transport project assessment. Potential benefits and costs of non-motorised transport investments are summarised in Table 2.2. Some benefits accrue to both users and society (e.g., health), and care must be taken to avoid double-counting (Börjesson & Eliasson, 2012).

Table 2.2: Potential benefits and costs of investing in bicycle projects (after Litman, 2014)

	User	Society
Benefits	Improved convenience and comfort Improved accessibility Option value (i.e., the value that a person may place on having an option available to them, even if they do not expect to use it) Lower travel costs Enjoyment Improved health and fitness Increased community cohesion and interaction	Business benefits (e.g., for local retailers and tourism operators) Reduced road and parking congestion Road and parking facility cost savings Reduced chauffeuring burdens Less road trauma Reduced public healthcare costs Increased community cohesion and interaction Improved passive security Energy conservation Reduction in local air pollution and stormwater contamination Reduction in noise pollution Reduction in greenhouse gas emissions Reduced sprawl Preservation of public and open space More liveable communities Improved equity
Costs	Increased risk of physical injury Generally slower travel Equipment costs	Project/facility costs

2.3 Social cost benefit analysis

Transport projects are often appraised using social cost benefit analysis (SCBA), in which the future welfare benefits and costs are estimated for the expected lifetime of the project, converted to monetary values if necessary using non-market valuation techniques, then discounted to present values. The net welfare benefit is then divided by the implementation cost to give a benefit-cost ratio (BCR). In theory, projects with the highest BCRs have the greatest population welfare benefit per dollar of expenditure, and should be prioritised (P. Stopher & Stanley, 2014).

There are four general criticisms of SCBA, and the way it tends to be used in practice. First, it does not consider how disbenefits, benefits and costs are distributed among the population (Levinson, 2002).

Second, BCRs are often misunderstood by decision makers, stakeholders and the public, who may be led to believe that the forecast 'economic benefits' represent real benefits to the national/state economy – i.e., GDP growth, increased productivity, deficit reduction, etc. – when they are largely social welfare benefits valued in dollar terms using economic valuation methods (Standen, 2015).

Third, there is significant scope at each stage of a SCBA for analysts to manipulate it to give the result the project proponents want to see (optimism bias) (Flyvbjerg, 2009): they can ignore social disbenefits that would lower the BCR, e.g., health impacts; they can include questionable benefits that would raise the BCR, e.g., agglomeration benefits (see Dobes and Leung (2015)); they can overestimate the magnitude of benefits and underestimate the magnitude of disbenefits (e.g., overestimate traffic forecasts for a toll road); and they can undervalue disbenefits and overvalue benefits (e.g., overestimate how much motorists would be willing to pay to use a faster road). Varying the appraisal period and discount rate can also affect the BCR significantly.

Fourth, a SCBA considers only the incremental impacts of an individual project, which may be considered by stakeholders to be acceptable in isolation (Tricker, 2007). Rarely are the cumulative impacts of multiple or successive projects considered, meaning human, social and environmental capital can be eroded over time through a "death by a thousand cuts" (Morrison-Saunders, Pope, Bond, & Retief, 2014, p. 40). This can be prevented by setting limits for environmental or social impacts, e.g., setting an air quality threshold for a city, and rejecting outright any project that would cause that threshold to be exceeded.

SCBA has been used to appraise road and public transport projects for many decades, but is not routinely used for bicycle projects. Lowry et al. (2016) note that using SCBA to appraise bicycle projects will always involve non-market benefits that are difficult to measure, monetise and communicate to stakeholders, so professional judgement and public opinion will invariably influence decisions.

Asplund and Eliasson (2016) found that forecasts of project costs and demand have been very inaccurate in SCBAs conducted for road and rail projects in Norway and Sweden. However, they conclude that SCBA is still "able to fairly consistently separate the wheat from the chaff and hence contribute to substantially improved infrastructure decisions" (Asplund & Eliasson, 2016, p. 195).

Van Wee and Börjesson (2015) acknowledge the challenges of estimating and valuing non-market benefits, adding that SCBA may not be considered cost-effective for low-cost bicycle projects, which are generally undertaken by local authorities that lack the requisite resources or expertise. They also highlight the concern that SCBA does not inform stakeholders about equity impacts, or the distribution of benefits and costs.

Nonetheless, they make some arguments for not *a priori* rejecting the use of SCBA for the appraisal of bicycle projects. First, while the cost of undertaking a SCBA may be considered high when compared to the low construction costs (relative to road and rail), it may appear more cost-effective in the context of the welfare benefits, which may far outweigh the infrastructure costs. Second, SCBA offers an objective method to prioritise projects competing for finite funding. Third, all the major benefits and costs of bicycle projects can, in theory, be estimated and valued, and in this regard bicycle projects are no different from other transport investments that are more routinely appraised with SCBA (e.g., road and public transport projects).

That said, van Wee and Börjesson identify a number of areas where SCBA of bicycle projects can be improved and refined. Among these are: better transport demand models to predict the impacts of new bicycle infrastructure on traveller behaviour; and – of particular relevance for this thesis – more research on the user benefits of bicycle policies, including the option value (refer to Table 2.2).

Unsurprisingly (given its high bicycle mode share), the Netherlands has been at the forefront of bicycle policy appraisal, and SCBA has been used to appraise a variety of projects. Recent applications include appraisals of an intercity bicycle highway between Cuijk and Nijmegen (Decisio, 2015), and of a bicycle bridge and parking station for 22,000 bicycles in Utrecht (van Ommeren, Lelieveld, & de Pater, 2012). The Dutch government has even developed a web tool for rapid SCBA of bicycle projects (CROW Fietsberaad, n.d.).

There are a number of steps involved in undertaking a SCBA. These include deciding which costs and benefits to include/exclude, and deciding how they are to be quantified and valued. These steps are reviewed in turn below.

2.3.1 Selection of costs and benefits

According to welfare economic theory, if any person's wellbeing is likely to be affected in any way by a project, then the impact (negative or positive) should be included in the SCBA (P. Stopher & Stanley, 2014).

In their systematic review of 32 SCBAs of non-motorised transport policy interventions, Brown et al. (2016) noted considerable inconsistency in the benefits and costs included (see Table 2.3). This contributed to a large range in the reported BCRs, from -31.9:1 to 59:1. Other contributing factors were differences in non-market valuation methods, and differences between the interventions themselves.

Table 2.3: Benefits and costs included in past SCBAs of active transport interventions (Brown et al., 2016)

STUDY	BENFEFITS/DISBENEFITS INCLUDED								
	COMFORT/ SECURITY	PRODUCTIVITY	TRAVEL TIME	ACCIDENTS/ INJURIES	ENVIRONMENT	CONGESTION	PARKING	VEHICLE OPERATING	OTHER
AECOM 2010		☑	☑	☑	☑	☑	☑	☑	Journey ambience, public transport cost savings
Beale et al 2012	☑	☑	☑						
Buis & Wittink 2000		☑	☑	☑	☑		☑		Bike theft
Co & Vautin 2014		☑							
Cope et al 2010	☑	☑		☑	☑	☑			Road infrastructure
COWI n.d.									
Deenihan & Caulfield 2014									
Department for Transport 2014		☑		☑	☑	☑			Journey quality, indirect taxes, road infrastructure
Fishman et al 2011			☑	☑	☑	☑		☑	Public transport cost savings.
Foltynova & Kohlova 2002	☑		☑	☑	☑				
Gotschi 2011								☑	
Guo & Gandavarapu 2010					☑				
Krag 2007								☑	Reduced income from reduced public transport demand
Li & Faghri 2014				☑	☑	☑	☑	☑	
Lind et al 2005	☑		☑	☑	☑				
Macmillan et al 2014				☑	☑			☑	
Meggs & Schweizer n.d.									
PWC 2009			☑	☑	☑	☑	☑	☑	Road infrastructure
Rabl & de Nazelle 2012				☑	☑				
Saari et al 2007					☑	☑			Road infrastructure
Saelensminde 2004	☑	☑	☑	☑	☑		☑		Public transport provision
Schweizer & Rupi 2014									
Sinclair Knight and PWC 2011			☑	☑	☑	☑	☑	☑	Road infrastructure
Sinnett & Powell 2012									
SQW Consulting 2007		☑			☑	☑			Journey ambience
SQW Consulting 2008		☑			☑	☑			Agglomeration
Stokes et al 2008									
Sustrans Scotland 2013	☑	☑		☑	☑	☑			Road infrastructure
Transport for Greater Manchester 2011	☑	☑		☑	☑				Cyclist user charges
Transport for London 2004	☑	☑	☑	☑	☑		☑		
Wang et al 2005									
Wilson & Cope 2011	☑	☑				☑			
Total (n=32)	**9**	**13**	**10**	**16**	**20**	**12**	**7**	**8**	

2.3.2 Quantification of costs and benefits

The magnitude of the welfare costs and benefits of a bicycle infrastructure project is generally assumed to be correlated with the resulting change in demand for bicycle travel, with demand typically measured in units of bicycle kilometres travelled (BKT).[7] To forecast the change in demand, it is necessary to (a) know the baseline bicycle travel demand, and (b) estimate how the project might affect that demand, relative to a 'Do nothing' scenario (Ortúzar & Willumsen, 2011). Baseline demand data can be obtained from travel surveys, while the change in demand is typically forecast using a transport demand model. Existing transport demand models for motor vehicles and public transport are usually inadequate for assessing the impact of bicycle projects, because their spatial scale is too large to model short distance bicycle trips, and they do not include enough detail about bicycle facilities, such as cycleways (van Wee & Börjesson, 2015). A number of bespoke transport demand models have been developed for forecasting the effects of bicycle network improvements (e.g., Hopkinson & Wardman, 1996; Ortúzar, Iacobelli, & Valeze, 2000; Yi, Feeney, Adams, Garcia, & Chandra, 2011).

A limitation common to most transport demand models is that they assume people's home and work location choices will not be affected by a transport intervention. In the case of road and rail projects, people in general move farther from work when faster transport options become available, cancelling out the forecast travel time savings and contributing to urban sprawl (Guranton & Turner, 2009; Metz, 2008). In the case of bicycle infrastructure, this is not likely to be an issue, though people with a preference for bicycle tend to self-select neighbourhoods with good cycling facilities (Pinjari, Eluru, Bhat, Pendyala, & Spissu, 2009).

To give an idea of the baseline cycling demand in a major Australian city, the Sydney Cycling Survey (BTS, 2013) reports cycling participation, trip rates, trip distances, trip purposes and mode share. In 2012, the cycling trip rate in the Sydney Greater metropolitan region was 0.071 trips per person per day, and the average bicycle trip distance was 5.01 km, giving an annual BKT per person of 130 km. This compares to 105 BKT per person in 2011.

[7] Or bicycle miles travelled, in countries using Imperial distance measurements.

2.3.3 Valuation of costs and benefits

The various benefits and costs of bicycle policies are quantified using different units. For example, improvements in health and life expectancy may be measured in quality adjusted life years (QALYs). Converting all these benefits and costs into monetary units is useful for comparing the net benefit of different projects, but placing a monetary value on non-market goods such as QALYs is problematic because they are generally not traded in competitive markets. For this reason, various valuation methods have been developed to monetise such non-market benefits and costs. These include hedonic pricing, where the impact on nearby property prices is measured, and contingent valuation, where people are asked how much they are willing to pay for an improvement (or to avoid a loss) (Litman, 2012). Willingness to pay can also be estimated using stated choice surveys, where respondents are asked to make trade-offs between the attributes of two or more alternatives (Hensher, Rose, & Greene, 2005).

The usual approach for a bicycle project SCBA has been to estimate the change in demand in units of BKT (as discussed in Section 2.3.2 above). Social benefits/costs (e.g., public health) are then calculated by multiplying the forecast change in demand (BKT) by the per BKT value. User benefits (e.g., travel time savings and journey utility) are estimated using the rule of half, whereby 100 per cent of the estimated per BKT benefit accrues to existing bicycle users (the area bounded by P_1, P_2 and Q_1 in Figure 2.1), while half the estimated per BKT benefit accrues to new bicycle users (the green shaded area in Figure 2.1.

The per BKT value has varied considerably in bicycle project SCBAs undertaken in Australia to date. Yi et al. (2011) calculated a net benefit of A$0.84 per BKT, while the Commonwealth Government cites a value of $A1.43 per BKT (Commonwealth of Australia, 2013), and consultants PricewaterhouseCoopers (2009) calculated $0.48 per BKT. The breakdown of these values is shown in Table 2.4. The variation can be explained by differences in the benefits and costs included/excluded, valuation methods used, and differing assumptions.

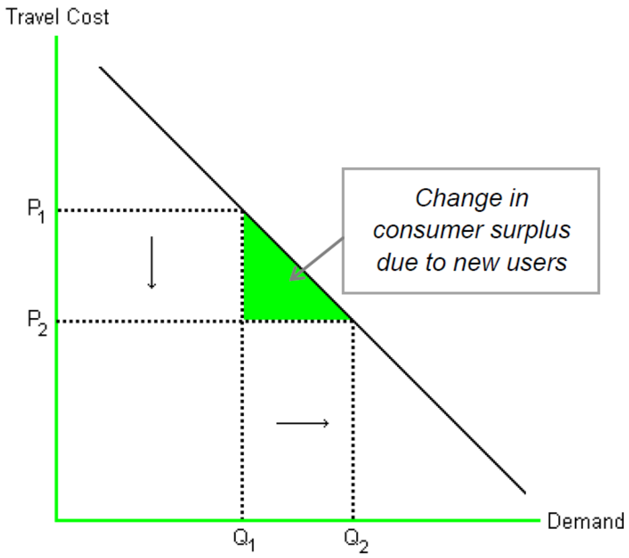

Figure 2.1: The rule of half (AECOM, 2010)

Table 2.4: Valuation of BKT in Australia (in cents per BKT)

	Yi et al. (2011)	**Commonwealth of Australia (2013)**	**PwC et al. (2009)**
Pricing year	2010	2010	2008
Benefit/cost			
Decongestion	11.34	20.70	24.28
Vehicle operating cost savings	12.42	35.00	16.39
Parking cost savings	3.10	1.60	1.00
Travel time savings	13.20	-	0.00
Journey ambience – on road bicycle lanes	8.91	-	-
Journey ambience – separated bicycle path	11.86	-	-
Absenteeism savings	16.70	-	-
Health benefits	6.00	112.00	1.42
Injury costs	-13.55	-37.00	-2.03
Improved air quality	1.60	2.80	1.73
Noise pollution reduction	0.43	0.90	0.85
Greenhouse gas reduction	1.12	2.20	0.66
Water pollution	0.16	-	-
Urban separation	0.25	-	-
Avoided infrastructure and services costs	10.42	5.20	3.91
Net benefit per BKT	**84**	**143**	**48**

2.3.4 Other considerations

The outcome of a SCBA can be significantly influenced by the choice of appraisal period and discount rate. Using a short appraisal period and high discount rate, future benefits and costs are undervalued, which will favour projects with short construction timeframes, and those with long term social and environmental costs

(Litman, 2009). In NSW, a discount rate of 7 per cent is used (Transport for NSW, 2013a).

2.4 Social benefits and costs

This section reviews the literature on some key social benefits and costs (externalities) of bicycle projects and policies, and the methods proposed/used to estimate and value them.

2.4.1 Road safety

In Australia, data on cycling crashes are collected by police and hospitals, though many minor injuries are not reported. In the five years to 2015, there were on average 1,225 road fatalities per annum across Australia, of which, on average, 39 (3 per cent) were bicycle riders (BITRE, 2015). Over this period, there was an upward trend in bicycle rider fatalities of 2 per cent per annum, while the trend for all other road users was downward. On average, there were 5,321 bicycle rider injuries per annum requiring hospitalisation over the same period.

The figure of 3 per cent of road fatalities being bicycle users may appear small, but bicycle trips account for a small amount of overall travel in Australia, with only 1.5 per cent of commuting trips made by bicycle in the 2009 Census (Australian Bicycle Council, 2010). To quantify the risk of injury whilst cycling, the injury rate should be divided by an exposure variable, usually distance travelled or number of trips.

When using distance as the exposure variable, cycling can appear riskier than other transport modes. For example, in the Sydney Metropolitan Area, Garrard et al. (2010) estimate there were 5.31 fatalities and 557.25 injuries per 10^8 BKT between 2002 and 2005. For car occupants, they estimate 0.37 fatalities and 34.02 injuries per 10^8 vehicle kilometres travelled (VKT) over the same period. Nationally, the fatality rates for light vehicle drivers and motorcyclists have been calculated as 0.39 and 12.04 per 10^8 VKT respectively (2003 to 2007 average) (Johnston, Brooks, & Savage, 2008). It should be noted that the figures for bicycle include both transport and sporting use, whereas the figures for motor vehicles exclude sporting use (e.g., motor racing).

However, Teschke (2014) reasons that number of trips, rather than distance, should be used as the exposure variable, because travel distance is dependent on transport mode. On this basis, Teschke et al. (2013) concluded that the risk of cycling in British Columbia (Canada) or the United States is comparable with that of walking or driving. All have a much lower risk than motorcycling, but a higher risk than travelling by bus (see Figure 2.2).

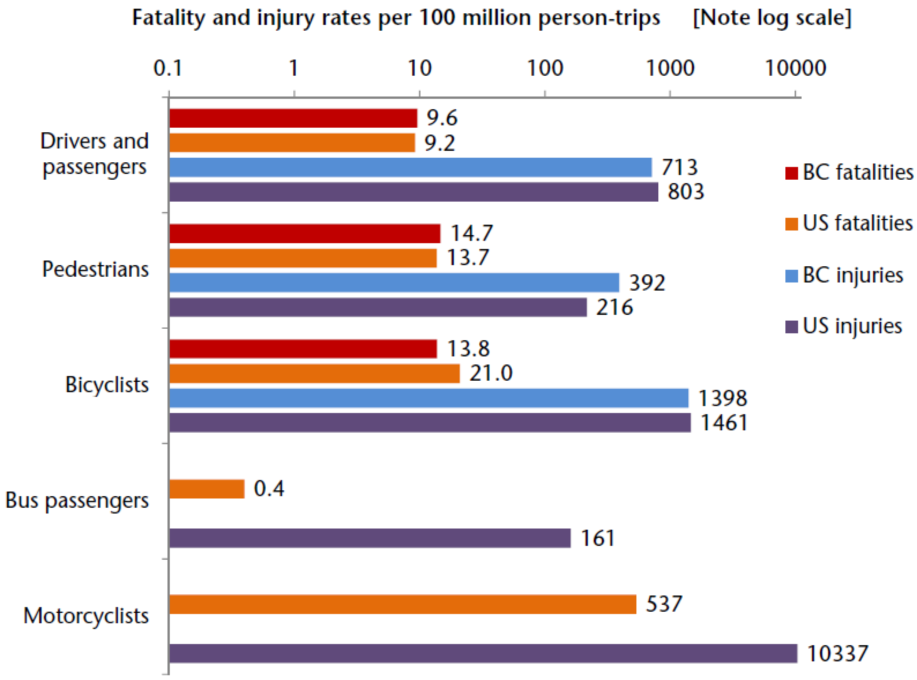

Figure 2.2: Fatality and injury rates per 100 million person-trips by road user class, British Columbia and the United States (Teschke et al., 2013)

Given that bicycle riders are vulnerable road users, a principle motivation for investing in bicycle infrastructure is to improve safety, not just to protect existing riders, but also to reduce fear, and thereby attract greater ridership.

Current best practice for improving road safety is the 'safe systems' approach, whereby it is acknowledged that humans will make mistakes, and infrastructure and regulations should be designed to minimise their likelihood and consequences (ARRB, 2015). For cycling, safe system measures such as separating bicycle and motorised traffic, and 30 km/h urban speed limits, have proved very effective in countries such as the Netherlands (Wegman, Zhang, & Dijkstra, 2012). The safety benefits of separated bicycle paths can be negated to some extent if intersections are not well designed, or if they are built along major roads and encourage riders to switch route from roads with lower traffic volumes (Scheepers et al., 2015).

State road authorities in Australia have made little progress in creating safe cycling environments (Garrard et al., 2010). In the 1990s, in an apparent acceptance that people are at high risk of being injured whilst cycling, they enacted laws requiring bicycle users to wear helmets. However, the efficacy of bicycle helmets, and the public health benefits of these laws, have been the subject of much debate (Curnow, 2005, 2007; Macpherson & Spinks, 2008; Sieg, 2016). Unfortunately, studies that associate helmet use with a significant reduction in injuries aggregate data from low-speed/low-risk transport cycling and high-speed/high-risk sport cycling. Meanwhile, there is evidence to suggest Australia's helmet laws are a barrier to higher cycling participation (Rissel & Wen, 2011), and may even make crashes more likely, because riders take more risks when helmeted (Gamble & Walker, 2016).

Road authorities also encourage bicycle users to wear high visibility clothing (Roads and Maritime Services, 2015), despite research which shows that contrast of clothing with the background is a greater determinant of daytime visibility – e.g., dark clothing is more visible than light clothing against a light background (Gershon, Ben-Asher, & Shinar, 2012; Roge, Douissembekov, & Vienne, 2012).

Many cycling advocates argue safety measures that may result in decreased cycling participation (such as helmet laws) are counter-productive, because they diminish the 'safety in numbers' effect. A number of studies have demonstrated that bicycle/pedestrian crash rates do not increase linearly with bicycle/pedestrian traffic volumes (e.g., Brüde & Larsson, 1993; Jacobsen, 2003). In a review of several such studies, Elvik (2009) calculated that the number of bicycle crashes increases with an exponent of between 0.31 and 0.65, relative to increases in bicycle use. The phenomenon has been observed at all spatial scales, from individual intersections (Brüde & Larsson, 1993), to entire countries (Jacobsen, 2003).

However, there is some uncertainty about the causal mechanism, or indeed, whether one exists. Jacobsen (2003) reasons it is unlikely that individual pedestrians and bicycle riders become more cautious when their numbers grow; therefore, the most plausible explanation is that motorists change their behaviour. Bhatia and Wier (2011) question this inference, and discuss possible confounding factors.[8] First, a safer environment (e.g., physical separation from traffic or better enforcement of traffic laws) may explain both volumes and safety increasing – although the effect has been observed with temporal fluctuations in bicycle volumes at the same location (Bonham, Cathcart, Petkov, & Lumb, 2006). Second, more people walking/cycling means fewer people driving and therefore lower traffic volumes – although there is no clear evidence an increase in bicycle usage leads directly to a decrease in motor vehicle traffic (see Section 2.4.4). Given these uncertainties, Bhatia and Wier caution against pursuing improvements in vulnerable road user safety through 'safety in numbers' alone.

Even taking into account 'safety in numbers', there remains the ethical dilemma that increased bicycle use will likely result in an increase in the absolute number of rider injuries and fatalities. On the other hand, the fact most injuries to bicycle riders are caused by motor vehicle drivers leads Gössling and Choi (2015, p. 111) to argue that "the cost [of bicycle rider injuries] should be attributed to [drivers] rather than cycling, as is currently the case". In other words, drivers crashing into bicycle riders could be considered a 'spillover externality' (Jansson, 1994) – as could perceived danger (Section 2.5.3) and air toxin exposure (Section 2.4.2).

There is considerable variation in the way the social cost of crashes and injuries is treated in economic assessments of bicycle projects. Injury costs were ignored in half of the of the 36 economic assessments reviewed by Brown et al. (2016) (Table 2.3). In Australia, the general approach is to calculate total injury cost, by multiplying the forecast increase in BKT by the expected number of injuries per

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[8] Bhatia and Wier limit their discussion to pedestrian safety, but the arguments apply equally to cycling safety.

BKT by the average cost per injury. Elsewhere, number of bicycle riders is sometimes used instead of BKT as the unit of demand. Table 2.5 compares injury valuations from a number of economic analyses found in the academic and grey literature.

Table 2.5: Valuation of bicycle injury costs[9]

Study author	Study type	Location	Bicycle injury rate	Cost per injury (AUD)	Pricing year	Injury cost rate (AUD)
Transport for NSW (2013a)	Government appraisal guidelines	NSW, Australia		\$6,698,897 (fatal) \$496,286 (serious) \$82,717 (other) \$119,516 (average)	2014	
Yi et al. (2011)	Project appraisal	NSW, Australia	2.4158 *per million BKT*	\$67,720 (average)	2010	\$0.16 *per BKT*
Pricewaterhouse Coopers (2009)	Project appraisal	NSW, Australia	2.4158 *per million BKT*	\$63,100	2009	\$0.15 *per BKT*
Sinclair Knight Merz and Pricewaterhouse Coopers (2011)	Appraisal guidelines	Queensland, Australia	0.03 (fatal) 0.98 (serious) 1.71 (other) *per million BKT*	\$1,811,164 (fatal) \$435,593 (serious) \$17,310 (other)	2010	\$0.37 *per BKT*
Rabl and de Nazelle (2012)	Academic policy appraisal	Netherlands	2.5×10^{-5} (fatal) *per year per bicycle rider*	\$2,456,625 (fatal)	2010	\$61 *per year per bicycle rider*
		France	6.5×10^{-5} (fatal) *per year per bicycle rider*	\$2,456,625 (fatal)	2010	\$160 *per year per bicycle rider*
Department for Transport (2014)	Government Appraisal guidelines	UK		\$2,853,047 (fatal) 24,716 (slight)	2010	
Lind et al. (2005)	Appraisal guidelines	Sweden		\$147,145 to \$331,077	2005	
Macmillan et al. (2014)	Academic policy appraisal	New Zealand		\$2,419,229 (fatal) \$253,629 (serious)	2010	

The NSW Government uses an average injury cost of AUD 119,516 (2014 prices), which was calculated using a stated preference study that estimated people's willingness to pay for fewer injuries (Transport for NSW, 2013a).

In appraising City of Sydney’s proposal for a 230-kilometre network of cycleways for inner-city Sydney, Yi et al. (2011) estimated the cost of increased bicycle

[9] All costs converted to AUD using the average exchange rate for the pricing year.

crashes at AUD 16.3 million over 30 years, against economic benefits totalling AUD 682.3 million. The average injury cost of AUD 67,720 was estimated using a human capital approach, which aims to capture actual costs such as medical expenses and lost workdays. To account for the 'safety in numbers' effect, Yi et al. assumed the bicycle injury rate would decline by 0.4 per cent for every 1 per cent increase in bicycle mode share. They also assumed an increase in BKT would be matched by a corresponding decrease in VKT by other modes, resulting in an injury saving of AUD 22.7 million for car occupants, and AUD 4.1 million for bus occupants. However, the proposed project was for a congested inner-city area, and did not involve the removal of any general traffic lanes, so capacity freed up by people switching form car to bicycle would be expected to be consumed within a short time by latent driving demand, meaning no lasting reduction in car VKT (Ortúzar & Willumsen, 2011).

Another consideration is potential injuries caused to other road or path users by bicycle riders, particularly in Australia where state and local road authorities often opt for building shared pedestrian and bicycle paths (this is seen as a cost-effective way of providing safe paths for bicycle riders, without the need to repurpose general traffic lanes or on-street car parking). In practice, the risk of a bicycle user injuring another road or path user has been found to be so low that it does not warrant inclusion in SCBA (Grzebieta, McIntosh, & Chong, 2011). However, pedestrians do perceive shared paths to be unsafe, and can feel intimidated or startled by less courteous bicycle riders (Taverner Research, 2009), so the issue does warrant consideration – though it is perhaps more appropriately dealt with during the development of facility design standards, or during individual project design.

While there is variation in the way increases in bicycle injuries are estimated and valued, the fact that more cycling injuries are likely with increased participation cannot be ignored. That said, a number of studies have found that, at the population level, the physical and mental health benefits of increased bicycle use far outweigh the injury costs (de Hartog, Boogaard, Nijland, & Hoek, 2010; Rojas-

Rueda & Nazelle, 2011; Woodcock, Tainio, Cheshire, O'Brien, & Goodman, 2014). These public health benefits are considered in the next section.

2.4.2 Public health

Physical inactivity is known to increase the risk of non-communicable diseases – including obesity, heart disease, stroke, breast cancer, colon cancer and diabetes – as well as dementia and depression (Brown et al., 2016; Reiner, Niermann, Jekauc, & Woll, 2013). Globally, physical inactivity is responsible for 6 per cent of global deaths, behind only high blood pressure (13 per cent), tobacco use (9 per cent) and high blood glucose (6 per cent) in the list of leading mortality risk factors (World Health Organization, 2009).

Encouraging active transport such as cycling and walking (including walking to/from public transport) is often suggested as a way to increase physical activity levels, and therefore improve public health. However, measuring the health benefits of new bicycle projects and policies presents a number of challenges (Mulley et al., 2013). First, changes in both mortality and morbidity need to be considered. Second, a person who increases their cycling activity because of an intervention may substitute other forms of physical activity. Third, the health benefit of increased physical activity will be much less for those who are sufficiently active to begin with.

In addition to changes in physical activity, there are other health impacts of bicycle interventions. Separated bicycle paths that laterally separate bicycle riders from motorised traffic may reduce their exposure to toxic vehicle exhaust emissions, but if built alongside major roads can increase exposure as a result of riders changing route from roads with lower traffic levels (Bigazzi & Figliozzi, 2015; Schepers et al., 2015). In hot climates, there are health risks associated with increased heat exposure (Karner, Hondula, & Vanos, 2015). Changes in injury risk are discussed above (Section 2.4.1).

Mulley et al. (2013) describe two existing approaches for quantifying the health benefits of new bicycle infrastructure. The first is to estimate the benefit for each traveller switching from an inactive travel mode to bicycle. The second is to estimate the benefit for each additional BKT resulting from an intervention. In both cases, the benefit is calculated in terms of the avoided costs to society of inactivity-related mortality and morbidity.

Brown et al. (2016) conducted a systematic review of 36 economic assessments of active transport interventions that included physical activity benefits (Table 2.3), and agree that many methodological challenges remain. First, little attention has been paid to morbidity impacts (the focus has been on mortality). Second, there is uncertainty about the effectiveness of interventions on physical activity levels. Third, none of the assessments controlled for substitution – i.e., increases in walking and cycling activity leading to reductions in other types of physical activity – nor fully addressed the issue of health benefits accruing more to individuals who are less active to begin with. Finally, they note variation in the assumed delay between an intervention and its maximum effect (between 0 and 10 years), and variation in assumed effectiveness decay (from 0 per cent to 10 per cent per year).

There have been attempts to standardise the assessment of public health benefits for active transport interventions. The World Health Organization has developed a tool for assessing the mortality impacts (Kahlmeier et al., 2014). It does not include morbidity impacts, and is based on the Danish population, so may not be generalizable to countries with different population health characteristics.

To value the public health benefits of bicycle projects, the general approach in Australia is to multiply the forecast increase in BKT by a dollar value per BKT. Mulley et al. (2013) estimate the per BKT health benefit to be AUD 1.12 (2010 prices), but others have estimated values ranging from AUD 0.06 (Yi et al., 2011) to AUD 1.42 (PricewaterhouseCoopers, 2009). The NSW Government's appraisal guidelines (Transport for NSW, 2013a) suggest AUD 1.11 per BKT (2014 prices). Börjesson and Eliasson (2012) argue that bicycle riders already take health benefits into account when making their travel choices, so they are already included in any estimates of user benefits (see Section 2.5.3), and including both user benefits and public health benefits in a SCBA would be double-counting. However, this reasoning assumes bicycle riders are able to assess correctly the benefits to their own health, which is difficult to prove. Furthermore, society will also benefit from avoided health and mortality costs, e.g., reduced public expenditure on healthcare, reduced sickness and disability payments, and increased labour productivity.

In appraising City of Sydney's 230-kilometre cycleway network proposal, Yi et al. (2011) estimated the public health benefits (excluding injuries) would amount to AUD 147.3 million over 30 years, which was 53 per cent of the total economic benefit of AUS$277.1 million, and nine times the estimated cost of injuries (AUD 16.3 million). This estimate was based on reduced mortality being valued at AUD 0.06 per BKT, and reduced morbidity (in the form of employee absenteeism savings) being valued at AUD 0.17 per BKT.

Brown et al. (2016) concluded their systematic review by acknowledging much progress has been made in quantifying and valuing the public health benefits of non-motorised transport, but noting there are many opportunities for further progress. In particular, the assessment of health benefits could be expanded to include mental health and quality of life (QoL) impacts. Some progress has been made in this area, with recent studies suggesting cycling offers physical and psychological QoL benefits for men (Crane, Rissel, Standen, & Greaves, 2014), and people who commute to work or study by bicycle enjoy their commutes more than those who drive (Rissel, Crane, Wen, Greaves, & Standen, 2015).

2.4.3 Transport equity and disadvantage

In recent decades there has been much written about the relationship between transport and social justice, and how transport improvements tend to favour those who are already most mobile (e.g., Preston & Rajé, 2007). However, these studies have been limited to describing the unjust *outcomes*, with little attention paid to the planning and policy processes which lead to them.

Equity impacts are not usually considered in SCBA in Australia. Benefit-cost ratios and NPVs are aggregate measures of welfare change for a whole population; they do not reveal who stands to benefit and who stands to lose out from a transport investment, or whether it is a Pareto improvement (i.e., one where losers are fully compensated).

Investing in bicycle infrastructure can improve access to economic and social opportunities for people who are unable to drive for financial or other reasons, e.g., young age, old age, illness, disability (Litman, 2016). In NSW, 31 per cent of the population does not have a driver licence (Roads and Maritime Services, 2014).

On the other hand, Welch et al. (2015) observed a possible positive correlation between proximity to bicycle paths and housing prices in Portland (Oregon, United States), suggesting that such investments may contribute to gentrification and displacement of low income households (John, 2015), if they are not balanced with effective affordable housing policies.

There are ways to enhance SCBA to capture potential equity impacts. Stanley et al. (2012) propose a method for valuing the ability of people at risk of social exclusion to make additional trips, based on the cost of a policy, program or project needed to facilitate those additional trips. They estimate that each additional trip by a person with average household income has a value of AUD 17 – more for a person with a lower income.

Another approach is disaggregate assessment of impacts, whereby the benefits and costs accruing to specific groups are identified, e.g. female or low income (de Jong et al., 2007). A disaggregate assessment approach is described in Chapter 3.

In the United Kingdom, distributional weighting is used, whereby it is assumed the marginal utility of consumption halves as income doubles (P. Stopher & Stanley, 2014). In other words, one additional dollar would improve the welfare of a poor person more than it would the welfare of a wealthy person.

Alternatively, SCBA can be complemented with other types of assessment, such as the capability approach, which assesses the impact on individuals' freedoms and opportunities, taking into account their needs, values and abilities (Beyazit, 2011).

2.4.4 Reduced motor vehicle externalities

Bicycle advocates often claim that one of the benefits of increasing bicycle usage and mode share is a consequent decrease in road congestion and other driving externalities – air pollution, noise pollution, fear and intimidation, crashes, greenhouse gas emissions, water contamination, etc. – because every person on a bicycle is "one less car" (Furness, 2010).

A study by the Institute for Transportation and Development Policy (Mason, Fulton, & McDonald, 2015) suggested a significant worldwide increase in bicycle and electric bicycle mode share from 6 per cent to 11 per cent could cut global carbon dioxide emissions from urban passenger transport by 7 per cent by 2030, relative to a 'Do minimum' scenario.

Gössling and Choi (2015) estimated that, in Copenhagen (Denmark), the cost of car driving to society is EUR 0.50 per kilometre, six times higher than the cost of cycling (EUR 0.08 per kilometre).

In appraising City of Sydney's AUD 153.4 million cycleway network proposal, Yi et al. (2011) estimated the value of reduced motor vehicle externalities to be AUD 213.3 million over 30 years – 31 per cent of the total economic benefit of AUD 682.3 million. A breakdown of these benefits is shown in Table 2.6.

However, a significant reduction in motor vehicle externalities would depend on a high cross-elasticity between driving and cycling. In practice, the bicycle competes mostly with public transport (Börjesson & Eliasson, 2012) – although reduced crowding on public transport may then encourage some mode switching from driving to public transport. Furthermore, in cities where there is high latent demand for driving, any congestion relief will likely be short-lived (Guranton & Turner, 2009; Metz, 2008). That said, a significant reduction in the number of drivers might make it easier for political leaders to repurpose public space currently used for traffic and parking, thereby reducing motor vehicle externalities.

Table 2.6: Estimated benefits of inner-city Sydney cycleway network due to reduced motor vehicle use (after Yi et al., 2011)

Benefit	Value (AUD million)
Decongestion benefit	97.8
Air pollution reduction	12.3
Noise pollution reduction	3.3
Greenhouse gas reduction	8.6
Water pollution reduction	1.2
Vehicle operating cost savings	53.3
Parking cost savings[a]	14.1
Reduction in motor vehicle crashes	22.7
Total	213.3

[a] Parking expenditure is a transfer payment, so would normally be excluded from SCBA.

Cities with a high bicycle mode share, such as Copenhagen, still have road congestion (Prato, Rasmussen, & Nielsen, 2014). It is therefore questionable whether decreases in motor vehicle externalities should be included in bicycle project assessment, especially where the road network is congested (indicating the presence of latent demand). Where there is a policy objective to reduce congestion or other driving externalities, there are more effective policy instruments, such as mobility and demand management (Olszewski & Xie, 2005; P. R. Stopher, 2004).

2.4.5 Economic growth and development

SCBA informs stakeholders about the economically valued welfare benefits of a transport project. However, these economic benefits are often misunderstood (or misrepresented) by non-economists to mean economic growth or other macroeconomic benefits (e.g., increased productivity and employment, or reduced national debt). Referring to a proposal to build a new AUDD$16.8 billion motorway in inner-city Sydney, Australia's former Assistant Minister for Infrastructure, Jamie Briggs, claimed it would “inject AUD 20 billion worth of benefits into the national economy” (Saulwick, 2015b). However the AUD 20 billion of ‘economic benefits’ to which he was referring comprised mostly welfare benefits, e.g., hypothetical personal travel time savings (Sydney Motorways Project Office, 2013).

Banister and Berechman (2001) note the relationship between transport investment and economic development is complex and not well understood. They argue additional transport investment will not on its own result in economic growth in developed countries that already have well-connected transport systems. Looking at the relationship between urban transport-land use patterns and transport expenditure, Newman and Kenworthy (1999) calculated that sprawling and car-dependent Australian and United States cities spend more than 12 per cent of their wealth – in terms of gross regional product (GRP) – on passenger transport, while more compact and public transport oriented cities in Europe and wealthy Asian nations spend 8.1 per cent and 4.8 per cent of GRP respectively. This suggests transport projects that result in increases in motor vehicle use and urban sprawl may significantly hinder economic development.

Economic development benefits have traditionally not been included in transport project appraisal. Recently, there have been attempts to incorporate 'wider economic benefits' (WEBs), such as agglomeration effects – productivity gains from firms clustering together and sharing knowledge (Graham, 2007) – and increased labour market supply. The SCBA for the aforementioned AUD 16.8 million Sydney motorway scheme includes AUD 1.7 billion of agglomeration benefits and AUD 0.5 billion of labour market supply benefits (NSW Government, 2015). However, methods for estimating WEBs are still in their infancy, and their inclusion in transport project appraisal remains controversial, with empirical data indicating they are likely to be exaggerated (Dobes & Leung, 2015).

There has been less interest in capturing possible 'wider economic costs', for example, where new transport infrastructure contributes to gentrification and displacement of low-income workers (Beyazit, 2015). In the case of a major road project, a forecast that it will increase productivity and labour market supply would seem to be at odds with Newman and Kenworthy's (1999) finding, that car-based sprawling cities have higher transport costs and poorer accessibility.

For bicycle infrastructure projects, previous assessments of economic development impacts have focused largely on benefits to local retailers (in the case of urban transport infrastructure) and regional tourism (in the case of recreational infrastructure such as rail trails). An evaluation of new bicycle parking facilities in Melbourne found that each square metre allocated to bicycle parking generated income of AUD 31 per hour for local retailers, compared to AUD 6 generated by a square metre of car parking (Lee and March, 2010). In an intercept survey of bicycle riders using new separated bicycle paths in United States cities, Monsere et al. (2014) found that 19 per cent stopped more frequently at businesses along the bicycle paths after they were built, with only 1 per cent stopping less frequently.

In her evaluation of recreational rail trails in Victoria (Australia), Beeton (2003) notes seven potential economic development benefits: job creation during and after construction; direct expenditure; induced and indirect regional income; increased tax revenue; land value uplift; opportunities for local enterprises; and increasing the general attraction of a region. She calculated that rail trail users spent on average AUD 132 per person per day during their visits.

Again, little attention has been paid to potential 'wider economic costs' of bicycle infrastructure. Its possible role in gentrification and displacing low-income households has been acknowledged (John, 2015), though this impact could be mitigated with effective affordable housing policies (Beyazit, 2015).

2.5 User benefits and costs

Appraisals of bicycle projects tend to be dominated by the social benefits, particularly public health benefits. However, as noted by Poorfakhraei and Rowangould (2015), benefits also accrue to individuals in the form of increased welfare, where individuals' wellbeing is improved because of increases in their enjoyment, perceived health, perceived safety, transport options, mobility and accessibility. However, the economic value of these non-market goods is difficult to estimate, meaning they do not often find their way into SCBAs.

2.5.1 Mobility

Conventional SCBA for major transport projects (road and public transport) is dominated by estimates of mobility benefits, measured in terms of the value that travellers place on being able to reach destinations quicker, or being able to reach more distant destinations in the same amount of time as before (Metz, 2008).

New bicycle infrastructure can reduce journey travel times in two ways. First, if the infrastructure enables travellers to switch to bicycle from other travel modes, these travellers may enjoy quicker journeys, *ceteris paribus*.[10] A European study found that cycling is generally quicker than driving for trips up to 5 kilometres, and quicker than public transport for trips up to 8 kilometres (Dekoster & Schollaert, 2000). Ellison and Greaves (2011) analysed GPS data from 36,858 car trips of 0 to 5 kilometres in Sydney, and estimated that an inexperienced bicycle rider would be able to make 90 per cent of those trips by bicycle within 10 minutes of the time taken by car.

Second, new infrastructure may allow bicycle riders to take a more direct route than before, for example a bridge over a geographic barrier (van Ommeren et al., 2012), a contra-flow bicycle path/lane on a one-way street, or a bicycle path through a road closure (Melia, 2012).

On the other hand, previous bicycle route choice studies (e.g., Sener et al., 2009; Wardman et al., 2007) show that riders will divert quite some distance to use a safe or pleasant bicycle facility, implying that new infrastructure can actually *increase* travel times. Furthermore, time spent cycling can have positive intrinsic utility – in terms of enjoyment, exercise and perceived health benefits – meaning that bicycle riders will sometimes opt for a longer travel time (Mokhtarian & Salomon, 2001). For instance, anecdotal evidence suggests a number of bicycle commuters in Sydney do laps of the 3.8-kilometre Centennial Park circuit on their way to or from work (Smale, 2003).

Previous studies have estimated a value of travel time saving (VTTS) for bicycle travel using stated preference surveys (Table 2.7). The VTTS has been found to depend on the type of bicycle facility, being significantly higher for roads with mixed traffic than for bicycle paths – confirming that people, in general, prefer the latter. In Sweden, the ratio of these values (mixed traffic to bicycle path) is less than two; in the United Kingdom, it is over three, suggesting that riding in mixed

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[10] In practice, destination and other travel choices may also change (Greaves et al., 2015).

traffic is perceived as more onerous in the United Kingdom. Börjesson and Eliasson (2012) also looked at how VTTS varies by trip time, and found it is higher for trips under 40 minutes. No bicycle VTTS studies for the Australian context could be found in the literature.

Table 2.7: VTTS estimates for bicycle travel

Study	Location	Pricing currency (year)	VTTS/hour for street with mixed traffic	VTTS/hour for bicycle path	VTTS ratio (mixed traffic street: bicycle path)
Wardman et al. (1997)	UK	GBP (1997)	5.7	1.7	3.4
Wardman et al. (2007)	UK	GBP (1999)	11.5	3.3 to 3.6	3.2 to 3.5
WSP (2007)	Stockholm (Sweden)	SEK	159	105	1.5
Börjesson and Eliasson (2012)	Central Stockholm (Sweden)	EUR (2008)	10.5 to 14.3	5.4 to 10.0	1.4 to 1.9

A travel time savings benefit was included in 10 of the 32 economic assessments of active transport interventions reviewed by Brown et al. (2016) (Table 2.3). Among these is the Yi et al. (2011) appraisal of City of Sydney's cycleway network proposal, which included a travel time benefit valued at AUD 143.6 million over 30 years – 21 per cent of the total economic benefit. Yi et al. assumed a VTTS of AUD 12.20 (the value recommended at the time by the NSW Government for all private travel) for both mixed traffic streets and bicycle paths. They estimated the user benefit of using a bicycle path separately, using a willingness to pay (WTP) approach (see Section 2.5.3).

The NSW Government's economic appraisal guidelines advise against including travel time savings in bicycle facility appraisal, because "choosing to ride a [bicycle] is aimed at improving health and gaining other social benefits but not to reach a destination faster" (Transport for NSW, 2013a, p. 157). However, this claim is not supported by available evidence. Numerous studies have estimated a VTTS for new bicycle facilities (Table 2.7). It has been shown that commuters are less willing to divert than are non-commuters to use a cycleway, suggesting saving time is somewhat important to bicycle riders when they have time constraints (e.g., arriving at work on time) (Standen et al., 2016). If mobility benefits are included in appraisals of road and public transport infrastructure, there is no logical reason for them not to be included in appraisals of bicycle infrastructure. The fact that bicycle facilities generate additional user and social benefits is no justification for ignoring the mobility benefits.

2.5.2 Accessibility

Most travel is undertaken to access economic and social opportunities: work, study, recreation, shopping, socialising, etc., although sometimes travel is the end rather than the means (or both) (Mokhtarian & Salomon, 2001). As such, it can be argued the principle aim of transport investment should be to improve *accessibility*, rather than *mobility*. Geurs and van Wee (2004, p. 128) define accessibility as "the extent to which land use and transport systems enable individuals to reach activities in different locations".

Various methods have been developed for measuring accessibility. Geurs and van Wee (2004) classify these into four categories: *Infrastructure-based measures* consider only the performance of the transport component, for example, average travel speed. Because they ignore the land use component, they are more measures of mobility than of accessibility *per se*. *Location-based measures* are aggregate counts of the number of activities within reach of a given residential location, or the number of residents that can reach a given activity destination. *Person-based measures* analyse accessibility from an individual's perspective, taking into account their time constraints. *Utility-based measures* attempt to measure the utility that individuals derive from the destination and mobility choices available to them. Previous studies of bicycle accessibility have mostly used location-based measures, of which there are two main variants: the gravity model and the cumulative opportunities model.

The gravity-based accessibility measure, developed by Hanson (1959), has the following form:

$$A_i = \sum_j a_j f(t_{ij}). \tag{2.1}$$

A_i is the accessibility for people living in zone i, a_j is the activity intensity (e.g., number of restaurants) in zone j, and $f(t_{ij})$ is a travel impedance function, which represents the generalised cost of travel between i and j. Conventional estimations of the impedance function $f(t_{ij})$ attempt to measure how willingness to travel between i and j decreases with increasing travel distance, time and cost, and are often fitted to a negative exponential curve.

The cumulative opportunities model is a special case of the gravity model, where the impedance function is equal to unity within a given time or distance, and zero outside it:

$$A_i = \sum_j a_j W_j. \tag{2.2}$$

W_j is unity for all zones j within a given travel time or distance from i, and zero for all zones j beyond. It is, therefore, simply a measure of the number of activities that can be reached within a given travel time or distance.

Iacono et al. (2010) developed a gravity model for measuring bicycle accessibility in Minneapolis (United States). The results for accessibility to shopping destinations are presented graphically in Figure 2.3, with the shading for each zone (grid cell) representing the level of shopping accessibility for that zone. Iacono et al. acknowledge their model does not take into account individual or environmental factors that can have significant effects on willingness to bicycle, and therefore bicycle accessibility (they measure willingness to bicycle based only on travel distance or time). As such, new bicycle infrastructure would tend not to affect their measured accessibility, except where it results in reduced travel times or distances (e.g., a new bicycle bridge that crosses a freeway).

McNeil (2011) used a cumulative opportunities model to measure cycling accessibility in Portland (United States), using the assumption that travellers would be willing to cycle up to 2.5 miles (4 kilometres) to access an activity destination. However, instead of using shortest path network distances, he used effective distances obtained by applying a weighing factor to each network link, with the weighting factor depending on the type of bicycle facility on each link.

Weighting factors were derived from a previous route choice study (Broach, Gliebe, & Dill, 2009). The weighting factor for separated bicycle paths was 1.35, implying that people would be willing to cycle up to 5.4 km (4 km × 1.35) to reach an activity destination, if riding exclusively on separated bicycle paths. Thus, bicycle facility improvements would tend to increase the number of activity destinations deemed accessible by bicycle in his model.

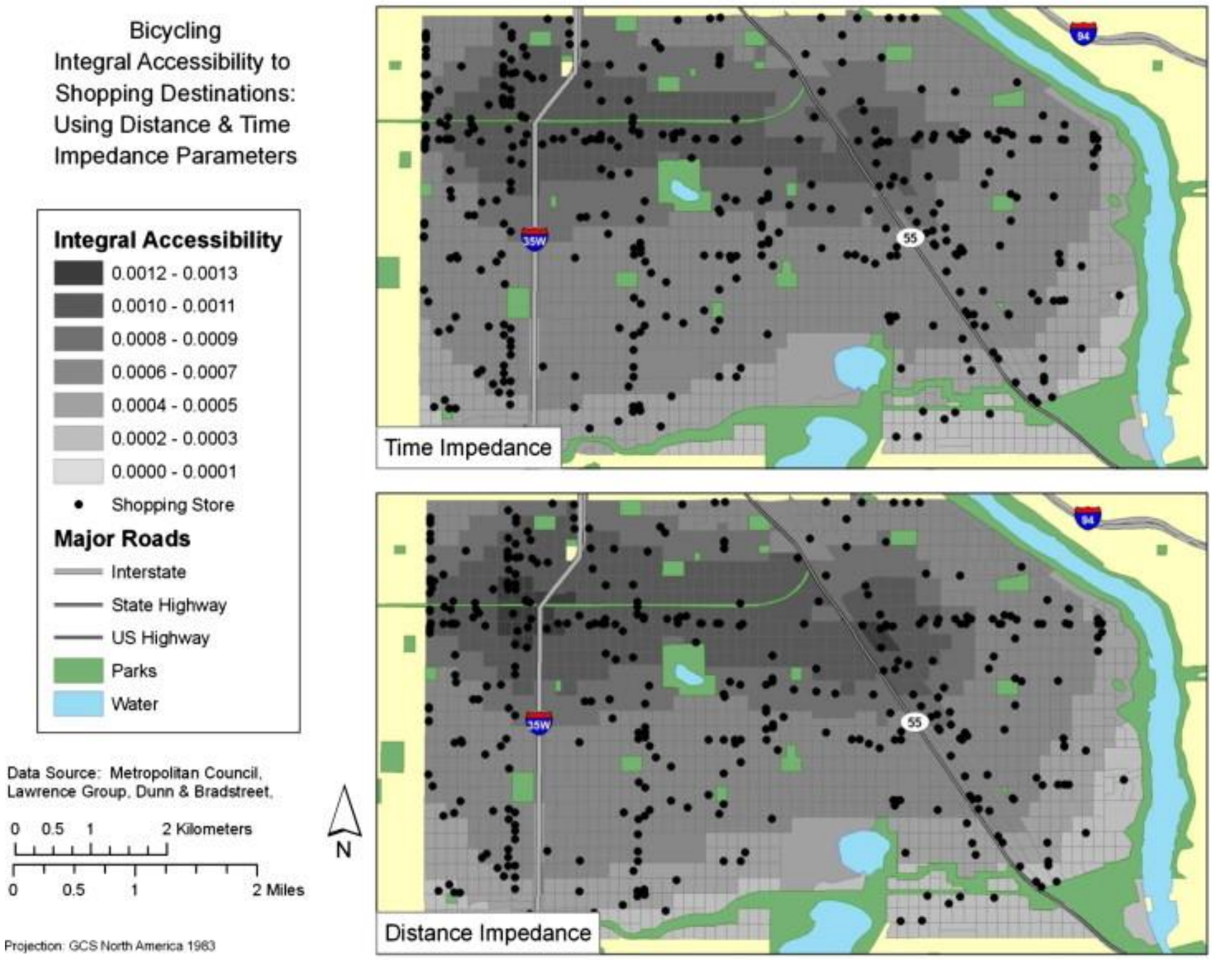

Figure 2.3: Bicycle accessibility to shopping in Minneapolis (Iacono et al., 2010)

Lowry et al. (2016) developed a GIS-based tool for measuring accessibility to a basket of non-work destinations, which took into account – in addition to distance – the 'cycling stress' of different roadway configurations, and the provision of bicycle facilities on each network link, as well as people's tolerance to this stress. With this tool, they were able to quantify (and present graphically) the accessibility benefits of alternative bicycle network improvement scenarios proposed for Seattle (United States) and, importantly, assess the contribution of individual projects (e.g., a new bicycle path) to the overall accessibility improvement (see Figure 2.4), allowing projects to be prioritised. However, they acknowledge that the assessed contribution of each project assumes all other projects in the scenario would also be implemented, rendering the priority ranking less useful. Furthermore, the assumptions on which cycling stress and tolerance to stress are rated are somewhat arbitrary, resulting in some unintuitive constraints – for example, that a person with low tolerance to cycling stress would not tolerate riding along a four-lane road with a 48-km/h speed limit, even if a physically separated bicycle path were provided. Finally, they weight destination attractiveness according to the number of employees, meaning that destinations with no/few employees (e.g., public parks) would be less attractive in their model.

While potentially useful for informing policymakers and stakeholders about the need for, and relative merits of, different bicycle infrastructure projects, accessibility benefits measured using location-based measures are difficult to monetise. As such, they are currently not suitable for inclusion in a SCBA – though they could complement one. None of the 32 economic assessments of active transport interventions reviewed by Brown et al. (2016) (Table 2.3) included accessibility improvements as a benefit. However, accessibility improvements can be valued using utility-based measures – this is covered in Chapter 3.

2.5.3 Journey utility

As discussed in Section 2.5.1, time spent travelling can have intrinsic value, and this is particularly true of bicycle travel. Some individuals will choose bicycle over faster modes, and choose a longer bicycle route over a more direct one, for a variety of reasons: enjoyment, exercise, scenery, or simply for variety (Mokhtarian & Salomon, 2001).

In his exploration of the positive utility of travel, Singleton (2017) shows that ability to multitask and travel satisfaction/enjoyment increase utility by differing amounts for different modes, and that including measures of these benefits in a mode choice model increases its explanatory power.

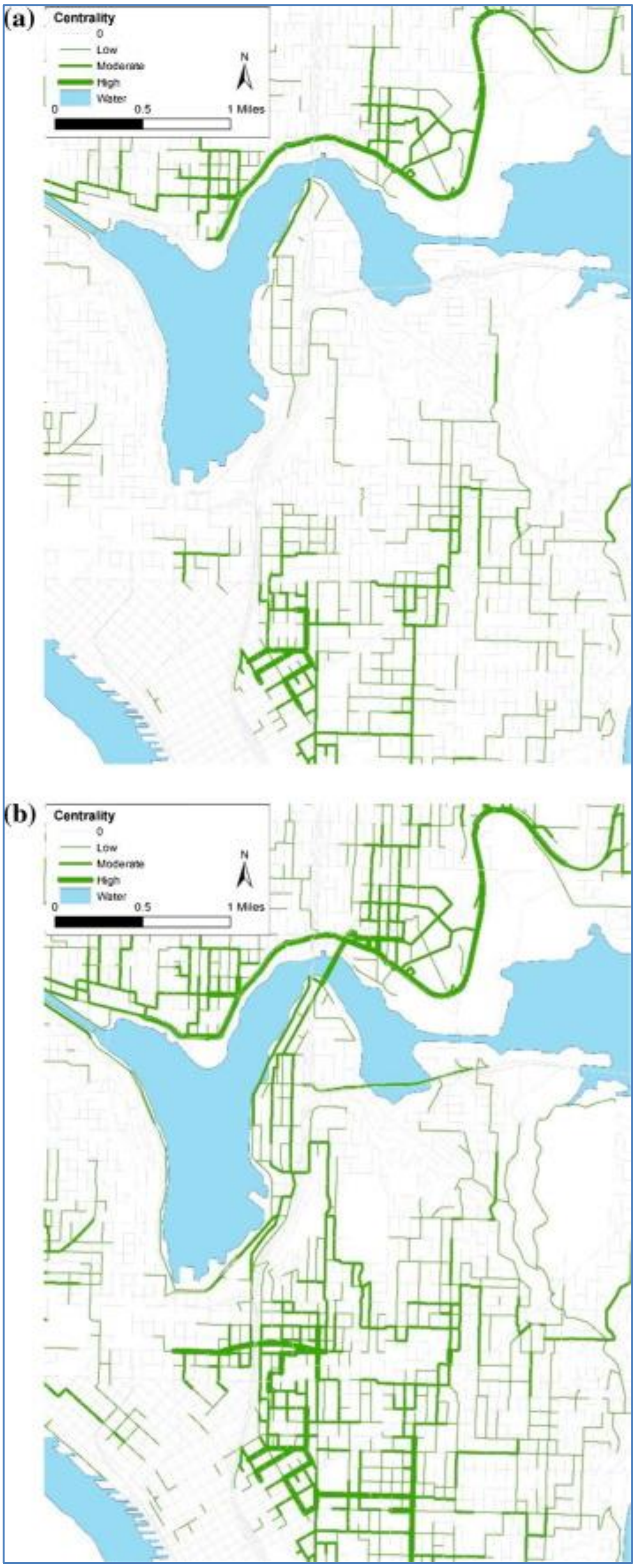

Figure 2.4: Contribution of individual network links to bicycle accessibility for (a) existing conditions, and (b) full implementation of Seattle Bicycle Master Plan (Lowry et al., 2016)

The positive utility of travel time can be increased (or the *disutility* of travel time decreased) in a number of ways. Travel time can be made more reliable/predictable (Li, Hensher, & Rose, 2010). For drivers, the proportion of their journey time spent in stop-start traffic can be reduced (Hensher, 2001). For public transport passengers, crowding levels can be reduced (Li & Hensher, 2011). For bicycle riders, separated bicycle paths can be provided (to reduce fear of traffic and increase comfort levels), among other interventions.

2.5.3.1 Factors affecting journey utility

Before discussing how the utility of a bicycle trip can be measured or valued, it is worth considering which factors, other than time or distance, might affect it. Mokhtarian and Salomon (2001) suggest enjoyment and perceived health benefit may both make a positive contribution. On the other hand, perceived danger is likely to decrease utility for many people, especially in Australia, where there are few bicycle paths and high urban speed limits (Pucher, Garrard, & Greaves, 2011).

To date, little attention has been paid to journey enjoyment in the transport literature. In a recent study of Sydney inner-city residents (Rissel et al., 2015), 52 per cent of those who commuted by bicycle claimed they enjoy their commute – despite Sydney having a hostile cycling environment, and a sparse and disconnected bicycle network. For comparison, 49 per cent of walkers, 14 per cent of car drivers and only 10 per cent of public transport users reported enjoying their commute.

The potential public health benefits of cycling were discussed in Section 2.4.2. However, it is the *perceived* health benefit to individuals that will affect their decision to cycle, and the utility they derive from doing so. Studies in the United States, United Kingdom and Netherlands have found an association between bicycle use and better perceived health (Bopp, Kaczynski, & Campbell, 2013; Humphreys, Goodman, & Ogilvie, 2013; Scheepers et al., 2015). Börjesson and Eliasson (2012) conducted a survey of regular bicycle riders in Stockholm (Sweden), in which 52 per cent stated that exercise was the main reason they chose to travel by bicycle.

Börjesson and Eliasson (2012) suggest that perceived health benefits are internalised in bicycle riders' travel choices and, therefore, captured in valuations of travel time savings (VTTS). However, they found no significant difference between the VTTS of bicycle riders who said that exercise was the most important reason to choose bicycle, and that of those who did not. They interpret this finding to mean the latter group do not disregard the health benefits; another interpretation could be that the perceived health benefits are tiny in comparison to other user benefits (e.g., enjoyment) in both groups. Alternatively, the perceived health *impacts* (e.g., from air pollution exposure or injury) could be equal in magnitude to the perceived health benefits – so they cancel each other out – in both groups.

The road safety impacts of bicycle use were discussed in Section 2.4.1. As with health benefits/impacts, the perceived crash/injury risk may be different from the objectively measured crash/injury risk (Reinhardt-Rutland, 2011).

In their evaluation of new separated bicycle paths in five United States cities, Monsere et al. (2014) used resident surveys and rider intercept surveys to assess changes in perceived danger. They found significant decreases in perceived danger associated with the new bicycle paths, with 96 per cent of bicycle riders and 79 per cent of residents agreeing the paths increased the safety of cycling. Parkin et al. (2007) analysed the risk perceptions of people shown video recordings of a variety of cycling scenarios. They found that people who never use a bicycle perceive residential roads and traffic-free routes to be more dangerous than people who do. Fitch et al. (2016) measured physiological stress (heart rate variability) in inexperienced bicycle riders exposed to different road environments, with initial pilot data appearing to confirm a positive correlation between rider stress and traffic volume/speed.

2.5.3.2 Estimation and valuation of journey utility

Journey utility benefits were included in nine of the 36 economic assessments reviewed by Brown et al. (2016) (Table 2.3).[11] Various methods have been used for estimating and valuing these benefits. In assessments that include travel time savings with different VTTS estimates for different bicycle facility types, the journey utility will be reflected in these values (Börjesson & Eliasson, 2012).

Yi et al. (2011), who used the same VTTS for all facility types, estimated the willingness to pay (WTP) for on-road bicycle paths over mixed traffic streets to be AUD 0.05 per minute or AUD 0.12 per BKT (assuming an average speed of 25 km/h).[12] This estimate was derived from Hopkinson and Wardman's (1996) analysis of the stated route choice preferences of bicycle riders in the United Kingdom. Using this WTP estimate, and applying the rule of half to new bicycle riders, they estimated a 'journey ambiance' benefit of AUD 128.9 million, which was 19 per cent of the total economic benefit.

If perceived health and perceived safety benefits are fully captured in the assessment of user benefits, then including the road safety and public health impacts could be considered double counting – with the exception of benefits that accrue to society in general. Elvik (2000, p. 40) suggests the correct approach in welfare economics is to value the *perceived* benefits:

> Most economists tend to accept observed demand for a commodity (which is based on the costs as perceived by purchasers) as the correct basis for estimating the value of the commodity, even if demand may in part be based on incomplete information or irrational behaviour.

Separated bicycle paths may also improve the journey utility of other road users. In a survey of road users' perceived comfort levels in the San Francisco Bay Area

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[11] Brown et al. use the term 'comfort and security'.

[12] Yi et al. may have overestimated average cycling speed. 25 km/h would be at the upper end of the design speed of Sydney's bi-directional bicycle paths, and average speed would be brought down by intersection delays.

(United States), motor vehicle drivers as well as bicycle riders reported greater comfort levels on multi-lane roads with separated bicycle paths, than on ones without (Sanders, 2016).

2.5.4 Option and non-use value

So far, this section has covered the assessment of benefits and costs that accrue to actual users of new infrastructure. However, welfare benefits can also accrue to non-users in two distinct ways: option value and non-use value (P. Stopher & Stanley, 2014).

Option value is the value individuals place on having the option to use a facility they do not use regularly. For example, habitual drivers having a railway station nearby in case they are ever unable to drive. Geurs et al. (2006, p. 616) interpret option value as "a risk premium that individuals with uncertain demand are willing to pay over and above their expected user benefit for the continued availability of a transport facility". An alternative view is put forward by Schwartz in his book *The Paradox of Choice* (2005), in which he suggests that having too much choice may decrease welfare, causing "bad decisions, … anxiety, stress, and dissatisfaction". He focuses more on retail choices – for example, having to choose from 175 types of salad dressing in a supermarket – and does not discuss transport options specifically.

Non-use value is the value individuals place on infrastructure they never envisage using themselves. This can be for altruistic reasons, i.e., recognising the benefit the infrastructure has to their community. Alternatively, there may be indirect user benefits, e.g., where a transport facility can be used by an individual's friends or relatives, who might otherwise depend on them for chauffeuring.

Option and non-use values are not included in conventional transport project assessment. Geurs et al. (2006) used a stated preference experiment to estimate option value and non-use value, in terms of willingness to pay (WTP), for two regional rail links in the Netherlands. They estimated people living near the rail links, and who did not use them, were hypothetically willing to pay EUR 12 per month to maintain them.

No previous studies assessing the option value of bicycle infrastructure could be found in the literature. Van Wee and Börjesson (2015) have highlighted the need for more research in this area as one important step in making SCBA more suitable for assessing bicycle projects. They suggest that the option value for bicycle infrastructure may be greater than that for road infrastructure, in places where a large proportion of the population does not ride a bicycle regularly, but would value the option of doing so.

2.6 Other appraisal methods

An alternative approach to SCBA is cost-effectiveness analysis, which can be used to identify the lowest cost way to achieve a policy objective. Wang et al. (2004) used this method to measure the cost-effectiveness of bicycle/walking paths in Lincoln (United States), against a target of increasing population physical activity levels. Various alternative and complementary methodologies have been proposed for assessing equity impacts, e.g., multi-criteria analysis (MCA) and the capability approach (Beyazit, 2011), though these are yet to gain much traction in practice.

2.7 Post project evaluation

With historical mode share data for many jurisdictions readily available, measuring changes in bicycle mode share following an intervention is relatively cheap and straightforward. In addition, bicycle policy objectives and targets are often based on mode share. The problem with measuring changes in mode share lies in determining how much of the observed change is attributable to the intervention, and how much is attributable to background/exogenous factors.

Counting bicycle movements at various points in a network, which can be done manually, or automatically using induction loop or infrared detectors, can provide some indication of the impact of new infrastructure. For instance, in their evaluation of new separated bicycle paths in five cities in the United States, Monsere et al. (2014) found that bicycle traffic on the new facilities increased by between 21 and 171 per cent within one year of opening.

There are a number of issues with using this method for measuring changes in bicycle use. First, it is difficult to know if a change in a bicycle count is due to existing riders diverting from an existing route to use a new facility, existing riders making more trips, or new riders switching from other modes. Second, it is difficult to determine to what extent any change is due to new infrastructure, rather than other factors, e.g., cost increases for other transport modes. Third, bicycle counts do not provide any information about changes in bicycle travel durations and distances. Fourth, they do not provide any information about who is using the new facilities.

Monsere et al. (2014) did conduct bicycle rider intercept surveys to help them understand the reasons for the ridership increases they observed – in which 10 per cent of riders reported they would have used a different mode before the facility was constructed, while 1 per cent would not have made the trip in the first place. The remaining 89 per cent said they would have cycled on the same route or on a different route.

There are no examples in the literature of policy evaluations in which actual changes in BKT have been measured, and compared to what was forecast at the appraisal stage. Rather, evaluations have tended to be based on changes in mode share and bicycle counts.

2.8 Before-after studies

While there have been a number *ex-ante* appraisals of bicycle policies (Brown et al., 2016), and many *ex-post* evaluations (Pucher et al., 2010), no studies have looked at how actual welfare benefits compared with what was forecast, in an empirical setting. Actual welfare benefits may differ from those forecast for three principle reasons. First, the actual demand may be more or less than forecast. The most sophisticated transport demand models struggle to make accurate forecasts: actual traffic volumes on Australian toll roads are on average 45 per cent lower than forecast (Li & Hensher, 2010), with optimism bias on the part of the modellers likely to play a part (Flyvbjerg, 2009). Bicycle transport demand models are nowhere near as mature as those for road and public transport (van Wee &

Börjesson, 2015). Second, the value that people place on non-market benefits/costs may change over time, or in response to the intervention itself. For example, once bicycle riders have experienced using a separated bicycle path, they may become even more averse to riding on a mixed traffic street. Third, there may be consequential impacts that reduce the magnitude of forecast benefits. For example, urban motorways encourage people to move further from work, which tends to cancel out forecast travel time saving benefits (Metz, 2008).

There have been some before-after studies of bicycle policy interventions, with many calls for more such studies in the literature (e.g., K. J. Krizek, Handy, & Forsyth, 2009; Parkin, Wardman, & Page, 2008). The few studies that have been done have mostly adopted a repeat cross-sectional design with only one follow-up wave (Yang, Sahlqvist, McMinn, Griffin, & Ogilvie, 2010). A controlled longitudinal panel study was undertaken in England by Goodman et al. (2013) to assess the outcomes of the Cycling Demonstration Towns program, in which 18 towns and cities were granted substantial funding to invest in cycling facilities and programs between 2005 and 2011. Using census data, they found a statistically significant difference in bicycle mode share increase between the 18 funded towns (0.97 per cent), and a control group of 18 unfunded towns with similar demographics (0.29 per cent) (i.e., the increase in mode share in the funded towns was 234 per cent more than in the unfunded towns, albeit off a low base).

2.9 Summary and research gaps

Governments worldwide are aiming to make cycling safer and increase its mode share. With finite financial resources available, decision makers and stakeholders need information about the relative merits of alternative projects and policies, to help ensure those that benefit society the most are prioritised. Social cost benefit analysis (SCBA) is an appropriate method for making objective comparisons of the overall benefits of infrastructure projects, although it is not as well developed for bicycle projects as it is for roads and public transport. There is a clear need for better travel demand forecasting capabilities and more rigorous and convincing valuations of non-market costs/benefits, and for longitudinal assessments where actual outcomes can be compared with those forecast. Other appraisal methods can be used instead or as well as SCBA, e.g., multi-criteria analysis or the capability approach. Cost-effectiveness analysis makes sense where there is a single overriding objective.

There is no standardised way of conducting SCBAs for bicycle projects, with much variation in the costs/benefits included, and the way they are measured and valued. There is a large body of work on the assessment of public health benefits, but much uncertainty remains, resulting in a large range of valuations. The assessment of road safety impacts is more settled, having been a part of road project appraisal for decades – though forecasts may be confounded by the possible 'safety in numbers' effect. Economic development benefits have mostly been considered in assessments of recreational (as opposed to transport) bicycle facilities, while equity impacts have largely been ignored. Some assessments have considered the benefits of reduced motor vehicle use and externalities, although there is no empirical evidence yet that this is a direct benefit of increased bicycle usage.

Much less attention has been paid to the benefits and costs perceived from the user perspective, even though this is the theoretically correct way of measuring consumer surplus (that is, the willingness to pay minus the perceived cost) in welfare economics.

Road and rail project appraisals are dominated by user benefits in the form of expected travel time savings, and some bicycle project appraisals have followed suit. There is a paradox here, in that new bicycle infrastructure can actually increase travel time, both for existing bicycle riders who may divert to use a more pleasant facility, and for new bicycle riders who switch from a faster mode. Furthermore, time spent cycling has intrinsic value, so minimising it may not always be desirable or the main goal.

An alternative to valuing travel time savings is to consider improvements in accessibility to economic and social opportunities, which is the ultimate purpose of most travel. Changes in accessibility can be assessed using gravity models or cumulative opportunities models, but this is difficult to monetise. Better suited to economic assessment are utility-based accessibility measures, which are covered in the next chapter.

As well as improving a person's accessibility, bicycle facilities can improve the utility of time spent travelling, through increased enjoyment, perceived health benefits and increases in perceived safety. Research on valuing journey utility improvements for bicycle riders is limited, and non-existent in the Australian context. Another overlooked benefit is option/non-use value, that is, the benefit individuals derive from having more transport options available to them or their community, even if they do not intend or expect to use them.

The next chapter reviews the literature on disaggregate assessment of user benefits, which in theory can be used to value improvements in both journey utility and option value, as well as accessibility. The disaggregate approach also facilitates assessment of the equity impacts of an intervention.

3 ECONOMETRIC ASSESSMENT OF USER BENEFITS

In Chapter 2, existing approaches for assessing the welfare impacts of bicycle projects and policies are critiqued. Both the social impacts (externalities) and the user benefits and costs are considered. It is concluded that existing approaches do not adequately capture potential user benefits, because they tend to assume time spent cycling is purely a cost to be minimised.

In this chapter, an alternative method for assessing and valuing user benefits is discussed – one that employs discrete choice analysis to investigate the trade-offs people make when choosing whether or not to cycle for transport. This approach is well suited to bicycle project assessment, because it considers overall journey utility and enjoyment, i.e., it can take into account the positive aspects of time spent cycling.

The chapter begins with an overview of discrete choice analysis – covering theory, outcomes and data requirements – with a focus on the aspects relevant to this thesis (Section 3.1). Section 3.2 is a review of the literature on the application of discrete choice analysis for understanding and predicting cycling choices. Section 3.3 describes how discrete choice models can be used to estimate and monetise the user benefits of a project or policy proposal. Previous applications in a transport context are reviewed. In Section 3.4, the issue of transferability is considered, that is, whether models developed to explain past choices can accurately predict future choices and welfare gains/losses – given that people's tastes and preferences may change over time, or in response to a policy intervention. The chapter concludes with a summary and a discussion of the research gaps (Section 3.5).

3.1 Discrete choice analysis

3.1.1 Theory

Discrete choice analysis (DCA) is an econometric method that models human decision making, in cases where there are a limited number of mutually exclusive alternatives from which to choose, e.g., choosing which transport mode to use for a trip. It is a disaggregate modelling method, whereby individual decision makers are the units of analysis. The advantages of disaggregate modelling include smaller prediction errors and lower sample size requirements (Horowitz, Koppelman, & Lerman, 1986).

DCA is grounded in utility theory, and Lancaster's (1966) proposition that consumers derive utility from the *attributes* of products, rather than the products themselves. The first practical applications were facilitated by McFadden's (1974) derivation of the conditional logit model. DCA is now used in a number of fields, including transport, marketing, health and environmental economics. The following overview is based on the texts of Train (2009) and Hensher et al. (2005).

In welfare economics, *utility* is a measure of the relative ability of different alternatives in a choice situation to satisfy a decision maker's wants and needs. The decision maker can be an individual, a household or even an organisation. In travel behaviour analysis, the choices that can be modelled include residential location, trip generation (make trip/stay home), destination, transport mode, departure time and route. DCA generally assumes decision makers choose the alternative that maximises their utility.

For a given choice situation, the analyst can observe various attributes of each alternative, the characteristics of the decision maker, and contextual factors that might influence the relative utilities of each alternative (see Table 3.1). However, there will always be influences that the analyst cannot observe, as well as random variation that cannot be explained.

Table 3.1: Some influences on transport choices

Attributes of the alternatives	Characteristics of the decision maker	Contextual factors
Travel time/distance	Age	Trip purpose (e.g., business/personal)
Cost	Gender	Weather
Brand or label (e.g., airline)	Income	

Thus, given a set of alternatives J that are mutually exclusive, collectively exhaustive and feasible, the utility U_{nj} that decision maker n derives from each alternative j consists of a systematic utility V_{nj} observed by the analyst, plus an unobserved error term ε_{nj} (Equation 3.1).

$$U_{nj} = V_{nj} + \varepsilon_{nj} \quad 3.1$$

The systematic (observed) utility takes the form:

$$V_{nj} = \alpha_j + \beta' x_{nj}, \quad 3.2$$

where x_{nj} is a vector of independent variables, including attributes of alternative j, characteristics of decision maker n, and contextual factors. β' is a vector of preference parameters to be estimated, and α_j are (optional) alternative specific constants.[13]

Examples of observed utility expressions for a transport mode choice situation are given in Table 3.2.

Table 3.2: Example choice set for a transport mode choice situation

Alternative (j)	Attributes (x_j)	Individual characteristics (x_n)	Contextual factors (x)	Observed utility (V_{nj})
Walk	Travel time ($Time_{walk}$)	$Gender_n$	*Rain*	$\alpha_{walk} + \beta_1 Time_{walk} + \beta_2 Gender + \beta_3 Rain$
Bicycle	Travel time ($Time_{bicycle}$)	$Gender_n$	*Rain*	$\beta_4 Time_{bicycle} + \beta_5 Gender + \beta_6 Rain$
Bus	Travel time ($Time_{bus}$)	$Gender_n$		$\alpha_{bus} + \beta_7 Time_{bus} + \beta_8 Gender$
Car	Travel time ($Time_{car}$)			$\alpha_{car} + \beta_9 Time_{car} + \beta_{10} Gender$

Assuming the error terms ε_{nj} have a Generalized Extreme Value Type I distribution, then the probability of decision maker n choosing alternative j is given by the multinomial logit (MNL) model[14] (Equation 3.3).

$$P_{ni} = \frac{\exp(V_{nj})}{\sum_j^J \exp(V_{nj})} \quad 3.3$$

If actual choices and variable values are known across a sample of decision makers and choice situations, then the parameters β' and constants α_j for each utility

[13] With the constant for one of the J alternatives normalised to zero.

[14] Or the binomial/binary logit model, if there are only two alternatives.

function V_{nj} can be estimated, typically by maximum likelihood estimation. Parameters can be specified to be generic across multiple alternatives, or specific to one alternative.

The basic MNL model is relatively easy and quick to estimate because it has a closed-form solution, but it has three notable limitations. First, the error term ε_{nj} for each alternative is assumed to be independent and identically distributed (IID), i.e., error terms for different alternatives are not correlated, but have the same variance. The behavioural implication of this assumption is that a change to the utility of one alternative will affect the utilities of the other alternatives in equal measure. For example, if an express bus service were to be ceased or made more expensive, an MNL model would predict that passengers would be just as likely to switch to normal bus, as they would be to switch to private car. Intuitively, however, one would expect most passengers would switch to regular bus.

Second, the MNL model produces point estimates for each parameter. However, parameters cannot be assumed to be the same for all decision makers, given that people's tastes and preferences are heterogeneous. Systematic sources of preference heterogeneity can be identified by interacting attributes with individual characteristics. For example, in a mode choice analysis, distance can be interacted with gender to test whether women are more sensitive to trip distance than are men, or vice versa. However, there will likely be some residual heterogeneity due to unobserved influences, or because people simply have different tastes. In the MNL model, this heterogeneity is accounted for in the random error terms ε_{nj}.

Third, the MNL model cannot take into account correlations between multiple choices made by a single decision maker – for example, transport mode choices reported in a multi-day travel diary.

To address these limitations, more advanced discrete choice models have been developed. In the mixed logit model, for example, one or more of the parameters can be randomly distributed over the sample of decision makers. This can account for some of the preference heterogeneity that would otherwise end up in the random error term ε_{nj}.[15] The type of distribution is chosen by the analyst, and may be specified so as to limit it to behaviourally realistic values – for example, a cost parameter would normally be forced to be negative, perhaps with the use of a lognormal distribution. Parameter values can be fixed to be the same value along the distribution for all choices by an individual decision maker. These properties make the mixed logit model particularly suitable for analysing panel choice data (e.g., multi-day travel diary data).

In addition, the mixed logit model allows random parameters to be associated with a subset of alternatives. This is achieved by introducing error components E_{nj} into the utility functions, which are normally distributed with a mean of zero and standard deviations θ_j. The greater the estimated standard deviation θ_j of an error component, the greater the likelihood decision makers will substitute between the alternatives associated with that error component. In other words, the mixed logit model relaxes the IID property of the MNL model, and allows flexible substitution patterns between alternatives.[16]

In the mixed logit model, the observed utility V_{njt} that decision maker n derives from each alternative j in choice situation t is given by Equation 3.4.

$$V_{njt} = \alpha_{nj} + \beta'_n x_{njt} + \theta_j E_{nj} \qquad 3.4$$

If random parameters are normally distributed, they take the form:

$$\beta_n = \beta_k + \sigma_k v_{nk}, \qquad 3.5$$

[15] Another way to account for preference heterogeneity is with the latent class logit model, in which the population is disaggregated into two or more classes, with an individual decision maker's class membership dependent on their characteristics (e.g., age and/or gender). Utility function parameters are then allowed to vary between classes (Greene & Hensher, 2003).

[16] Other models have been developed that relax the IID assumption, including those of the generalised extreme value (GEV) family – of which the nested logit model is the most widely used.

where β_k is the population mean, v_{nk} is individual-specific heterogeneity and σ_k is the standard deviation of β_k. Other distributions can be specified, e.g., lognormal, uniform or triangular.

A mixed logit model cannot be estimated using maximum likelihood estimation, because the resulting probability expression is an integral without a closed-form solution. Estimation is therefore performed using simulation, as detailed by Train (2009).

With both MNL and mixed logit analyses, care must be taken when comparing parameters estimated form different datasets, because the magnitude of the random error term ε_{nj} can change. For example, with longitudinal data, a new systematic influence on utility may emerge between data collection waves, which is unobserved by the analyst. In this case, the error term ε_{nj} would grow, while the observed utility V_{nj} would shrink, i.e., choices would become less deterministic. There would be what is referred to as a *scale* difference between the datasets. The scale parameter can be estimated by pooling the data and modelling them jointly using a nested logit model, with one branch for each dataset (Hensher & Bradley, 1993). As explained in the next section (3.1.2), some model outputs, e.g., elasticities and marginal rates of substitution, are scale-free.

3.1.2 Model outcomes

An estimated discrete choice model provides information about the relative influence of different factors affecting choices, and the probability of an individual choosing a given alternative. In addition, it can be used to:

- forecast how market shares may be affected by a change to the attributes of one or more alternatives, or a change in population demographics;
- estimate marginal rates of substitution, for example, the willingness to pay (WTP) for a change in one or more attributes (discussed further in Section 3.3.1); and

- estimate the consumer surplus associated with a choice situation, and forecast how this will be affected by a policy intervention (discussed further in Section 3.3.2).

3.1.3 Data sources

Discrete choice models require choice data, where the dependent variable for each observation is the choice made by the decision maker (e.g., transport mode choice),[17] and the independent variables can include attributes of the choice alternatives (e.g., travel distance), characteristics of the decision makers (e.g., gender), and attributes of the choice context (e.g., whether it is raining at the time the choice is made).

Choice data can be collected in two ways. *Revealed preference* (RP) data reflect choices made by people in the real world, and are obtained through surveys or observation, e.g., travel diaries. S*tated preference* (SP) data reflect choices made by people in hypothetical situations, and are obtained through stated preference surveys. Hensher et al. (2005) outline the advantages and disadvantages of each approach; these are summarised in Table 3.3.

Table 3.3: Comparison of RP and SP data (after Hensher et al., 2005)

Revealed preference (RP)	Stated preference (SP)
• Choices are made in real market situations; they have actually occurred. • Cannot be used to analyse alternatives that do not yet exist. • Choices are bound by the real-world constraints faced by decision makers, e.g., income. • There is limited variation in attribute levels between alternatives, which can make it difficult to explain variation in choice. • With travel surveys, decision makers usually report only the attributes of the alternatives they actually chose; the attributes of other alternatives need to be imputed (see Section 3.1.3.1). • Data collection can be costly, except where data already exist, e.g., a household travel survey or census.	• Choices are hypothetical; decision-makers may behave differently in the real world. • Useful for considering alternatives that do not yet exist. • Decision makers can choose options that may not be available to them in real life, e.g., choosing a Ferrari over a Toyota. • Attribute levels can be varied beyond existing levels (though they should be feasible for decision-makers if they are to make rational responses). • Attributes of all alternatives are specified by, and therefore known by, the analyst. • Data collection is relatively cheap.

[17] It is also possible to estimate discrete choice models using aggregate market share as the dependent variable.

When collecting and analysing RP data, an important consideration is the distinction between *objective* and *perceptual* data (Hensher et al., 2005). When faced with a choice situation in the real world, decision makers will choose from the set of alternatives they are actually aware of, based on what they *perceive* the attributes of those alternatives to be (Adamowicz, Swait, & Boxall, 1997; Lancaster, 1966).[18] However, the analyst will often only know the *objectively measured* attribute levels of the alternatives, which may differ from those perceived by decision makers. In addition, when responding to surveys, respondents may report different values from those that they truly perceive, because of rounding, uncertainty or recall errors. As such, there may be three values for an attribute: objective, perceived and reported.

3.1.3.1 Attribute imputation for RP travel surveys

There is a particular issue when modelling transport mode choice using RP data obtained using a travel survey: respondents typically only provide information about the alternative they chose in each choice situation. Consider the case where a respondent reported making a trip by public transport, and provided the origin, destination, and travel time. The analyst would not know the travel times for the alternative modes the respondent did not choose (walk, bicycle, car, etc.), yet these data are necessary for model estimation.

Washington el al. (2014) describe five approaches for imputing the travel time (or distance) for a non-chosen transport mode:

1. Estimate the travel time for the given origin-destination pair using a transport demand model.
2. Identify trips in the dataset with the same origin and destination zones, but where the non-chosen mode *was* used, and average the reported travel times of these trips.

[18] An interesting implication here is that utility and welfare can be changed simply by changing perceptions.

3. Identify respondents in the dataset who travelled between the origin and destination zones using both the chosen mode and the non-chosen mode, and average the reported travel times for the non-chosen mode.
4. Use Bayesian imputation, conditioned on known inter-zonal travel times and socio-demographic characteristics.
5. Ask respondents to report the travel times of the non-chosen modes.

To model short walking and bicycle trips, origin and destination zones need to be as small as possible, meaning methods 2 to 4 would require a very large sample. Method 5 places additional burden on respondents, but does capture the *perceived* attributes of the alternatives, which are ultimately what determines their utilities.

Similarly, in route choice studies, the analyst does not know the attributes of the route alternatives respondents did not choose. As Broach et al. (2012; 2009) explain, these can be imputed using a variety of algorithms. However, if alternative routes have overlapping segments, the MNL or mixed logit model should not be used, because the error terms will be correlated. In this case, the path-size logit (PSL) model can be used instead (Frejinger & Bierlaire, 2007).

3.1.4 Decision processes

DCA assumes decision makers act rationally, examine all alternatives and all their attributes, and choose the alternative that maximises their utility.

However, in practice, humans tend to choose the same alternative habitually – a phenomenon described by Uttley and Lovelace (2014) as 'behavioural inertia'. Making choices involves mental effort, so people are prone to taking mental shortcuts (Gigerenzer & Gaissmaier, 2011). There is an emerging literature on the incorporation of such *decision heuristics* into choice models (see Leong & Hensher, 2012).

There is also evidence that decision makers ignore certain attributes when choosing (attribute nonattendance), and this can bias model outputs if not accounted for (Collins, 2012).

Alternative decision processes to utility maximisation have been suggested, including regret minimisation (whereby decision makers aim to avoid making choices they might later regret) (Chorus, Arentze, & Timmermans, 2008) and elimination by aspects (whereby attributes are considered in descending order of importance) (Tversky, 1972).

3.2 Bicycle choices and the factors that influence them

This section presents a review of the literature on bicycle choice studies. Scopus and Google Scholar were searched for choice studies specifically concerned with bicycle ownership and use. Search terms included 'bicycle', 'cyclist', 'logit', 'mode choice', 'route choice', 'destination choice', 'departure time choice' and 'speed choice'. Sixteen relevant studies were identified – these are presented in Table 3.4.

Both SP and RP choice data have been modelled. The rationale for choosing SP or RP is never explicitly stated, though it can usually be inferred. For example, Hopkinson and Wardman (1996) wanted to forecast the impact of a hypothetical user charge for using protected bicycle paths. Such a user charge did not exist in the real world, so its potential impact could only be assessed within a hypothetical SP framework.

Wardman et al. (2007) combined both RP and SP data in a nested logit model, with which they forecast that a package of measures – including separated bicycle paths, financial incentives and end-of-trip facilities – could have a significant impact on cycling demand in the United Kingdom. They note, however, the need for validation: "There remains a need to monitor the impact of … improvements in facilities on demand and to assess this against predicted increases" (Wardman et al., 2007, p. 349).

Table 3.4: Previous bicycle choice studies

Study	Location	Choice model(s)	Trip/tour[b] purpose(s)	RP	SP	Mode choice	Route choice	Other choice(s)
Rodríguez and Joo (2004)	Chapel Hill, USA	MNL, nested logit, HEV	Commute	X		X		
Hunt and Abraham (2006)	Edmonton, Canada	Binary logit	Business, social		X		X	
Tilahun et al. (2007)	Minnesota, USA	Mixed logit	Commute		X		X	
Stinson and Bhat (2003)	USA	Binary logit	Commute		X		X	
Wardman et al. (2007)	UK	Nested logit	Commute	X	X	X		
Ortúzar et al. (2000)	Santiago, Chile	MNL	All		X	X		
Sener et al. (2009)	Texas, USA	Mixed logit	All		X		X	
Broach et al. (2012, 2009)	Portland, USA	Path-size logit	All	X			X	
Hopkinson and Wardman (1996)	Bradford, UK	MNL	All		X		X	
Pinjari et al. (2009)	San Francisco, USA	Binary logit, ordered logit	N/A	X				Bicycle ownership; residential location
Soltani and Allan (2006)	Adelaide, Australia	MNL	Not stated	X		X		
Börjesson and Eliasson (2012)	Stockholm, Sweden	Mixed logit, MNL	Commute		X	X	X	
Hood et al. (2011)	San Francisco, USA	Path-size logit	All	X			X	
Cherry et al. (2016)	Kunming, China	Mixed logit	All	X				Second choice mode for e-bike users
González et al. (2016)	Santiago, Chile	Path-size logit	All	X			X	Destination
Zimmermann et al. (2017)	Eugene, USA	Recursive logit	All	X			X	
Total (n = 16)				8	8	5	9	

The bicycle choices most commonly analysed are mode choice and route choice. Börjesson and Eliasson (2012) developed both a mode choice and a route choice model: the former to estimate values of travel time savings for cycling in mixed traffic and on bicycle paths; the latter to value end-of-trip parking facilities, waiting time at intersections and number of intersections along the route. Others have examined destination choice (González et al., 2016) and bicycle ownership choice (Pinjari et al., 2009).

Many studies model only commuting trips/tours;[19] others combine all trip purposes in the same model (sometimes with trip purpose as an attribute). However, the preferences of commuters and non-commuters differ to such an extent that it may be appropriate to model them separately – as is the norm when modelling driving and public transport use (Ortúzar & Willumsen, 2011).

No studies of the choice of bicycle type (road, mountain, hybrid, electric, etc.) could be found in the literature, although Cherry et al. (2016) did model the second preference modes of electric bicycle users in China. There have been no studies of bicycle riders' choice of departure time or speed. No previous study has modelled bicycle choice data (whether SP or RP) collected over multiple years, or before and after a policy intervention.

When designing a DCA study, it is useful to know which independent variables have previously been tested and found to be significant. Previous bicycle choice studies have examined a range of individual characteristics, trip attributes and contextual factors. Sections 3.2.1, 3.2.2 and 3.2.3 respectively discuss these variables in more detail.

3.2.1 Individual characteristics

Table 3.5 summarises the individual characteristics that have been tested in previous bicycle mode and route choice studies. They include socio-demographic characteristics (e.g., age, gender, income), and others believed to affect cycling

[19] A tour is a sequence of one or more trips beginning and ending at the same location.

choices (e.g., fitness, cycling ability). These are discussed below, along with other potential factors identified elsewhere in the literature.

Table 3.5: Bicycle mode and route choice studies – individual characteristics

Study	Choice	Gender (female)	Age (older)	More tired	More cycling experience	More cycling frequency	Higher household income	More educated	Larger household	Higher bicycle availability[20]	Higher car availability
Wardman et al. (2007)		–	+	–	+		±				
Ortúzar et al. (2000)		±	+			+	–	±		+	±
Rodríguez and Joo (2004)	Mode	–									
Soltani and Allan (2006)							–				
Börjesson and Eliasson (2012)		±	+				+				
Sener et al. (2009)		+	+		–						
Tilahun et al. (2007)	Route	±	±		±		+		–		
Hunt and Abraham (2006)			±		–						

+ More likely to choose bicycle/low-stress route ($p < 0.05$)
– Less likely choose bicycle/low-stress route ($p < 0.05$)
± Not significant ($p \geq 0.05$)

Gender

In many countries, including Australia, travel surveys show that cycling for transport is significantly more common amongst men than amongst women. Notable exceptions to this pattern include the Netherlands, Germany, Denmark and Sweden (Pucher & Buehler, 2007).

These data are consistent with transport mode choice studies that predict men in the United Kingdom and United States are more likely to travel by bicycle than women (Sener et al., 2009; Wardman et al., 2007); and one that predicts no difference in Stockholm (Sweden) (Börjesson & Eliasson, 2012). In Santiago (Chile), males are more likely to choose bicycle (90 per cent confidence level) (Ortúzar et al., 2000).

[20] Number of bicycles in household divided by household size.

Garrard et al. (2012) discuss two possible reasons why the propensity to cycle for transport may differ between genders. First, women may have more complex trip patterns and less time, due to additional domestic responsibilities (e.g., childcare and chauffeuring). However, this is also true in the countries where cycling participation does not differ between genders. Second, women may feel less comfortable and safe riding in mixed traffic, even though their actual crash/injury risk is no greater than that of men. This may explain why gender is not a significant factor in those Northern European countries that have networks of bicycle paths physically separating bicycle riders from high-speed, high-volume traffic. Higher perceived danger may also explain why women are more likely than men to avoid routes with on-street parking (Sener et al., 2009).

Age

Transport mode preference for bicycle increases with age, and older people place a greater value on the perceived health benefits of cycling (Börjesson & Eliasson, 2012; Ortúzar et al., 2000; Wardman et al., 2007).

In terms of route choice, older riders prefer streets with angled on-street parking to ones with parallel parking, while younger riders are indifferent (Sener et al., 2009). In Sydney, older riders are more likely to change their route to use a new bicycle path (Standen et al., 2016).

Household size

Individuals from larger households (more than two persons) are less likely to go out of their way to use a lower stress route (e.g., one with better separation from traffic) – possibly because they have parenting responsibilities and more time constraints (Tilahun et al., 2007).

Household income/education level

The effect of household income on propensity to cycle varies by country. In Santiago (Chile) and Adelaide (Australia), people from low-income households are more likely to cycle (Ortúzar et al., 2000; Soltani & Allan, 2006). In Stockholm (Sweden), people from high-income households are more likely to do so (Börjesson & Eliasson, 2012). This could be due to the way bicycle transport is viewed in different cultures. In Chile, for example, the bicycle is seen as a mode of transport for less successful people, with a famous 1980 television advertisement showing a man being ridiculed for riding one (Long, 2016). Similarly, a government road safety campaign in South Australia suggested that men who are banned from driving will have difficulty attracting women, if they use a bicycle instead (Milnes, 2011).

Despite a positive correlation between household income and education level, Ortúzar and Willumsen (2011) found that education level is not significant, while household income is, in Santiago (Chile). However, In Dublin (Ireland), Commins and Nolan (2011) found – using RP (census) data – that highly educated people are more likely to cycle (or walk) to work. They suggest that educated people may be more aware of the social impacts of driving, or can afford to live within cycling distance of work.

In terms of route choice, people from high-income households are more likely to choose low-stress bicycle routes (Tilahun et al., 2007).

Tiredness and cycling experience/frequency

As one would expect, lower tiredness and more cycling experience are associated with greater propensity to cycle (Wardman et al., 2007).

Route choice studies show that less experienced riders tend to favour lower stress routes (Hunt & Abraham, 2006; Sener et al., 2009).

Bicycle and car availability

People from households with greater bicycle availability (number of bicycles divided by household size) are more likely to cycle, while the number of cars in the household is not significant (Ortúzar et al., 2000).

Psychosocial factors

As discussed in Chapter 2 (Section 2.5.3.2), the utility of cycling to an individual may be affected by the extent to which they believe they will derive a health benefit.

In studying people's motivations for cycling in the United Kingdom, Gatersleben and Appleton (2007) found there is general agreement that cycling is healthy, but perceived health benefit is not one of the major motivations for cycling. They suggest this may be because health benefits are generally detected over the long term, whereas other benefits can be experienced on a daily basis.

On the other hand, 52 per cent of bicycle commuters surveyed in Stockholm (Sweden) stated that exercise is the most important reason to choose bicycle (Börjesson & Eliasson, 2012). However, this group had the same sensitivity to travel time as the other respondents, which Börjesson and Eliasson suggest could be because (a) health was not a factor in their mode choice, or (b) the other group also considered perceived health benefit, but it was not their primary motivation for cycling. Another explanation is that sensitivity to travel time is determined at the margins: whereas a 30-minute bicycle commute may be preferred to a 40 minute one, both might be perceived as sufficient to offer a health benefit.

In Belgium, regular bicycle riders have higher self-reported levels of self-efficacy, social support (relatives who will accompany them when cycling), modelling (relatives who cycle), and environmental awareness. Non-riders report having less time, and less interest in cycling (De Geus, De Bourdeaudhuij, Jannes, & Meeusen, 2008).

3.2.2 Trip attributes

Table 3.6 summarises the various attributes of bicycle trips that have been tested in previous mode and route choice studies. They include typical generalised cost components (e.g., travel time, distance, financial cost), and others specific to cycling (e.g., gradient). These are discussed in more detail below, along with other potential factors identified elsewhere in the literature.

Table 3.6: Bicycle mode and route choice studies – trip attributes

Study	Choice	Trip distance	Travel time	Financial cost/incentive	Number of turns/intersections	Route directness	Gradient	Air pollution	Noise	Personal security	Surface type/condition	Presence/type of bicycle facility	Bicycle facility continuity	Presence/type of on-street parking	Motor vehicle traffic volume	Motor vehicle speed limit	End-of-trip facilities (showers, parking)	Trip purpose
Wardman et al. (2007)			S	S			NS	NS	NS	NS		S					S	
Ortúzar et al. (2000)			S															S
Rodríguez and Joo (2004)	Mode		S				S											
Soltani and Allan (2006)			S			S												
Börjesson and Eliasson (2012)			S		S							S						
Stinson and Bhat (2003)			S		S		S				S	S	S	S				
Hood et al. (2011)		S			S							S						
Sener et al. (2009)		S	S				S					S	S	S	S	S		S
Tilahun et al. (2007)			S									S						
Hunt and Abraham (2006)	Route		S		S							S					S	
Hopkinson and Wardman (1996)			S	S								S						
Börjesson and Eliasson (2012)			S		S												S	
Broach et al. (2012, 2009)		S			S		S					S			S			S
Zimmermann et al. (2017)		S			S		S					S			S			

S: Significant at the 95% confidence level ($p < 0.05$)
NS: Not significant at the 95% confidence level ($p \geq 0.05$)

Trip distance/time

There is general agreement that bicycle utility decreases as travel time or distance increases. Disutility is higher for time spent riding on high-stress links/routes, and for commuting trips (Börjesson & Eliasson, 2012; Ortúzar et al., 2000; Rodríguez & Joo, 2004; Soltani & Allan, 2006; Wardman et al., 2007; Zimmermann et al., 2017).

Usually, disutility is assumed to increase linearly with trip distance/time. Broach et al. (2012, 2009) used the natural log of distance in their route choice model – implying that the marginal disutility diminishes as distance increases – but did not give any justification for doing so. Börjesson and Eliasson (2012) estimated a lower marginal disutility of travel time for bicycle riders whose total commute time is 40 minutes or more. They attributed this difference to long-distance commuter bicyclists having fewer time constraints to begin with (i.e., self-selection).

Financial cost/incentive

Trip costs – such as fuel, tolls and fares – have long been known to affect the utility of driving and public transport (Hensher et al., 2005). However, the operating costs of a bicycle are negligible. There are no fuel costs or direct user charges, except in the case of (a) bicycle share schemes, where time charges apply, usually after an initial free period (Fishman, Washington, & Haworth, 2013), and (b) casual use of commercial end-of-trip facilities.

Hopkinson and Wardman (1996) included in their SP route choice model a hypothetical cost to use a separated bicycle facility, and found this cost to negatively affect cycling utility. Wardman et al. (2007) included a hypothetical financial incentive to cycle in their joint RP-SP mode choice model. Respondents valued the incentive at twice the magnitude of the cost of driving or public transport. Wardman et al. suggest the difference may be the result of respondents having differing sensitivities to gains and losses – although prospect theory suggests they would be *more* sensitive to losses (costs) than to gains (incentives) (Tversky & Kahneman, 1992). From this model, Wardman et al. estimated that paying people GBP 2 a day[21] to cycle to work would double the commuting mode share for bicycle in the United Kingdom.

Turns and route directness

Using RP data collected with personal GPS devices, both Broach et al. (2012, 2009) and Hood et al. (2011) found that a route with more turns has a lower utility than one with fewer turns, *ceteris paribus*. Broach et al. estimated that each turn per mile (1.61 km) has the same disutility as a 4.2 per cent increase in commuting distance. They also estimated that each left turn[22] per mile has an additional disutility equivalent to between 5.9 per cent and 32.2 per cent of commuting distance, depending on traffic volume. Hood et al. estimated that each turn (left or right) has a disutility equivalent to an additional 0.17 km of travel.

Other studies show that the utility of a bicycle route decreases with the number of traffic signals, stop signs and major cross streets (Börjesson & Eliasson, 2012; Stinson & Bhat, 2003). Additionally, propensity to cycle increases with route directness (calculated as the quotient of straight-line distance and network distance) (Soltani & Allan, 2006).

Gradient/hilliness

Cycling up hills requires additional physical effort and travel time, so would be expected to decrease the utility of cycling, or of a hilly bicycle route – except in the case of recreational or sport cycling, where hills are sometimes sought out for the physical challenge or the scenery (Belbin, 2016).

Cole-Hunter et al. (2015) found that a more elevated work/study location was associated with a lower propensity to commute by bicycle in Barcelona (Spain). They estimated work/study location elevation as the average elevation of a 400-metre buffer around the geocoded work/study location.

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[21] 2007 prices.

[22] The data were from Portland (United States), which has right-hand traffic – making left turns more difficult.

Using an RP mode choice model, Rodríguez and Joo (2004) determined that increased hilliness between a respondent's origin and destination significantly decreases cycling utility. However, their model assumed hills have no deterrent effect other than the increase in travel time, i.e., travellers do not consider the additional physical effort required. In their RP mode choice study, Wardman et al. (2007) found that hilliness is not significant, although their data were obtained from relatively flat study areas.

A number of previous route choice studies predict that bicycle riders will opt for a less hilly route, *ceteris paribus* (Broach et al., 2012, 2009; Sener et al., 2009; Stinson & Bhat, 2003; Zimmermann et al., 2017).

All these studies assumed that respondents use a conventional bicycle. However, in recent years, there has been an increasing uptake of electric-assist bicycles (e-bikes), fuelled by improvements in battery technology and lower costs (Weiss, Dekker, Moro, Scholz, & Patel, 2015). When using an e-bike, it is possible to climb hills with minimal physical effort – though they are still slowed down by hills.

Surface type/condition

Bicycler riders, particularly older ones, prefer a smooth pavement to a rough or sandy one, according to a SP route choice study conducted in the United States (Stinson & Bhat, 2003).

Presence/type of bicycle facility

Mode and route choice studies, both SP and RP, have consistently shown that the presence of bicycle facilities that separate riders from high speed/high volume traffic is one of the most important determinants of cycling utility (Börjesson & Eliasson, 2012; Broach et al., 2012, 2009; Hood et al., 2011; Hopkinson & Wardman, 1996; Hunt & Abraham, 2006; Stinson & Bhat, 2003; Tilahun et al., 2007; Wardman et al., 2007; Zimmermann et al., 2017). The utility of cycling increases with the level of separation: physically separated bicycle paths offer the greatest utility, followed by marked bicycle lanes, followed by mixed traffic.

For United Kingdom commuters, Wardman et al. (2007) estimated the marginal rate of substitution (MRS) between time spent in mixed traffic and time spent on bicycle paths to be 3.2 (implying people will ride for 3.2 minutes on a bicycle path to avoid riding for one minute in mixed traffic). For commuters in Stockholm (Sweden), the MRS is 1.4 for trips less than 40 minutes, and 1.9 for trips of 40 minutes or more.

However, in modelling SP route choice data from Texas (United States), Sener et al. (2009) found that bicycle users prefer mixed traffic to bicycle lanes. They note their respondents were more likely to be enthusiastic riders who subscribe to the 'vehicular cycling' philosophy, in which it is believed bicycle users have as much right to use public roads as anyone else, and the onus is on other road users to adapt to their presence, rendering separation unnecessary (Forester, 2001).

In the United Kingdom, bicycle riders are permitted to use bus lanes. These are preferred to roads with no facilities, but preference for separated bicycle paths is much greater (Hopkinson & Wardman, 1996).

Bicycle facility continuity

According to Krizek and Roland (2005, p. 56), a bicycle route can be viewed as a system that is "only as good as its weakest link", and interruptions in bicycle facilities significantly affect self-reported comfort levels. In order of increasing negative impact on comfort levels, the interruptions they analysed included: bicycle lanes that end mid-block and deposit riders into mixed traffic flow; bicycle lanes that terminate just before an intersection; and contra-flow bicycle lanes that end abruptly and deposit riders into oncoming traffic.

Modelling SP route choices, Stinson and Bhat (2003) found that a discontinuous bicycle route (defined as one where there is no bicycle lane for 25 per cent or more of the route) has a lower utility than a continuous one. Similarly, Sener et al. (2009) found a significant preference for continuous bicycle routes (defined as ones with a bicycle lane for 100 per cent of their length). In neither study is it clear how the disutility of discontinuity is distinguished from the disutility of riding in mixed traffic.

On-street parking

Bicycle routes with parallel on-street parking are less preferred than ones without, while angle parking is preferred over parallel parking. The utility of a route decreases with increases in the parking occupancy rate and parking zone length (Sener et al., 2009; Stinson & Bhat, 2003).

Motor vehicle traffic volume and speed

Roads with lower average daily traffic volumes are preferred by bicycle riders, especially commuters who typically ride during peak times when traffic volumes are at their highest (Broach et al., 2012, 2009; Sener et al., 2009; Zimmermann et al., 2017).

Most riders prefer roads with a lower posted speed limit (Sener et al., 2009). An exception is experienced riders commuting long distances, who prefer roads with a moderate speed limit (32 to 56 km/h). However, even they avoid roads with a high speed limit (over 56 km/h).

It is likely that rider comfort levels are affected more by a road's operating speed than by its posted speed limit, although the latter is usually a reasonable proxy for the former (Fitzpatrick, Carlson, & Wooldridge, 2003), and easier to ascertain.

End-of-trip facilities

The lack of end-of-trip facilities (showers and secure parking) is often cited as a structural barrier to bicycle use, especially for commuting trips (Gatersleben & Appleton, 2007; Pucher et al., 2010).

In their commuting mode choice study, Wardman et al. (2007) found that secure bicycle parking is valued the same as a 4.3 minute reduction in travel time, while secure parking plus shower/changing facilities are together valued the same as a 6.0 minute reduction in travel time. Similarly, Börjesson and Eliasson (2012) found that bicycle routes with bicycle parking facilities at the destination are preferred to those without, with parking valued as equivalent to a 3.7 minute reduction in travel time.

Air toxin and traffic noise exposure

Bicycle riders are exposed to air toxins and noise pollution from motor vehicles, with exposure increasing with traffic volumes (Bigazzi & Figliozzi, 2015; Tang & Wang, 2007). Air toxin levels also depend on the volume of trucks and buses, emission standards, fuel quality, and prevalence of diesel-powered vehicles (P. F. Nelson, Tibbett, & Day, 2008).

It is not known to what extent air toxin and noise exposure affect mode and route choices. Where bicycle paths are built along high-traffic roads, there may be a trade-off between the desire to minimise air toxin inhalation and noise exposure, and the desire for physical separation from traffic (Bigazzi, Broach, & Dill, 2015).

Perceived accessibility

As discussed in Section 3.1.3, the utility of an alternative to an individual depends on how they *perceive* the attributes of that alternative. According to Dill and Voros (2007), people often overestimate the time needed to travel somewhere by bicycle, and they may not be aware of the existence of a low-stress bicycle route, if they are only familiar with the major roads. Scheepers et al. (2016) found that propensity to cycle decreases as perceived accessibility by car increases (odds ratio (OR) range: 0.09 to 0.66), while it increases as perceived accessibility by bicycle increases (OR range: 2.18 to 10.43).

This implies that cycling utility can be increased simply by changing perceptions of accessibility, e.g., through route signage. Equally, it could change through experience (temporal preference instability is discussed further in Section 3.4)

3.2.3 Contextual factors

Table 3.7 summarises the various contextual factors have been examined in previous mode and route choice studies. These are discussed in more detail below.

Table 3.7: Bicycle mode and route choice studies – contextual factors

Study	Choice	Season	Weekday/weekend	Weather	Trip purpose
Ortúzar et al. (2000)	Mode			S	S
Soltani and Allan (2006)			S		
Sener et al. (2009)	Route				S
Tilahun et al. (2007)		S			
Broach et al. (2012, 2009)					S

S = Significant at the 95% confidence level ($p < 0.05$)

Trip purpose

Many previous choice studies have included only commuting trips (e.g., Börjesson & Eliasson, 2012; Rodríguez & Joo, 2004; Stinson & Bhat, 2003; Tilahun et al., 2007; Wardman et al., 2007). Others have pooled multiple trip purposes in the same model. In a couple of studies, a trip purpose variable was interacted with other attributes to test whether sensitivity to those attributes varies by trip purpose. Using this approach, it has been found that commuters are more sensitive than are non-commuters to travel time and traffic volume (Broach et al., 2012, 2009). Furthermore, long distance commuters are more sensitive to on-street parking and bicycle facility discontinuity, and less sensitive to moderate speed limits, while non-commuters are less sensitive to hills and traffic volume (Sener et al., 2009).

Climate

Bicycle users are exposed to the elements, and adverse weather (e.g., wind, rain, extreme cold, extreme heat and humidity) is often cited as a barrier to cycling (Gatersleben & Appleton, 2007). Nankervis (1999) studied the commuting patterns of students in Melbourne (Australia), which has a temperate climate. He concluded that cycling does decline in the winter months, and on days with adverse weather. The decline in winter may be partly attributable to fewer daylight hours.

Few bicycle choice studies have included weather or climate variables. In one SP mode choice study conducted in Santiago (Chile), hot weather was found to significantly decrease cycling utility (Ortúzar et al., 2000).

Darkness

The crash risk for bicycle riders increases in darkness, by 55 per cent according to Johansson et al. (2009) based on data from Sweden, Norway and the Netherlands (see Figure 3.1). In addition, cycling in darkness requires lights with batteries that need regular charging or replacing (or a dynamo system).

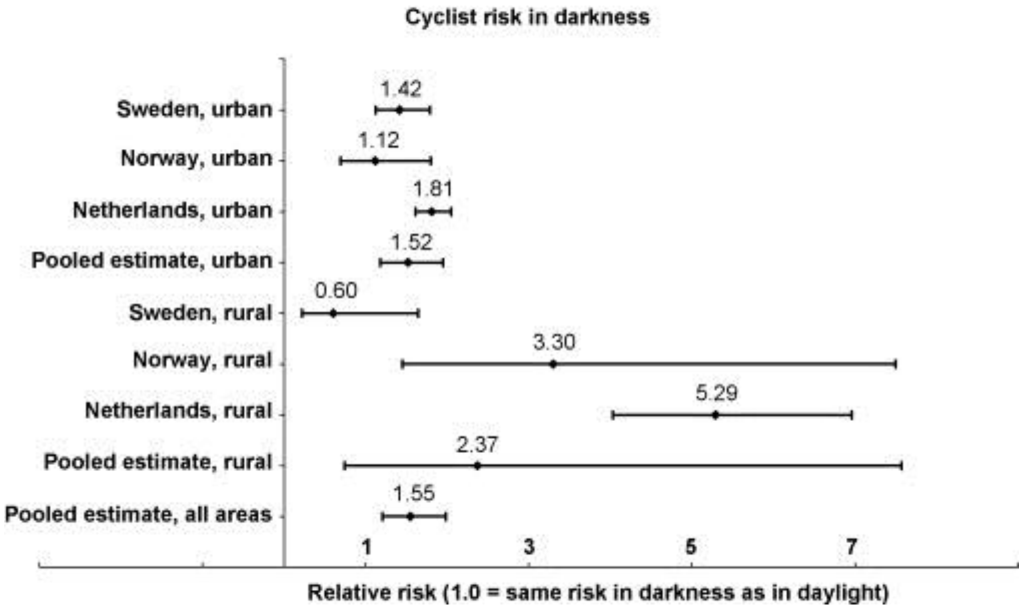


Figure 3.1: Bicycle rider crash risk in darkness (Johansson et al., 2009)

Using a generalised estimating equation to model self-reported commuting data from the Netherlands, Heinen et al. (2011) found that women are more sensitive than are men to cycling in the dark.

Darkness and street/path lighting were not included as contextual factors in any of the bicycle choice studies found in the literature.

3.3 Derived welfare measures

A useful feature of discrete choice models is that they can be used to forecast changes in welfare (user benefits) resulting from an intervention that will improve (or worsen) the choices available to individuals. Both changes in willingness to pay (WTP) and consumer surplus can be estimated.

A criticism of both these approaches is that attempting to maximise individual utility/welfare can lead to suboptimal social and environmental outcomes, and inter-generational inequity. In an example of Hardin's (1968) 'tragedy of the commons', attempts to satisfy motorists' preferences to drive in free-flowing traffic (by expanding road capacity) have led to increases in motor vehicle traffic and consequential social and environmental impacts.

3.3.1 Marginal rate of substitution and willingness to pay

3.3.1.1 Theory

In choosing between the alternatives in a discrete choice situation, decision makers are assumed to make trade-offs between their attributes. For example, a driver may opt to pay more money (less utility) to use a faster toll road (more utility). The rate at which a decision maker will substitute one attribute for another is the marginal rate of substitution (MRS). It is defined as the ratio of the change in the marginal utility of one attribute to the change in marginal utility for another (Hensher et al., 2005). In the simplest case, where the attribute has a linear influence on utility, unmoderated by any other variable, this simplifies to the ratio of the attributes' parameter estimates (Equation 3.6). Scale factors cancel out, so MRS values can be compared across datasets with error terms of differing magnitude.

$$\frac{\frac{d}{dx_a}\beta_a x_a}{\frac{d}{dx_b}\beta_b x_b} = \frac{\beta_a}{\beta_b} \qquad 3.6$$

In welfare economics, an important MRS ratio is willingness to pay (WTP), which is defined as the maximum price a consumer is willing to pay for a good or service (Mankiw, 2007). It is widely used for valuing goods that are not traded in a free market. In environmental economics, WTP values have been estimated for a variety of environmental goods, e.g., wilderness (Lienhoop & MacMillan, 2007). In transport economics, considerable attention is paid to estimating the WTP for travel speed increases (see Section 2.5.1) – arguably too much attention, given the negative environmental and social consequences of faster vehicle speeds (Cervero, 2011).

For estimating WTP from a discrete choice model, the denominator x_b in Equation 3.6 would be a cost attribute – normally a monetary cost, but not necessarily so. For example, it could be a distance cost, in which case WTP could be interpreted as the willingness to pay in terms of a longer trip distance, in exchange for an improvement in attribute x_a. An example here is the distance bicycle riders are willing to go out of their way to use a more pleasant or safe facility.

It is important to note that parameter estimates are just that, and have confidence intervals. It follows that a MRS or WTP estimate, being the ratio of two parameter estimates, must also have a confidence interval. Methods for calculating these include the bootstrap method, the Krinsky and Robb method, and the Delta method (Hole, 2007). The formula for the latter is:

$$Var\left(\frac{\beta_a}{\beta_b}\right) = \frac{1}{{\beta_b}^2}\left[Var(\beta_a) - \frac{2\beta_a}{\beta_b}Cov(\beta_a, \beta_b) + \left(\frac{\beta_a}{\beta_b}\right)^2 Var(\beta_b)\right] \qquad 3.7$$

A further consideration is how to estimate MRS or WTP in the mixed logit model, where a randomly distributed cost parameter (denominator) could take a value of zero, resulting in a singularity with a MRS or WTP of infinity. Hensher et al. (2005) suggest some ways of avoiding this issue:

1. Specify the cost parameter to be non-random.
2. Specify a cost parameter distribution that is constrained to be non-zero, e.g., lognormal or constrained triangular.
3. Calculate MRS/WTP values for each individual respondent, using parameter estimates conditioned on their actual choices.

There is some debate in the literature as to whether WTP does actually measure welfare or wellbeing. Sagoff (2003, 2004) contends that WTP measures only preferences, not welfare, and that there is no empirical or testable correlation between them. To say that WTP measures welfare is tautologous, if welfare is measured in terms of WTP – in other words, WTP measures WTP. Furthermore, preference satisfaction may lead to both good and bad social outcomes. In response, Zerbe et al. (2006) asks: who should decide which preferences are good, and which are bad?

An emerging question in the literature is whether WTP differs between short-term travel choices and long-term ones (Beck, Hess, Cabral, & Dubernet, 2017). For example, when an individual is deciding where to live, WTP for lower travel time may be relatively low. When they are running late for work and deciding which transport mode to use, they may value travel time savings much higher. Then, when they are held up in traffic, they may value travel time savings even higher, to the extent they will switch route to use a toll road. It is debatable which value of VTTS should be used for calculating the time saving benefit of policies aimed at increase travel speeds.

3.3.1.2 Application

Few attempts have been made to value new or improved bicycle facilities using the WTP approach. Using data from a SP survey, Poorfakhraei and Rowangould (2015) calculated WTP for bicycle paths, bicycle lanes and street lighting. Based on a reference scenario of a 20-minute trip on an unimproved road, they estimated that respondents are willing to pay USD 1.76 to 2.47 for bicycle paths, USD 1.37 to 1.90 for street lighting, and USD 0.86 to 1.40 for bicycle lanes along the whole route. WTP values were higher for older respondents, and lower for those with more cycling experience. Poorfakhraei and Rowangould's model did not include a monetary cost parameter, but it did include travel time, which they valued as 50 per cent of respondents' hourly wage rate.

Similarly, Krizek (2006) estimated that bicycle users in Minneapolis (United States) are willing to ride for an additional 16.3 minutes, if a bicycle lane is provided along their entire route. Multiplying this by a VTTS of USD 12 per hour,[23] they estimated a WTP of USD 3.26 for a 20-minute bicycle trip – which is considerably more than the USD 0.86 to 1.40 estimated by Poorfakhraei and Rowangould, even before taking inflation into account.

[23] This was the value recommended by the Minnesota Department of Transportation.

There are some issues with using this approach to value the welfare benefits of new bicycle infrastructure. First, there is the potential for hypothetical bias associated with SP surveys (Hensher, 2010). Second, a uniform trip time is assumed, and trips are assumed to be 100 per cent on the new facility. This issue could be overcome by presenting respondents with route alternatives involving a mixture of facility types, though this would increase survey complexity and respondent burden.

3.3.2 Consumer surplus

3.3.2.1 Theory

A general problem with using WTP as a measure of the welfare benefit of new transport infrastructure is that user charges are considered a transfer payment, and are therefore not included in economic assessment. For example, if 1,000 motorists are willing to pay $5 to use a toll road that saves them each 10 minutes of travel time, and they each do pay $5 to use the toll road, then from their perspective the net welfare benefit would be nil. However, from an economist's perspective, the net welfare benefit would be $5,000 ($5 x 1,000).

For this reason, it may be more appropriate to measure changes in *consumer surplus*, which is defined as the difference between consumers' WTP for something, and the price they actually pay for it (Mankiw, 2007). Changes in consumer surplus can therefore take into account additional costs to consumers, financial or otherwise, of a project or policy.

For transport projects, the consumer surplus has traditionally been estimated using the rule of half (as described in Section 2.3.3). However, it can also be estimated from a discrete choice model. The following summary is based on the work of Train (2009), de Jong et al. (2005) and de Jong et al. (2007).

The natural log of the denominator of the choice probability (Equation 3.3), known as the *logsum* or *inclusive value*, gives the maximum expected utility available to an individual. In other words, it is a measure of an individual's expected utility associated with a choice situation. The inclusive value increases with the number of alternatives, but with decreasing marginal utility owing to the logarithmic form – it can therefore capture changes in option value (see Section 2.5.4).

The expected value of the consumer surplus CS_{nt}^{s} for an individual n in scenario s can be calculated by dividing the inclusive value by the marginal utility of income α_n (Equation 3.8). By definition, α_n is the negative of any cost parameter in the utility functions V_{njt}^{s}. The unknown constant C is added because the inclusive value includes only observed utility.

$$E(CS_{nt}^{s}) = (1/\alpha_n)\ln\left(\sum_j e^{V_{njt}^{s}}\right) + C \qquad 3.8$$

For a mixed logit (random parameters) model, the inclusive value is calculated as the average of all random draws. If the cost parameter used to calculate α_n is randomly distributed, then the division by α_n must be done *before* the average is taken (Kristoffersson & Engelson, 2009).

As an aside, if destination choice is also included in the model, then the consumer surplus can be interpreted as a measure of accessibility (Ben-Akiva and Lerman, 1985). This is the basis of utility-based accessibility measurement (discussed in Section 2.5.2).

The change in consumer surplus for a policy intervention $\Delta E(CS_{nt})$ is calculated as the difference in inclusive value between the before and the after scenarios (b and a respectively), divided by α_n (Equation 3.9). The unknown constant C drops out.

$$\Delta E(CS_{nt}) = (1/\alpha_{\mathrm{n}})\left[\ln\left(\sum_j e^{V_{njt}^{\mathrm{s=a}}}\right) - \ln\left(\sum_j e^{V_{njt}^{\mathrm{s=b}}}\right)\right] \qquad 3.9$$

Thus, if an attribute x_{pij} of the observed utility V_{njt} improves because of the intervention, then $V_{njt}^{\mathrm{s=b}}$ will be greater than $V_{njt}^{\mathrm{s=a}}$ and $\Delta E(CS_{nt})$ will be positive.

The change in population consumer surplus can then be calculated by applying expansion factors representing the number of people of each type n affected by the intervention.

This approach assumes that the marginal utility of income α_i is the same before and after the intervention, and that error terms between the before and after scenarios are perfectly correlated. Zhao et al. (2012) found that changes in consumer surplus are robust to a relaxation of the latter assumption. A third assumption is that the intervention does not cause decision makers' tastes and preferences (represented by the model parameters) to change. This assumption is critiqued in Section 3.4.

A major advantage of this discrete choice/inclusive value approach is that it is disaggregate and can therefore take into account heterogeneity in the preferences of individuals (Dong et al., 2006). This is particularly important when assessing cycling projects, because preferences underlying bicycle utility are very dependent on individual characteristics such as age, gender, income and risk-perception (Wardman et al., 2007).

Table 3.8: Applications of consumer surplus estimation

Study	Objective	Choice(s)	Location	Data sources	Bicycle included?
Geurs et al. (2010)	Forecast the user benefits of land use/transport strategies for adapting to climate change.	Transport mode/destination (simultaneous)	The Netherlands	TRIGIS XL transport/land use model	Bicycle and walk combined into one mode
Geurs et al. (2012)	Forecast the user benefits of three land use and six rail alternatives for development of Almere growth area.	Transport mode/destination (simultaneous)	Randstad region, the Netherlands	TRIGIS XL transport/land use model	Bicycle and walk combined into one mode
Niemeier (1997)	Value current employment accessibility for different population groups.	Transport mode/destination (simultaneous)	Puget Sound, Washington, US	Household travel survey, census, Puget Sound Transportation Model	No
Dong et al. (2006)	Forecast the user disbenefits of a peak period toll, for different population groups.	Daily activity schedule	Portland, Oregon, US	Not stated	Not stated
Robson (2014)	Forecast the user benefits of a proposed metro network.	Transport mode	Sydney, Australia	Census (journey to work data)	Not stated
Zorn et al. (2012)	Measure the user benefits of new bicycle lanes.	Bicycle route	San Francisco, California, US	GPS traces	Yes

3.3.2.2 Application

While the theoretical basis for estimating consumer surplus based on changes in inclusive value is well established, there have been relatively few applications in practice. Table 3.8 lists relevant examples found in the literature.

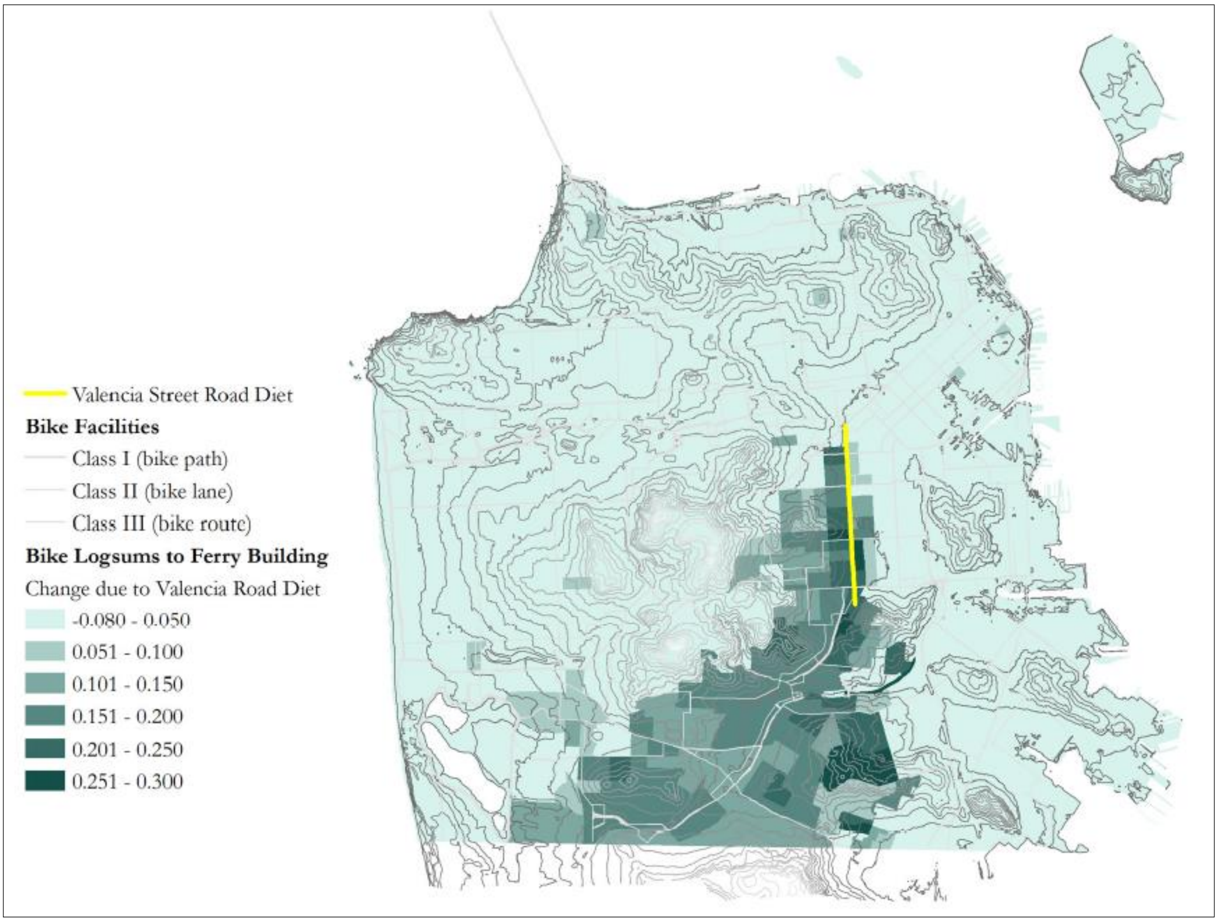


Figure 3.2: Change in cycling inclusive value to downtown San Francisco after introduction of Valencia Street bicycle lanes (Zorn et al., 2012)

No examples could be found in the literature of the inclusive value approach being used to monetise the user benefits of bicycle projects or policies. Zorn et al. (2012) developed a route choice model using RP data from San Francisco (United States), in which the chosen routes were obtained from existing bicycle users using a smartphone tracking app, and the non-chosen routes were generated using a doubly stochastic shortest path algorithm. Their model generated inclusive value parameters representing the maximum expected utility of cycling between any given origin-destination pair. They used this model to assess (retrospectively) the change in bicycle accessibility to the city centre when new bicycle lanes were installed along a major cycling route in 1999. Figure 3.2 illustrates how bicycle accessibility to the city centre changed for each origin zone: people living in the darker shaded zones experienced the greatest increase in bicycle accessibility. Zorn et al. did not attempt to value these accessibility improvements.

Using a route choice model as opposed to a mode choice model means that only the impact on existing bicycle users is measured (Hopkinson, 1996). Inclusive values of bicycle route choice situations could potentially be used in place of the generalised cost of cycling in a mode choice model (Hood et al., 2011). Alternatively, if factors affecting cycling utility are included directly in the mode choice model, then consumer surplus can be evaluated across the whole population – and therefore incorporate the option value that people who do not currently use a bicycle derive from gaining the possibility of doing so.

3.4 Transferability

An implicit assumption in DCA – whether it is used to forecast changes in demand, future market shares, WTP or consumer surplus – is that the parameters of the utility functions remain constant over time, and are not affected by an intervention. In other words, it is assumed that preferences are transferable, and models developed to explain past behaviour can be used to predict future behaviour (Fox & Hess, 2010).

However, it is feasible that preferences could change over time, or be affected by experience of a new alternative, or a significant change to an existing alternative. For example, an economy class aeroplane seat may be less appealing after experiencing business class. Similarly, if a city builds some new bicycle paths, users may become accustomed to the comfort and perceived safety they offer, and more averse to riding in mixed traffic. In this example, models estimated using *ex-ante* data would underestimate the user benefits of the intervention.

In the context of transport mode and destination choices, Fox and Hess (2010) reviewed six articles (covering 11 studies) that statistically compared models estimated before and after an intervention (Table 3.9). They found four of the six articles supported the hypothesis that preferences are transferable over time. Models that included socioeconomic variables performed better than those that did not.

Table 3.9: Temporal mode choice transferability studies

Study	Location	Intervention	Timeframe (years)	Data sources[a]	Choice(s) analysed	Trip purposes analysed	Modes
Train (1978)	California (US)	New train line (BART)	3	Not stated (RP presumed)	Mode	Commuting	Car, carpool, bus, train
McCarthy (1982)	California (US)	New train line (BART)	1.5	RP	Mode	Commuting	Car, bus, train
Karasmaa and Pursula (1997)	Helsinki (Finland)	None	7	RP	Mode and destination	Commuting	Walking, bicycle, car, public transport
Gunn (2001)	Netherlands	None	10	RP	Mode and destination	Commuting, shopping, social/recreation	Car, public transport, slow (walk or bicycle)
	Netherlands	None	None	RP	Mode and destination	Commuting, shopping, social/recreation	Car, public transport, slow (walk or bicycle)
	France	None	None	RP	Mode and destination	Commuting, shopping, social/recreation	Car, public transport, slow (walk or bicycle)
	Netherlands	None	None	SP	Not stated (mode only presumed)	Commuting, business, other	Car, public transport
	Netherlands	None	None	SP	Not stated (mode only presumed)	Commuting, business, other	Car, public transport
	United Kingdom	None	None	SP	Not stated (mode only presumed)	Commuting, business, other	Car, public transport
Silman (1981)	Tel-Aviv (Israel)	1973 oil crisis, reduced tax concessions for car travel	4	RP	Mode	Commuting	Car, bus
Badoe and Miller (1995)	Toronto (Canada)	Not stated	22	Not stated (RP presumed)	Mode	Commuting	Car, public transport, walk

[a] RP = revealed preference; SP = stated preference

However, they note all but one of the studies they reviewed focused on a single trip purpose (commuting), and most were conducted over a short time frame (up to 10 years), relative to typical forecasting and appraisal periods (up to 30 years). They also note all the studies used a simple model (MNL), and suggest future research could test whether transferability is improved with more advanced models, such as mixed logit. However, in the case of one long-term (22-year) study (Badoe &

Miller, 1995), a simple MNL model (specified with just constants and trip attributes) was found to be more transferable than one with individual characteristics added – even though the latter gave a better model fit.

Most of the studies used RP data. However, Gunn (2001) used SP data to investigate changes in the value of travel time savings (VTTS) in the Netherlands and the UK between 1988 and 1997. They found that the VTTS for business travel by rail decreased significantly, which they attribute to the availability of mobile phones allowing rail travel time to be used more productively. (Perversely, this makes investment in new railways less attractive from a social cost benefit analysis perspective, meaning funding could be directed instead to infrastructure that provides less opportunity to use travel time productively, e.g., motorways.)

In the same publication, Fox and Hess (2010) reviewed four validation studies that compared modelled predictions of mode shares with actual future mode shares. In two of these, overall predictive performance was good. In another (Silman, 1981), future shares for major modes (car driver and bus) were accurately predicted, but that for the *minor mode* (car passenger) was not.

Forsey et al. (2014) investigated the temporal transferability of a RP mode choice model of commuting trips in Ontario (Canada) between 2001 and 2006, during which time a new transport mode was introduced (rapid bus transit). They did find a significant change in model parameters (preferences). However, their 2001 model did perform well in forecasting 2006 mode shares. It is not discussed whether the change in preferences may have been caused by the introduction of BRT.

None of these previous preference transferability studies included bicycle as an alternative in the mode choice model (however, Karasmaa & Pursula (1997) combined walk and bicycle as a single alternative). None assessed preference transferability in the context of bicycle project/policy interventions.

The preference transferability assumption has been tested in other fields. Mueller and Remaud (2010) conducted a SP experiment to understand factors affecting wine purchase choice in the year 2009, and compared the results with those from an identical experiment conducted in 2007 (with a different cross-sectional sample). They observed small changes in sensitivity to price and region of origin, and a strong increase in sensitivity to organic labelling.

In the healthcare field, Miguel et al. (2002) conducted a SP experiment to understand parents' preferences in relation to out-of-hours healthcare for their children. After re-surveying the same sample two months later, they found preferences had remained stable. Similarly, Severin et al. (2001) found evidence of stability in preferences underlying shopping centre and supermarket choice, using repeat cross-sectional survey data collected over four years.

Investigating the choice to purchase an electric vehicle (EV) or internal combustion vehicle (ICV), Jensen et al. (2013) found that preferences changed significantly after consumers had experienced using an EV for three months. Using a hybrid choice model to jointly estimate SP data collected from respondents before and after they had experienced an EV, they found sensitivity to an EV's range and top speed almost doubled after experience with it. In addition, sensitivity to an ICV's fuel cost increased after EV experience. Jensen et al. did not survey a control group of respondents who did not experience an EV, so there is no certainty that the changes in senstivity they observed were a result of EV experience. There may have been background factors that affected preferences, for example, publicity about EVs.

In a different approach to investigating the impact of changes in attribute levels on preferences, Vij and Walker (2014) developed a latent class logit model with feedback, in which an individual's class membership (set of preferences) could be influenced by attribute level changes in one or more alternatives. They assumed latent class membership to be a function of the inclusive values of the underlying class-specific choice models (as well as of individual characteristics). Using this model with cross-sectional RP mode choice data from San Francisco (United States), they were able to forecast changes in the class membership distribution (i.e., the propensity of people to adopt a different set of preferences) in response to increases in car travel time and cost. This class membership redistribution resulted in the forecast mode shift away from car being significantly lower than that forecast with a conventional latent class logit or nested logit model. Accordingly, they stress the need for future research that addresses "the question of how preference endogeneity [to the choice situation] might best be reconciled with existing frameworks of welfare analysis and policy [appraisal]" (p. 104), highlighting the need for longitudinal studies:

> The hypothesis that travel demand models currently in use by [metropolitan planning organisations] could be improved through the inclusion of endogenous preferences cannot be fully tested without fairly long *panel data over periods where urban infrastructure and travel costs change significantly* (Vij & Walker, 2014, p. 104, emphasis added).

No previous research has investigated whether preferences underlying bicycle mode or route choice are stable over time, or following improvements to the bicycle alternative. A finding that cycling preferences change after supporting infrastructure is provided would raise concerns over using DCA to predict changes in demand or consumer surplus, but would lend weight to the 'build it and they will come' argument often used by cycling advocates (A. Nelson & Allen, 1997). Conceptually, it is feasible that some people's preferences for transport cycling might change once they have experienced it as an activity than can be undertaken without the need to mix with traffic.

Another type of transferability to consider is spatial, whereby behaviour and preferences in one location are used to explain or predict behaviour and preferences in another. The review of bicycle choice studies (Section 3.2) indicates there is wide variation in preferences between and within countries, suggesting a model estimated using data in one location might not be particularly reliable for predicting demand or welfare changes elsewhere.

3.5 Summary and research gaps

This chapter demonstrates that discrete choice analysis is a potentially useful tool for understanding choices relating to bicycle use, and estimating the user benefit of new bicycle infrastructure.

There have been a number of studies of cycling choices in a variety of countries, in which both observed (RP) and hypothetical (SP) mode and route choices have been modelled. A range of independent variables (individual characteristics, trip attributes and contextual factors) have been tested in these models, and estimated parameters have largely had the expected sign.

Model parameter estimates (preferences), and marginal rates of substitution between them, vary considerably between locations – indicating they are not spatially transferable. The hypothesis of temporal transferability before and after an intervention – which underpins forecasts made using these models – has, to date, not been tested. The temporal transferability hypothesis has been tested for other transport modes, and in other fields of study (e.g., healthcare), but these studies used rather simple model specifications (e.g., MNL), and did not control for background factors which may have affected preferences.

4 RESEARCH DESIGN AND DATA COLLECTION

Chapters 2 and 3 reviewed the literature on cycling project assessment, and on the application of discrete choice analysis (DCA) to understanding cycling behaviour. Much scope for improvement in bicycle project appraisal (both theory and practice) was identified, particularly in terms of assessing and valuing user benefits – such as improved accessibility, confort and option value. DCA was identified as a potential tool for addressing these needs: as well as modelling changes in travel demand for a project proposal, it can be used to forecast changes in consumer surplus, for inclusion in welfare economic appraisal (cost-benefit analysis). DCA-based forecasts assume people's preferences do not change over time, yet there has been little research on whether, or how, cycling-related preferences may change.

This chapter begins with a statement of the research questions and hypotheses for this thesis (Section 4.1). An overview of the experimental design proposed to address them is provided in Section 4.2. The case study intervention (George Street Cycleway) and its setting are described in Section 4.3. Details of the primary data source, the Sydney Travel and Health Study, are provided in Section 4.4. Secondary data sources are described in Section 4.5, followed by a chapter summary (Section 4.6).

4.1 Research aims, questions and hypotheses

This research was funded by an Australian Research Council Linkage Project grant, with the broad aim to make major contributions to the assessment of the transport, health and economic impacts of bicycle infrastructure (The University of Sydney, 2012). Following a review of the relevant literature (Chapters 2 and 3), the following two research questions and two hypotheses were formulated.

Research question 1

Which trip attributes, individual characteristics and contextual factors affect people's decisions to travel by bicycle or not, in a car-oriented Australian city?

Research question 2

How can discrete choice analysis be used to measure and value the user benefits of new bicycle facilities, in a way that fits into existing infrastructure appraisal frameworks?

How do these benefits compare in magnitude to other benefits normally attributed to cycling projects (e.g., public health benefits)?

Are there any implementation issues?

What are the implications for the economic assessment of future cycling projects?

Hypothesis 1 (Null)

Following the construction of a new bicycle path, measured changes in bicycle travel are no different from those that are forecast using a discrete mode choice model.

Hypothesis 2 (Null)

Preferences underlying bicycle mode choice are stable over time.

4.2 Experimental design

A high-level overview of the experimental design framework is presented in Figure 4.1. Travel survey (revealed preference) data are obtained from residents living near the proposed intervention (George Street Cycleway), and from residents living in a control area with similar characteristics, but where no new cycling infrastructure is planned (Wave 1). The travel data are analysed using a discrete mode choice model, which is then used to forecast the travel demand and consumer surplus for the four future scenarios listed in Table 4.1.

Table 4.1: Economic appraisal scenarios

Identifier	Name	Year	Description	Corresponding data collection wave
A	'Do nothing'	2013	No changes to the transport network.	1
B	George St Cycleway	2014	Construction of the George Street Cycleway (see Section 4.3.4).	2
C	George St + CBD Cycleways	2015	Scenario B, plus new cycleways in the CBD providing a continuous route between the George Street Cycleway and the Sydney Harbour Bridge.	3
D	Complete Network	2017	Full implementation of the City of Sydney's *Cycle Strategy and Action Plan* (City of Sydney, 2007).	N/A

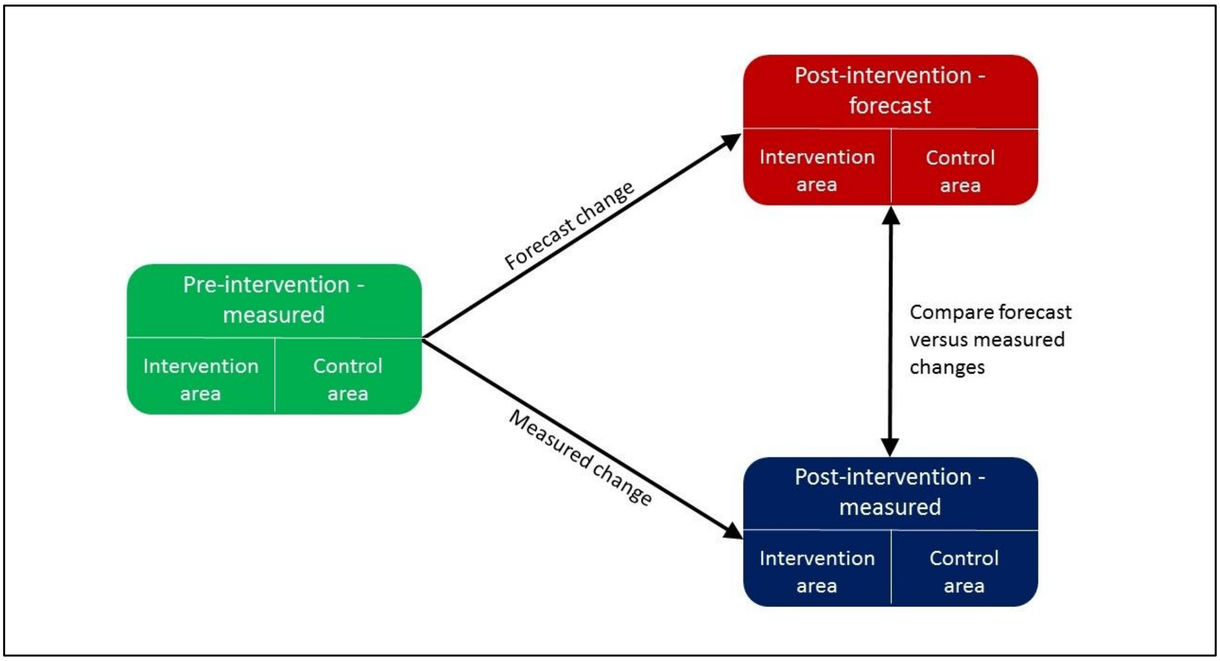


Figure 4.1: High-level experimental design

The same residents are re-surveyed 12 months later (Wave 2), four months after the George Street Cycleway opens (corresponding with Scenario B). They are re-surveyed again at 24 months (Wave 3), at which time new cycleways in the CBD have opened (corresponding with Scenario C). Actual changes in travel demand among the resident panel are compared with what was forecast. Finally, travel data from all three data collection waves are combined and analysed to test for temporal preference stability.

4.3 Study area and intervention

4.3.1 Geography and land use

The City of Sydney is a local government area (LGA) within the Greater Sydney metropolitan region, the capital city of the state of NSW. It has an area of 27 square kilometres, and in the 2011 Census had a residential population of 169,501 (63.4 persons per hectare) (ABS 2011b). Sydney's Central Business District (CBD), a major employment, tourism and retail centre, is located in the northern part of the LGA. To the north of the CBD is Port Jackson (Sydney Harbour). To the immediate east, south and west of the CBD are gentrified inner-city residential suburbs. The Redfern-Waterloo public housing community is in the centre of the LGA. The southern part of the LGA contains the Green Square urban renewal area: 278 hectares of former light industrial land that is being redeveloped as high-density residential and commercial. Land use planning is largely the responsibility of the City of Sydney, with employment and housing growth targets set by the NSW Government.

4.3.2 Transport

Transport planning in Greater Sydney is mainly the responsibility of the NSW Government, which controls public transport, taxis, arterial roads and all traffic signals. The management of local roads (including speed limits, on-street parking, traffic calming and bicycle infrastructure) is the responsibility of councils, but changes require approval by the state government roads authority, Roads and Maritime Services (RMS). Councils are also responsible for paths in most parks and other public spaces.

An important component of the metropolitan transport system is the Sydney Harbour Bridge (opened 1932), which connects the CBD to North Sydney on the other side of Port Jackson, and acts as a funnel for private/freight vehicles and numerous bus services. It also has a double-track railway (T1 Line) and segregated pedestrian and bicycle paths. Starting in the 1970s, motorways began to sprout from the southern and northern ends of the bridge into the suburbs. In 1992, the Sydney Harbour Tunnel was opened, increasing cross-harbour road traffic capacity.

In addition to these motorways, the City of Sydney LGA also has an extensive network of arterial and local roads. There is no congestion charge, although there are southbound-only tolls on the harbour crossings.

Commercial car parks are costly in the CBD, with an average daily rate of AUD 70.85 (Farren, Milou, & Volakos, 2015). In other parts of the LGA, most roads have free on-street parking. This creates a buffer between footpaths and traffic lanes, but poses a hazard for bicycle riders (vehicle doors being opened into their path). On-street parking is prohibited on many arterial roads during peak times, to create space for additional vehicle traffic.

New residential and commercial developments are built with off-street parking, even if well-served by public transport (City of Sydney, 2017). Shopping centres offer free customer parking.

Fuel is inexpensive by international standards (Australian Institute of Petroleum, 2015), with an average petrol price of AUD 1.34/litre in March 2015 (Caltex Australia, 2016).

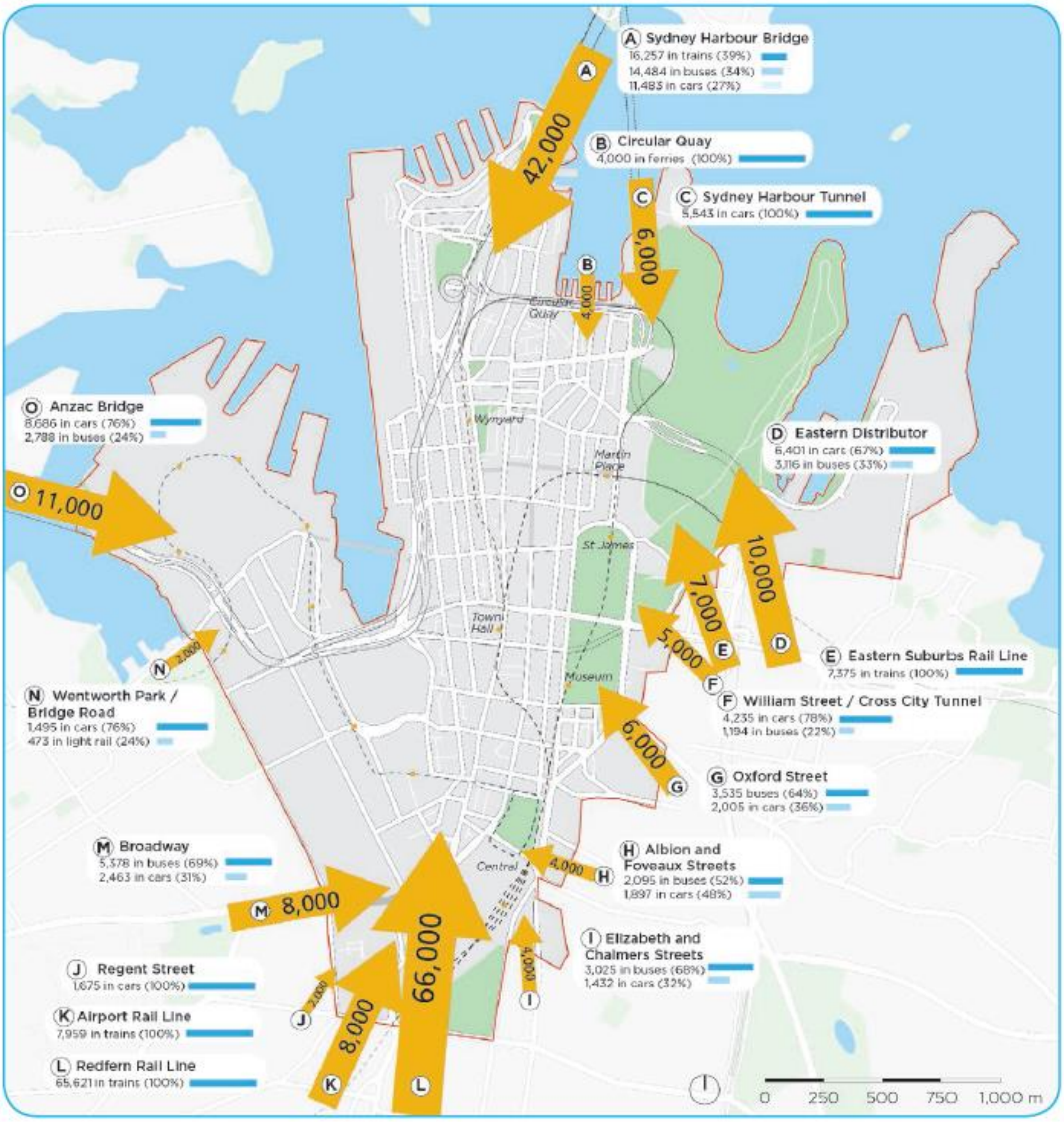


Figure 4.2: Passenger volumes entering CBD 08:00 to 09:00 (Transport for NSW, 2013c)

By Australian standards, the LGA is well served by public transport, with a number of frequent heavy rail, light rail, ferry and bus services radiating from the

CBD. However, with few bus priority lanes, high traffic congestion, and dozens of bus routes sharing some corridors, bus travel can be slow and unreliable. There are few non-radial services, making public transport often inconvenient for people not travelling to/from the CBD or along radial corridors. In 2014, the rollout of the Opal smartcard ticketing system was completed. However, the system retained some of the problems of the previous paper-based one, including a penalty for travellers for changing mode. Figure 4.2 shows the car and public transport passenger volumes entering the CBD along major corridors during the morning peak (08:00 to 09:00).

People walking in the City of Sydney experience narrow footpaths, high motor vehicle traffic volumes and speeds, vehicle exhaust and noise, and low priority and long waits at intersections.

4.3.3 Cycling environment

Sydney is car-oriented and not conducive to everyday cycling for a large part of the population. The speed limit on most arterial roads is 60 km/h, while for residential streets the default is 50 km/h. Bicycle lanes are often situated in the 'door zone' between parked vehicles and traffic lanes, and the few separated cycleways are disconnected and lack continuity. There are some recreational paths (shared with pedestrians) alongside motorways and waterways, but these are not planned with access to destinations or public transport in mind. Inner-city Sydney has a number of hills, and sales of electric-assist bicycles are growing (Charleston, 2016). The current climate is temperate, with warm summers and mild winters, and an average of 144 rainy days per year (Weatherzone, 2016).

The centrepiece of cycling safety policy since the early 1990s has been laws that mandate the wearing of helmets for all types of cycling, including low-speed transport and recreational riding, with a fine of AUD 330 for non-compliance (NSW Centre for Road Safety, 2016). Despite this policy, the injury risk for bicycle riders has remained high by international standards (Garrard et al., 2010; Poulos et al., 2015).

While Australians buy more bicycles than cars (Austroads, 2014), suggesting a desire to ride, most do not in practice. In the Greater Sydney metropolitan region, the bicycle mode share for trips under 10 kilometres was 2.5 per cent in 2012 (Bureau of Transport Statistics, 2013). According to the same source, in the 15 to 49 age category, the mode share for males (3.3 per cent) was three times that for females (1.1 per cent). The vast majority of bicycle trips under 10 kilometres were for sport/recreation (63 per cent), rather than utilitarian transport purposes (e.g., work or shopping). In the City of Sydney, transport cycling is more common, with 3.5 per cent of workers (but only 2.2 per cent of women) commuting by bicycle (Australian Bureau of Statistics, 2011).

As part of a policy to give more people the option to use a bicycle for everyday transport, City of Sydney released a *Cycle Strategy and Action Plan* in 2007 (City of Sydney, 2007). This included a target to increase the cycling mode share for all trips from 2 per cent in 2006 to 10 per cent by 2016. The centrepiece of this strategy is a planned 200-kilometre bicycle network, including 55 kilometres of separated cycleways. The first cycleway, along King Street in the CBD, opened in 2009. Since then, progress has been slow, largely due to opposition by the state roads authority. As of 2015, 110 kilometres of the network, including 10 kilometres of separated cycleways, had been completed (City of Sydney, 2015).

4.3.4 The George Street Cycleway

One of the new cycleway links, and the one chosen as the case study for this research, is the 2.4-kilometre George Street Cycleway, which was constructed between June 2013 and June 2014 in the suburbs of Redfern and Waterloo, south of the CBD. The cycleway is bidirectional and is separated from motor vehicle traffic by raised kerbs. It was complemented by new traffic speed restrictions (40 km/h), improved footpaths, pedestrian crossings and additional tree coverage.

The cycleway provides a continuous route between Central Station in the CBD and the Green Square urban renewal area to the south, and passes through the Redfern-Waterloo public housing community. At its southern end, the cycleway connects with the existing Bourke Road Cycleway, providing access to Sydney

Airport, and the suburbs of Botany and Mascot (another urban renewal area). When it opened, there were no connecting bicycle facilities at its northern end, meaning anyone wanting to ride into the CBD beyond Central Station had to mix with traffic. This changed in September 2015, with the opening of new cycleways along Castlereagh Street South and Liverpool Street. This provided access to western parts of the CBD, as well as the Sydney Harbour Bridge. However, low priority at intersections makes travel through the CBD slow – it is significantly faster to ride in the general traffic lanes, for those with the confidence to do so. Changes to the bicycle network from 2013 to 2015 are shown in Figure 4.3.

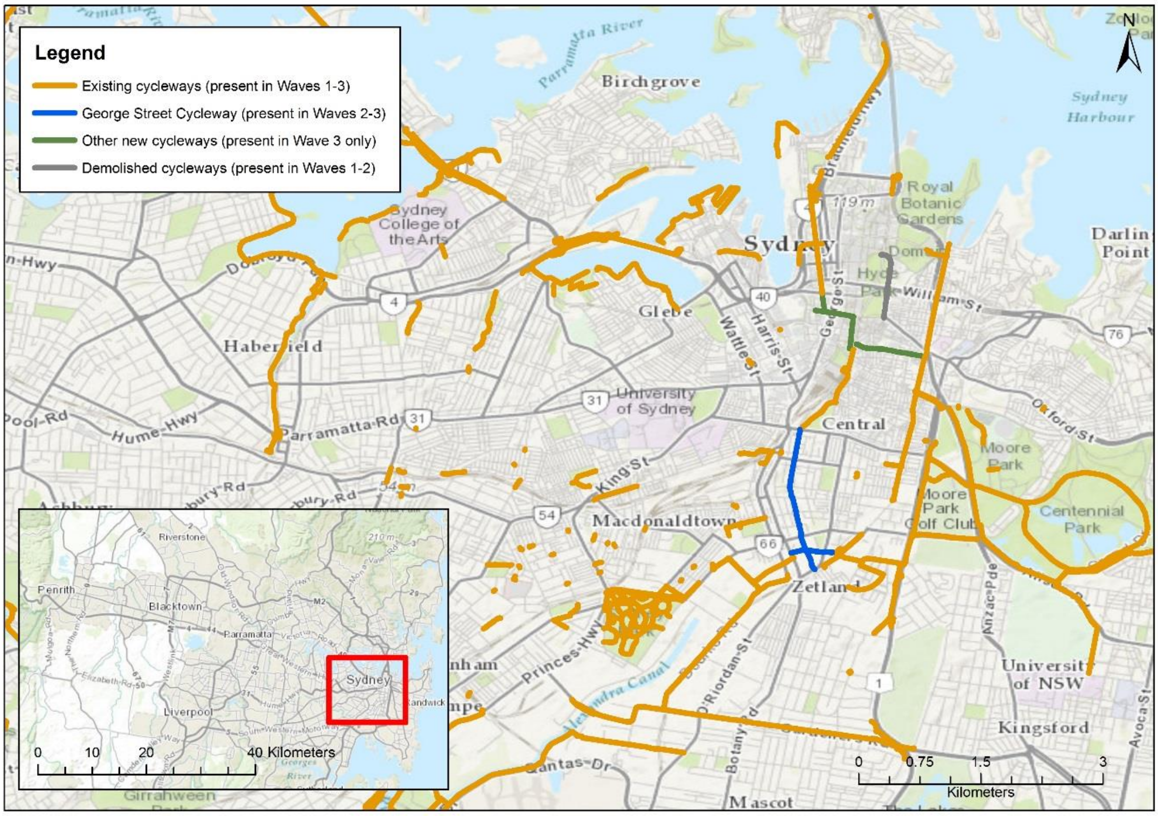
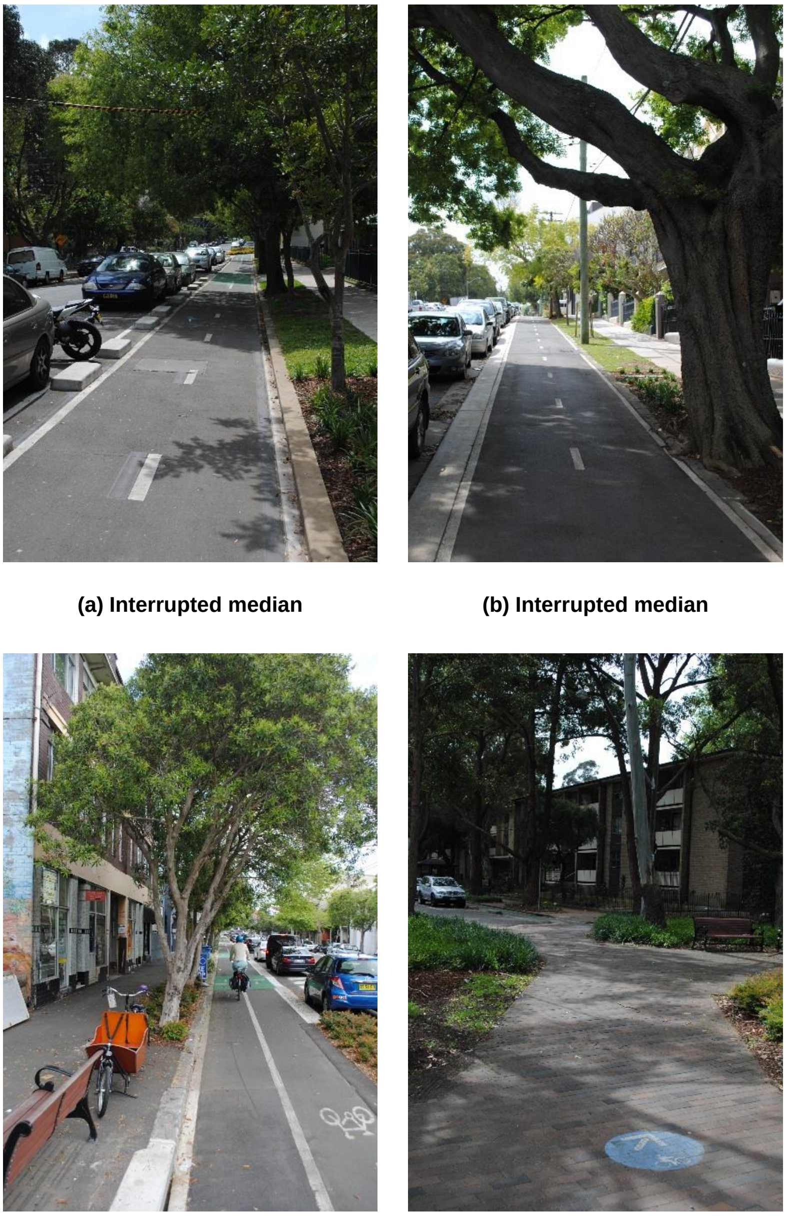


Figure 4.3: Changes to the inner-city Sydney bicycle network 2013 to 2015

A variety of path treatments is used along the cycleway (Figure 4.4), with differing intersection treatments used, depending on the nature of the cross or side street: signalised crossings at major cross streets (Figure 4.5(a)); marked crossings with priority for bicycles (Figure 4.5(b)); unmarked crossings without priority (Figure 4.5(c)); bend out intersections, which provide storage space for vehicles entering or leaving the side road (Figure 4.5(d)); shared environments with raised thresholds (Figure 4.5(e)); and driveways (Figure 4.5(f)).



(a) Interrupted median

(b) Interrupted median

(c) Two step

(d) Shared path

Figure 4.4: George Street Cycleway path treatments

(a) Signalised (b) Marked (c) Unmarked

(d) Bend out (e) Shared environment (f) Driveway

Figure 4.5: George Street Cycleway intersection treatments

In terms of other transport options along the George Street corridor, there is a suburban railway line (T2) running underground directly beneath the cycleway, with stations at both ends, providing services to and from the city centre that are swift and frequent, but increasingly crowded at peak times. There are a number of bus routes serving the area, though services can be overcrowded and impacted by traffic congestion during peak times. Despite road space allocation and traffic signals prioritising driving over walking and (non-vehicular) cycling,[24] the area experiences typical inner-city road congestion. Walking the length of the cycleway takes about 30 minutes along lit paths, and involves passing through the Redfern-Waterloo public housing community.

The cycleway is the subject of other studies focusing on: community development and engagement (Crane et al., 2015); changes in bicycle use and destination choice (Crane, Rissel, Greaves, et al., 2017; Greaves et al., 2015; Standen et al., 2016); quality of life (Crane, Rissel, Greaves, & Gebel, 2016; Crane et al., 2014; Rissel et al., 2015); and broader health, transport and economic benefits (Rissel et al., 2013).

4.4 Sydney Travel and Health Study

The primary data source for this research is the Sydney Travel and Health Study (STAHS), a quasi-experimental study to evaluate the transport, health and economic impacts of new bicycle infrastructure in Sydney, Australia (specifically, the George Street Cycleway).[25] The aim of the study was to develop improved methods for evaluating the transport, environmental, health, and economic impacts of new bicycle infrastructure. The study is described in a previously published protocol paper (Rissel et al., 2013); details relevant for this thesis are provided in this section.

Briefly, the travel behaviour, health and quality of life of a panel of residents living within the expected catchment area for the cycleway, and of a control group, were assessed in September to November 2013, eight months before the cycleway opened (Wave 1). Respondents were assessed again 12 months later (September to

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[24] Non-vehicular cycling is the practice of riding a bicycle on dedicated infrastructure (i.e., avoiding general traffic lanes).

[25] The Sydney Travel and Health Study was funded as an ARC Linkage Project (number LP120200237) between the University of Sydney, City of Sydney Council, Transport for NSW, National Heart Foundation of Australia, NSW Health and NSW Premier's Council for Active Living. The Chief Investigators were Professor Chris Rissel, Professor Stephen Greaves, Associate Professor Li Ming Wen and Professor Anthony Capon. The project team comprised Dr Melanie Crane, Christopher Standen, Dr Adrian Ellison, Dr Richard Ellison and Dean Rance. A market research company was engaged to assist with recruiting and managing respondents, and programming the online questionnaire.

November 2014), by which time the cycleway had been open for four months (Wave 2). A final wave of data collection was undertaken at 24 months, in September to November 2015 (Wave 3). A timeline showing the dates of the data collection waves, and other relevant events, is provided in Figure 4.6. Of particular relevance is the phased rollout of the Opal smartcard ticketing system for public transport services. Other noteworthy events include the Sydney launch of the Uber ridesharing service in April 2014.

Ethics approval for the study was granted by the University of Sydney's Human Research Ethics Committee (Project No. 2012/2411).

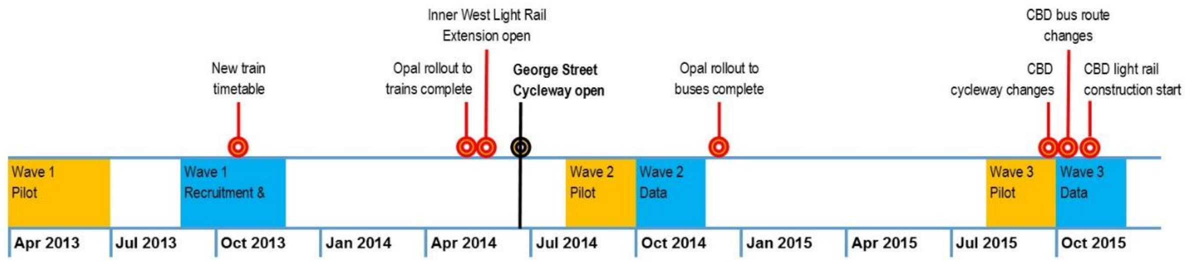

Figure 4.6: Sydney Travel and Health Study project timeline

4.4.1 Survey components

Four survey instruments were used for the STAHS: an online questionnaire covering health, quality of life, transport and demographics; an online travel diary completed by respondents for seven consecutive days; a smartphone tracking app; and personal GPS devices. They were supported by a relational database for data storage and retrieval, and a web-based administration interface. The system architecture is shown in Figure 4.7. Further details are provided in Sections 4.4.1.1 to 4.4.1.6.

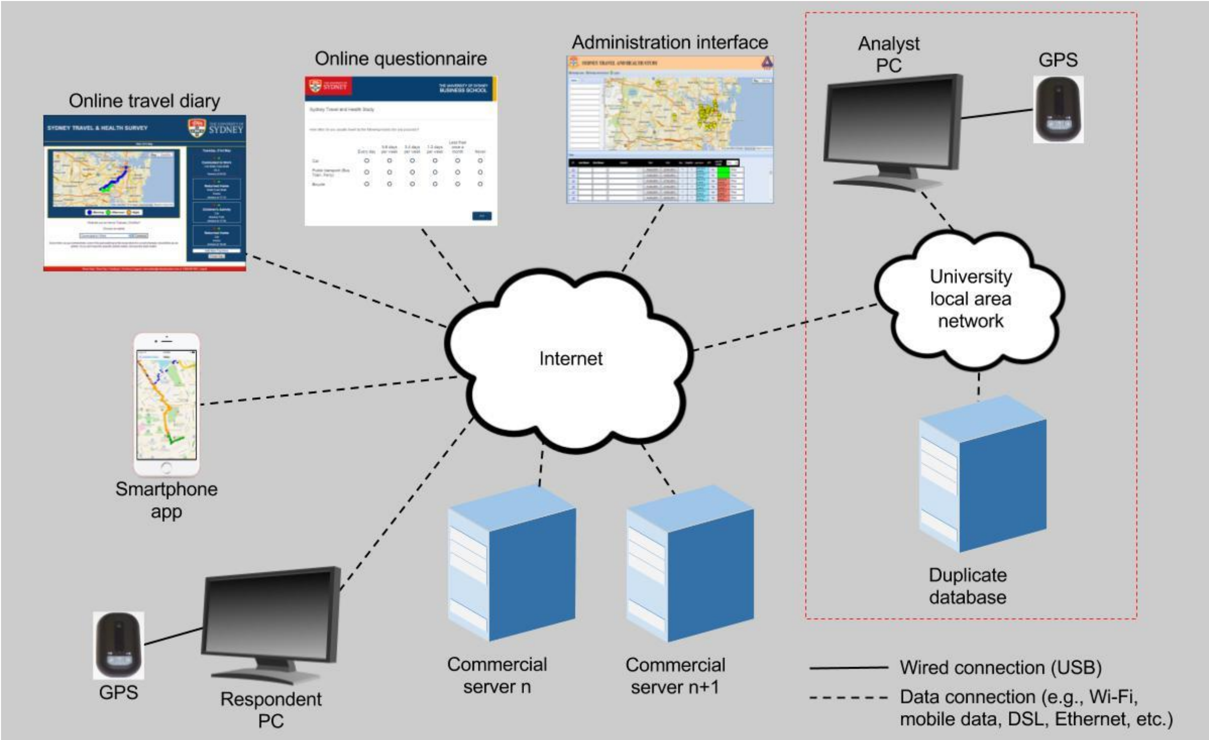

Figure 4.7: Sydney Travel and Health Study system architecture

4.4.1.1 Online questionnaire

In Wave 1, the online questionnaire included questions on:

- socio-demographic characteristics (including age, gender, educational attainment, income, marital status, household structure, driver licence type, bicycle availability and car ownership);
- physical activity (based on the validated Active Australia questionnaire (AIHW 2003));
- quality of life (based on the validated WHOQOL-BREF instrument developed by the World Health Organization (WHOQOL Group, 1998));
- transport use and perceived accessibility to work, education, leisure and services;
- perceptions of community cohesion;
- exposure to messages promoting cycling; and
- availability and perceived safety of bicycle facilities.

The questionnaire also included anchoring vignettes, to correct for scale perception bias in responses to the questions on quality of life and perceived cycling safety

(Rissel et al., 2014). In Waves 2 and 3, respondents were also asked about awareness and use of the new George Street Cycleway.

The way respondents first accessed the Wave 1 questionnaire varied depending on how they were recruited (see Section 4.4.3). In subsequent waves, each respondent was sent an email with a link containing a unique identifier, allowing responses to be matched to respondents. Daily reminder emails were sent to respondents until they completed the questionnaire. If a respondent did not complete the questionnaire after one week, an SMS reminder was sent to their mobile phone; after two weeks, they were called by telephone. Anyone not completing the questionnaire after four weeks was removed from the study. Upon completing the questionnaire, respondents were redirected to the online travel diary.

4.4.1.2 Online travel diary

The online travel diary was designed as an activity-based diary to capture travel over seven consecutive days (see Greaves, Ellison, Ellison, & Standen, 2014). It comprised a succession of web forms for each day.[26] Form 1 asked the respondent if he/she had travelled on the day. If yes, the respondent was asked about their first activity (Form 2). Table 4.2 lists the activities from which the respondent could choose, in the order in which they were listed. If the respondent selected as their final activity one not allowed to be the final activity of a day, they would be asked to confirm that this was indeed the final activity of the day before completing the diary day. Form 3 captured trip origin, trip destination and trip departure/ arrival times. Form 4 asked which travel modes were used for the trip. If a public transport mode was selected, respondents were prompted to provide the access and egress modes. Form 5 captured additional information about each mode, including duration and, where applicable, bus route number, origin station or wharf, and destination station or wharf. Form 6 asked about intermediate stops, and if there had been any more activities that day. If yes, the respondent was taken back to Form 2 to enter details of the next activity. If no, the respondent was taken to Form

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[26] Example screenshots of the online travel diary are provided in Appendix A.

7, which provided a summary of all activities entered that day, and asked for confirmation that the information was complete. Trips could be saved as 'favourite trips' to save time filling in the details of regular trips. Table 4.3 summarises the data collected for each trip reported in the online travel diary.

Table 4.2: Trip activities in travel diary

Trip purpose	Allowed to be final activity of day?
Returned Home	Yes
Commuted to Work	No
Work-related	No
Attended College/University	No
Shopping/Personal Business	No
Other Social/Recreation	Yes
Religious/Community	No
Dropped Off/Picked Up a Passenger	Yes
Holiday/Vacation	Yes
Filled up with Fuel	Yes
Went For a Walk/Run	Yes
Went For a Bike Ride	Yes
Returned to Work	No
Children's Activity	No
Eating Out	No
Visiting Friends/Family	Yes
Working Out/Playing Sport	No

Table 4.3: Data collected about each trip

Attribute
Trip purpose
Departure date
Departure time
Origin address
Destination address
Transport mode(s) used
Access mode (for public transport trips)
Egress mode (for public transport trips)
Travel time per mode
Cycleways used
Bus routes used

Daily email reminders were sent to respondents to remind them to start or to fill in their travel diaries. Respondents who did not start the travel diary within one week of completing the online questionnaire were sent a reminder by SMS. Respondents who did not start the travel diary within two weeks of completing the online questionnaire were called by telephone.

4.4.1.3 Smartphone tracking app

Respondents with an iPhone or Android smartphone were invited to download and install an app that tracked their position during each data collection wave (A. B. Ellison, Ellison, Rance, Greaves, & Standen, 2014). Location data from the app were presented to respondents while they were completing their online travel diaries (in the form of daily travel maps), to assist them in recalling the places they had visited (see Figure 4.8).

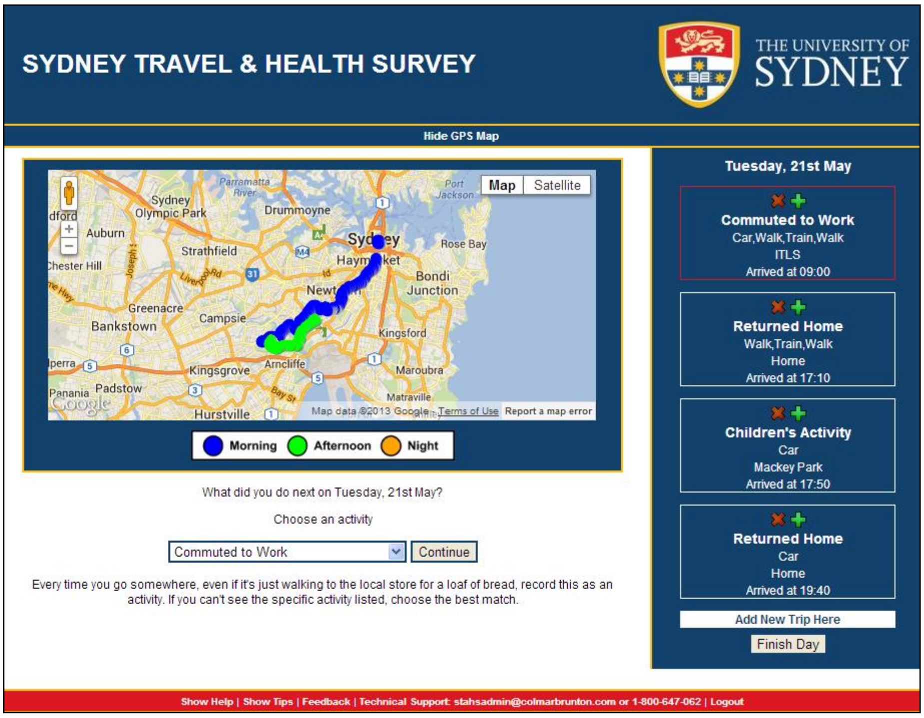

Figure 4.8: Travel diary with daily travel map

4.4.1.4 GPS

In Wave 1, 151 early recruits were invited to take a personal GPS device. Those who agreed (n = 62) were sent a GPS device by courier and asked to take it with them wherever they went during the seven-day travel diary,[27] and to recharge it every day. GPS data could be uploaded to the database in two ways. Firstly, the respondent could download and install an upload utility on their computer. Then,

[27] Respondents were advised to attach the GPS device to their home/vehicle keys so they remembered to take it with them.

whenever they plugged the GPS device into the computer's USB port, the data were automatically uploaded over the Internet (if connected) to the database. In this case, the respondent would be able to view a map of their daily travel when completing the travel diary (Figure 4.8). Alternatively, data could be uploaded by a project team member when the GPS device was returned (in the pre-paid/addressed satchel provided).

However, analysis of these respondents' GPS data, and those of pilot study participants (n = 35), revealed that the quality was poor. In particular, recording would often start many minutes after a trip started, due to the time required to acquire a fix (the 'cold start' issue). Furthermore, accuracy levels were low in built-up areas, due to the urban canyon effect caused by signals bouncing off high-rise buildings (Clifton & Muhs, 2012). Many short walking and cycling trips recorded in the travel diary were not recorded at all by the GPSs. Because these types of trip were of particular interest for the study and this research, the decision was made to discontinue this component of the data collection. However, the data were used to assess the accuracy of imputed bicycle trip attributes (see Section 5.1.2.1).

Nine respondents who took a GPS also downloaded and used the smartphone app, allowing the two tracking approaches to be compared (A. B. Ellison et al., 2014, p. 1). It was found that the smartphone app provided “data of equal, and in many cases, better quality than the GPS device, [particularly] in heavily built-up areas and on short trips”.

4.4.1.5 Database

Data from all four survey instruments were stored in a relational database on commercially hosted servers, offering a high level of security and geographical redundancy. For data cleaning and analysis purposes, a copy of the database was maintained on a secure local server.

Questionnaire data (collected by a market research company) were delivered in spreadsheet format and then imported into the database. Data collected with the online travel diary were uploaded directly to the database after every form submission. Data collected by the smartphone app were uploaded to the database at regular intervals, whenever the device had a working Internet connection.

4.4.1.6 Administration interface

A web-based administration interface allowed project team members to access and view key respondent data stored in the database in a convenient format (Figure 4.9). For each respondent, the interface could display details of trips recorded in the travel diary, GPS or smartphone app data (if available), and general status information. The interface could be accessed only by members of the project team using a strong password. It facilitated a number of administrative tasks, including: monitoring respondent progress; determining reward eligibility; and investigating issues reported by respondents.

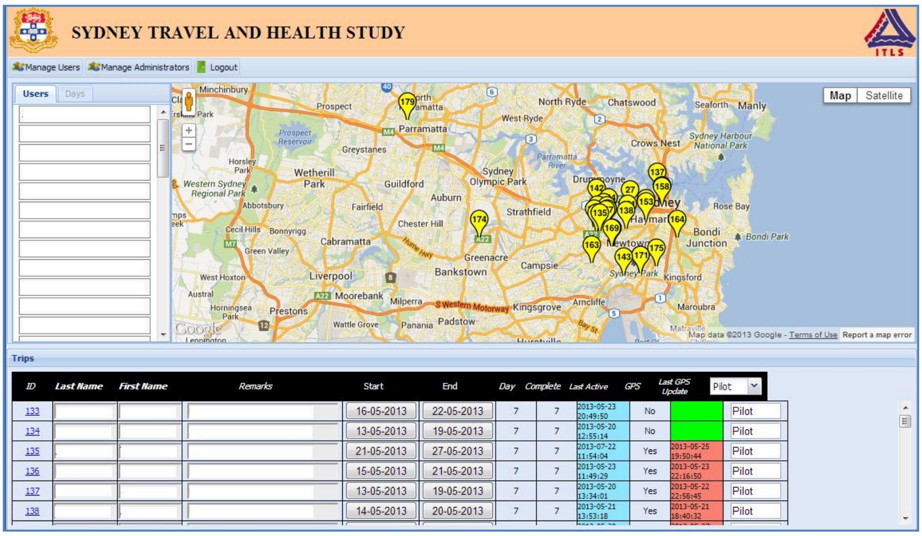

Figure 4.9 Travel diary administration interface

4.4.2 Measures

The measures obtained through the various STAHS survey instruments are summarised in Table 4.4.

Table 4.4: Summary of Sydney Travel and Health Study measures

Survey instrument	Measures	Purpose
Online questionnaire	Self-reported: • socio-demographic characteristics; • driver licence type; • bicycle availability and car ownership; • physical activity; • quality of life; • transport use; • perceived accessibility to work, education, leisure and services; • perceptions of community cohesion; • exposure to messages promoting cycling; • availability and perceived safety of bicycle facilities; • awareness and use of the new George Street Cycleway (Waves 2 and 3).	The questionnaire data were used in the mode choice data generation (5.1.2) and modelling (5.1.4), economic appraisal (5.3) and before-after analysis (5.4.2.1).
Online travel diary	Self-reported travel over a seven-day period: • activities; • intermediate activities; • origin address; • destination address; • transport mode(s); • bus route(s); • start and end times; • trip duration.	The travel diary data were used for mode choice modelling (5.1), before-after analysis (5.4.2.2) and temporal preference stability tests (5.5).
Smartphone app	Location data from smartphone sensors (mobile network location, Wi-Fi and GPS).	The smartphone app and GPS location data were displayed to respondents to assist them in recalling their travel while they were completing their travel diaries. The data were also used to validate the bicycle travel demand model (5.1.2.1).
GPS	Second-by-second GPS location data.	

4.4.3 Respondent recruitment and retention

The sample was recruited from an intervention area corresponding with the expected catchment area for the new cycleway, and from a control area with a similar demographic profile and land use pattern to the intervention area – but where no new cycleways were planned during the study period. These areas are shown in Figure 4.10. Origin/destination data from a separate intercept survey of users of the new cycleway, conducted in March 2015 (see Section 4.5.2), indicated that a large number of trips originated or terminated in the intervention area, while few originated or terminated in the control area (see Figure 4.10). This suggests that the boundaries of the intervention and control areas were reasonably well selected, although the number of trip origins/destinations immediately south and west of the intervention area suggests that it could have been expanded into these areas. (The area north of the intervention area is the CBD, a major employment and commercial centre. Therefore, the numerous trip origins/destinations recorded in this area are likely to indicate work, study, shopping or leisure destinations, rather than home locations.)

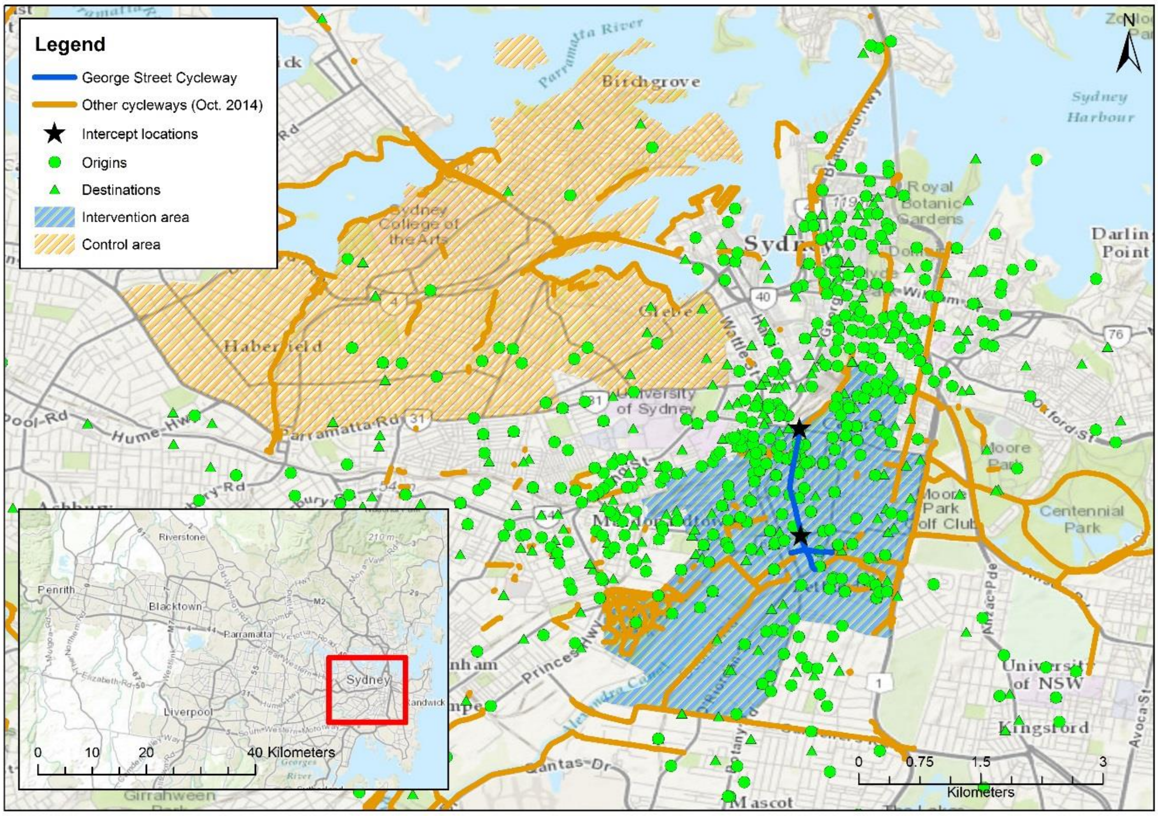

Figure 4.10 Sydney Travel and Health Study areas and intercept survey origins/destinations

To be eligible to participate in the study, respondents had to be living in one of the study areas, speak sufficient English to complete the questionnaire and travel diary, be aged 18 to 55,[28] have ridden a bicycle in their lifetime and have no

[28] This age range was chosen because (a) it was anticipated people in this age range would be most likely to take up cycling for transport and (b) there was a limited budget. Given a larger budget, the maximum age could have been increased to 65 years. While many people over 65 do cycle, few take up cycling for transport over this age.

disability preventing them from riding a bicycle. The target sample size was 900 individuals (450 in each area), based on being able to detect a 12 per cent increase in bicycle kilometres travelled (BKT) with type I error of 0.05 and power of 0.8, and assuming an attrition rate of 15 per cent at each follow-up (Waves 2 and 3). Multiple respondents per household were allowed. Respondents were offered a financial reward of up to AUD 70, comprising AUD 20 for completing the questionnaire, AUD 30 for completing the travel diary (increasing to AUD 35 in Wave 3) and AUD 15 for downloading and activating the smartphone tracking app. To minimise selection and response bias, the purpose of the study was masked: it was promoted as a general travel and health survey, aiming to investigate how the way people get around affects population health and wellbeing.

Initial recruitment was through online consumer panels.[29] When this method was exhausted, random digit dialling (RDD) was used. The study was also advertised using letterbox drops, social media and electronic mailing lists (primarily aimed at tertiary students). Finally, respondents were recruited at two *Ride2Work Day* breakfast events organised by the City of Sydney.

Figure 4.11 shows the distribution of recruitment method for the 608 respondents completing both the questionnaire and travel diary in Wave 1. RDD was the most successful method, in both the intervention and control areas.

During initial recruitment, quotas were set for each gender and age group, to ensure that the sample was representative of the study area population. When it became apparent that the target sample would not be reached, these quotas were relaxed, resulting in a convenience sample not representative of the population.

[29] These are lists, maintained by market research companies, of respondents who have expressed a willingness to participate in online market and/or social research.

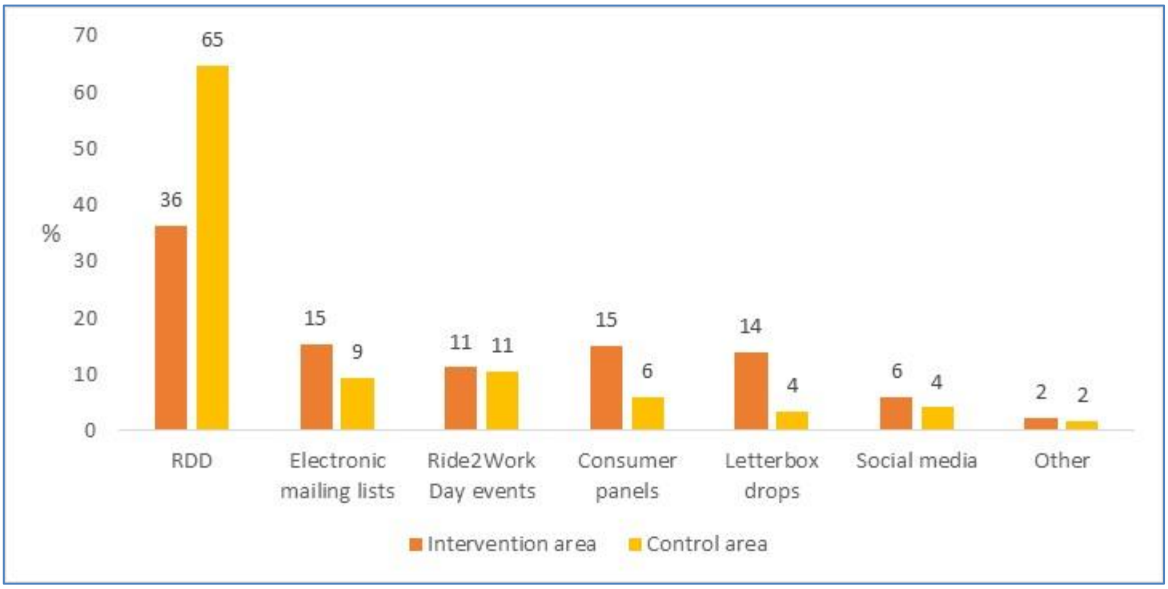

Figure 4.11: Recruitment method by study area (n = 608)

4.4.4 Completion rates

A total of 846 people completed the initial questionnaire, of which 608 went on to complete the travel diary (32 per cent below the 900 target). Completion rates for each wave are shown in Table 4.5. Most analyses for this research required both questionnaire and travel diary data; the relevant completion rates are shown in bold. The attrition rate of those completing both the questionnaire and diary was 25 per cent between Waves 1 and 2, and 20 per cent between Waves 2 and 3. This was considerably more than the anticipated 15 per cent.

The baseline (Wave 1) sample was already very physically active, with 84.2 per cent meeting the National Physical Activity Guidelines recommendation of 150 minutes of physical activity over five or more separate sessions per week (AIHW 2003). The intervention and control samples were similar in the regard, with 85.8 per cent and 83.0 per cent respectively meeting the recommendation. For the state of NSW, only 44.9 per cent of adults meet the recommendation (ABS 2014). This difference is not overly surprising, given (a) the sample was recruited from an inner-city area where physical activity levels tend to be higher than in outer-suburban, regional or rural areas (ABS 2013), and (b) cycling and walking commuters were over-represented in the sample. It is also possible that the study, which was promoted as a 'travel and health study', attracted respondents who were more health-conscious and physically active. Data on physical activity levels for the study area population are not available.

Table 4.5: Survey completion rates

Wave		Intervention area	Control area	Total	Attrition rate vs. previous wave
1	Valid questionnaire completions	398	448	846	-
	Valid questionnaire and travel diary completions	**267**	**341**	**608**	-
2	Valid questionnaire completions	240	272	512	39%
	Valid questionnaire and travel diary completions	**203**	**251**	**454**	**25%**
3	Valid questionnaire and travel diary completions	183	228	411	20%
	Valid questionnaire and travel diary completions	**148**	**215**	**363**	**20%**

4.5 Secondary data

4.5.1 Bicycle counts

The City of Sydney commissioned manual counts of bicycle riders at 100 intersections across the LGA in March and October, from 2010 to 2016. Two of these sites were along the route of the George Street Cycleway, which opened in June 2014. One of these (Site A) was at the northern (CBD) end of the cycleway; the other (Site B) was at an intersection near the southern end. Counts were undertaken on weekdays during the times of 06:00 to 09:00 and 16:00 to 19:00. All bicycle movements through the intersections were counted, whether or not the cycleway was being used.

4.5.2 Intercept survey

An intercept survey of bicycle riders and pedestrians using the George Street Cycleway was conducted in March 2015, nine months after opening).[30]

There were two intercept sites. Site 1 was near the southern end and Site 2 was at the northern end (see Figure 4.10). Pairs of interviewers were positioned at both

[30] Data collection was supported by City of Sydney (Grant number 2014/39637). The Chief Investigator was Dr Melanie Crane.

sides of signal-controlled crossings to engage waiting bicycle riders and pedestrians travelling in both directions. Surveys were conducted during a variety of three to five hour timeslots between 07:00 and 18:00 over a two-week period, including weekdays and weekends. The schedule was designed to capture a wide cross-section of users travelling at different times and for different purposes, and was spread over two weeks to account for variability in weather. Surveys were interviewer-administered, with observations and survey responses recorded on paper forms. To minimise interview duration, the forms had pre-coded response categories. (For details of the questions and pre-coded response categories, see Appendix B.)

Trained research staff recorded each respondent's approximate age, gender, and attire, as well as the date and time. Respondents were asked for their origin, destination and trip purpose. They were then asked what mode of travel they would have used for their trip before the cycleway opened. Those who said they previously used a bicycle were asked if they had changed their route since the cycleway opened. (Hereafter, the term 'existing rider' is used to describe a respondent who stated they used a bicycle before the cycleway opened.)

To measure bicycle riding experience, respondents were asked: 'How long have you been riding regularly?'. This question was used because, in pilot testing, it was found that respondents were likely to exaggerate if simply asked about their level of riding experience. The qualifier 'regularly' was included in the question to discourage respondents who had resumed riding in adulthood from including the time they spent riding as a child. Hereafter, the term 'length of time riding regularly' is used for this measure. The measures obtained through the intercept survey are summarised in Table 4.6.

All responses were given anonymously and no financial or other inventive was offered or given. For practical reasons, only verbal consent was obtained. Ethics approval for the survey was granted by The University of Sydney's Human Research Ethics Committee (Project No. 2015/056).

Table 4.6: Intercept survey measures

Provided by respondent	Trip origin
	Trip destination
	Trip purpose
	What transport mode the respondent would have used for the trip before the cycleway opened
	Length of time riding regularly
	Whether respondent's bicycle route has changed since the cycleway opened
Observed by interviewer	Attire
	Gender
	Approximate age

4.5.3 Meteorological data

Daily precipitation data for central Sydney (Observatory Hill, station number 66062) during the three data collection waves were obtained from the Bureau of Meteorology. A logbook was kept during the three data collection waves, in which extreme metrological events that might affect travel were recorded (e.g., extreme heat, bushfires, and storms).

4.6 Summary

This chapter began by enumerating the research questions and hypotheses for this thesis. It then described the experimental design, case study and data used to address them.

The primary data source for the research is the Sydney Travel and Health Study (STAHS), a natural experiment designed to evaluate the transport, health and economic impacts of new bicycle infrastructure in Sydney, Australia. Secondary data include official bicycle counts and an intercept survey of users of the new infrastructure.

5 ANALYSIS METHODS

This chapter describes how the Sydney Travel and Health Study data were analysed using discrete modelling, to (a) understand the factors affecting bicycle mode choice in inner-city Sydney, (b) estimate/value the user benefits of new bicycle infrastructure, and (c) test the hypothesis of temporal preference stability.

Section 5.1 describes how the baseline mode choice models were estimated. Section 5.2 explains how these models were used to forecast the transport impacts and user benefits of a new cycleway in inner-city Sydney (the George Street Cycleway), as well as other scenarios. Section 5.3 describes how these user benefits were incorporated into an economic appraisal. Section 5.4 details how changes in actual travel behaviour were measured. Finally, section 5.5 describes how temporal preference stability, a key assumption underpinning the forecasts, was tested.

5.1 Baseline mode choice modelling

The mode choice analysis of the baseline travel diary data involved the following steps: selection of model variables; attribute imputation for all transport mode alternatives; data cleaning and formatting; and model estimation. Each of these steps is described below. The analysis involved a recursive process, with a number of iterations required to optimise the models.

5.1.1 Selection of variables

The dependent (choice) variable was the main transport mode for each trip, categorised as walk, bicycle, public transport, or car.[31] Where a trip involved multiple modes, the 'main transport mode' was taken to be the one with the highest priority in Table 5.1. This hierarchy is based on that used by the NSW Bureau of Transport Statistics (2014). There were very few trips by taxi[32] or 'other mode', and these were excluded from the analysis.

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[31] 'Car' includes driver or passenger in a private car.

[32] 'Taxi' includes ridesharing services, e.g., UberX.

Table 5.1: Main transport mode hierarchy

Transport mode	Priority
Train	Highest
Bus	↑
Ferry	
Light rail	
Car/truck/motorcycle	
Bicycle	
Walk/run	Lowest

The selection of dependent variables was guided by the literature review of previous choice studies (Section 3.2), and by the research aims. It was constrained by the data available from the Sydney Travel and Health Study and other sources (described in Chapter 1).

Table 5.2 lists the individual characteristics, trip attributes, and contextual factors that were available for each mode choice situation (trip). Some variables are applicable to all transport modes, and some to a subset (identified in the second column). The columns on the right indicate whether a variable has been found to be significant (S) in previous bicycle mode or route choice studies,[33] and in which context(s).

Given the aims of this research, it was important to choose bicycle trip attributes that varied sufficiently as a result of a cycling project intervention (i.e., the George Street Cycleway), such that any resulting changes in bicycle utility (and therefore bicycle demand and consumer surplus) could be predicted and measured. Various approaches were tested; the one that gave the best behavioural interpretation was to partition the bicycle distance for each trip into two discrete distance variables: cycleway distance (*CW distance*) and non-cycleway distance (*Non-CW distance*).

[33] Those included in the literature review (Section 3.2).

Table 5.2: Candidate dependent variables

Dependent variables	Applicable modes	Previous studies of bicycle route choice		Previous studies of bicycle mode choice	
		Stated preference	Revealed preference	Stated preference	Revealed preference
Individual characteristics					
Age	All	S		S	S
Gender	All	S	S	S	S
Education level	All				
Driver licence type	All				
Household income	All	S		S	S
Car available	All			S	
Bicycle available	All			S	
Proximity of home to nearest cycleway	All				
Proximity of work location to nearest cycleway	All				
End of trip facilities at workplace	All	S			
Body-mass index	All				
Employment status	All				
Household size	All	S		S	
Number of children	All				
Relationship status	All				
Bicycle rider type	All				
Trip attributes					
Travel time (duration)	All	S		S	S
Travel distance	All	S	S		
Distance on cycleway	Bicycle				
Non-cycleway distance	Bicycle				
Bicycle facility provision/type	Bicycle	S	S	S	
Gradient	Bicycle	S			S
Trip ends/starts in CBD	All				
Contextual factors					
Travel on weekend or public holiday	All				
Travel during peak time	All				
Rainfall	Walk, bicycle			S	
Tour purpose	All				

Thus, the observed utility expression for the bicycle alternative takes the form:

$$V_{bicycle} = \alpha_{bicycle} + \beta_1 \text{CW distance} + \beta_2 \text{Non-CW Distance} + \beta' x, \qquad 5.1$$

where β_1 and β_2 are the preference parameters for *CW distance* and *Non-CW Distance* respectively, x is a vector of other independent variables (individual characteristics, trip attributes and contextual factors), β' is a vector of associated preference parameters, and $\alpha_{bicycle}$ is the alternative specific constant.

5.1.2 Choice data imputation

As discussed in Chapter 3, a discrete choice model requires information about the attributes of the alternatives available to decision makers, both chosen and non-chosen. In a transport mode choice model, the key attribute is typically the 'generalised cost', which comprises the travel time or distance, and financial costs (e.g., fuel, tolls, fares), of a given trip. However, the online travel diary asked respondents to report only the travel time for the transport mode they actually chose for each trip (see Table 4.3). Respondents were not asked to report the attributes of the transport modes they did not choose. It was therefore necessary to impute the attributes of the non-chosen modes. Of the five potential imputation methods described in Section 3.1.3.1 (and recapped in Table 5.3), the first method, namely using a transport demand model, was considered the most appropriate. Given the need for a fine level of spatial resolution to model short non-motorised travel with reasonable accuracy, the sample size was not sufficiently large to impute attributes using methods 2 to 4. Method 5 (asking respondents to state the attribute values of non-chosen modes) would have been ideal, but would have placed an unacceptable burden on respondents.

Table 5.3: Attribute imputation methods (after Washington et al., 2014)

1	Use a transport demand model to estimate travel times/distances between origins and destinations.
2	Average the travel times/distances reported by respondents who did use a given mode for the origin-destination pair.
3	Use attribute values provided by respondents who used different modes for the same origin-destination pair at different times.
4	Bayesian imputation.
5	Ask respondents to report the attributes of non-chosen modes.

While respondents did report the travel time for their chosen transport modes, using these data would have meant mixing reported and imputed attributes, which have differing biases and errors (Adamowicz et al., 1997; Hensher et al., 2005). For consistency, the attributes of the chosen alternative for each trip were imputed also (as opposed to using reported values).

To begin with, the reported origin and destination addresses for all trips were geocoded – i.e., converted into geographic coordinates (degrees of latitude and longitude) in the WGS 84 coordinate system – using the Google Maps Geocoding

Application Programming Interface (API)[34] (Google Inc., 2016). Error checking was done by plotting each geocoded location in ArcGIS[35] (ESRI, 2013b), and checking that it was within the boundary of the stated post code. Post code boundary data were obtained from the Australian Bureau of Statistics (2011a).

Next, travel distances or times were imputed for each origin-destination pair, via bicycle (see Section 5.1.2.1), walking, public transport and driving (see Section 5.1.2.2).

5.1.2.1 Imputation of bicycle distance

A number of existing transport demand models were considered for estimating cycling distances between trip origins and destinations; these are compared in Table 5.4. None fulfilled all requirements, these being: the ability to edit network data to model past or future scenarios; the ability to modify the routing algorithm, to assign lower impedances to links with bicycle facilities; and a very fine spatial resolution needed to model short trips with reasonable accuracy. Therefore, a bespoke bicycle demand model was developed for the Greater Sydney metropolitan region using ArcGIS software with the Network Analyst extension (ESRI, 2013c).

Any demand model used to assess the impact of an intervention on bicycle travel requires network data that accurately replicate the bicycle network (van Wee & Börjesson, 2015). Given that coding a bicycle network for the whole Greater Sydney metropolitan region would have been very time consuming, open source network data from OpenStreetMap were used, and modified using ArcGIS Editor for OpenStreetMap (ESRI, 2013a).

[34] The Geocoding API is one of a number of Google Maps APIs, which allow custom applications to query Google Maps data. More details can be found on the web page: https://developers.google.com/maps/web-services/overview.

[35] Geographical Information System (GIS) software.

Table 5.4: Available bicycle transport models

	Existing models		Bespoke GIS-based model	
	Sydney Strategic Transport Model (BTS 2011)	**Google Maps Directions API (Google Inc., n.d.)**	**RideTheCity (Ride the City, n.d.)**	**ArcGIS Network Analyst plus OpenStreetMap**
Type	Desktop PC-based	Web-based	Web-based	Desktop PC-based
Underlying network data	Bespoke	Google Maps	OpenStreetMap	OpenStreetMap
Ability to edit network data to model past or future scenarios	Yes	No	OpenStreetMap network data can be edited to model past or future scenarios, but doing so would affect other users of the data.	Yes. The OpenStreetMap data can be downloaded and edited.
Spatial resolution	Variable. Origins and destinations approximated to zone centroids.	Infinite. Exact origin and destination coordinates used.	Infinite. Exact origin and destination coordinates used.	Infinite. Exact origin and destination coordinates used.
Routing algorithms)	Shortest path.	Routing algorithm gives preference to bicycle facilities, but the exact algorithm has not been made public, and cannot be modified.	Three routing algorithms: direct route (true shortest path); safe route (shortest path, but links with bicycle facilities are treated as shorter than they actually are); safer route (shortest path, but links with bicycle facilities are treated as much shorter than they actually are). Routing algorithms have not been made public, and cannot be modified.	Modifiable shortest path algorithm.
Batch processing of multiple origin-destination pairs	Yes	Yes	No API available for batch processing.	Yes

OpenStreetMap data for the Greater Sydney metropolitan region [36] were downloaded on 6 March 2015 from the BBBike.org website and imported into ArcGIS. The data were then cleaned and corrected, informed by a mixture of local knowledge and bicycle maps published by local authorities, with a particular focus on bicycle facilities in the study area. This mainly involved adding missing cycleway links, and reclassifying links that had been coded incorrectly. A link was classified as a cycleway if it was either (a) an exclusive bicycle path physically separated from motor vehicle traffic (in or not in a road reserve) (see examples in Figure 5.1(a) and in Figure 5.1(b)), or (b) a shared bicycle and pedestrian path with

[36] The area bounded by latitude -34.6 to -32.8 and longitude 149.9 to 151.9 in the WGS 84 coordinate system.

reasonable continuity and minimal friction (see example in Figure 5.1(c)). Footpaths designated as shared paths,[37] but with poor continuity and/or high friction (e.g., high pedestrian volumes, street furniture or other obstructions, inadequate width, and/or abutting property entrances), were not classified as cycleways (see example in Figure 5.1(d)). In reality, the distinction between bicycle facility types is not so binary, but previous analyses of bicycle route choice (e.g., Wardman et al., 2007) indicate that physical separation has the greatest effect on cycling utility. There is relatively little difference in utility between roads with a marked bicycle lane, and those without.

The network data were converted into a routable bicycle network dataset, which included all cycleways and all roads in the OpenStreetMap data. Each link in the network dataset was assigned a *highway type*, a *distance*, a *speed* and a *travel time*. The *highway type* (e.g., *cycleway*, *trunk road*, *primary road*, *secondary road*, *tertiary road* or *residential road*) was copied from the equivalent OpenStreetMap tag.

Figure 5.2 shows a portion of the network dataset, illustrating the different *highway types*. *Distance* was calculated as the great circle distance between the vertices that defined each link. The *speed* for all non-cycleway links was set to 16 km/h. The speed for cycleway links was set to 3.1 times this value (49.6 km/h), to reflect route preference for cycleways, such that a Dijkstra shortest path route calculation between two points on the network (with *travel time* as the impedance variable) would treat 3.1 km of cycleway as having the same impedance as 1 km of any other type of link.[38] The value of 3.1 was derived from Wardman's (2007) finding that the value of travel time saving for segregated bicycle paths is 31 per

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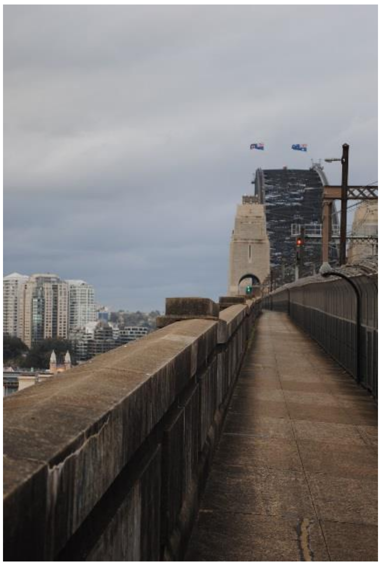
[37] In NSW, adults may not legally cycle on a footpath, unless it is a designated shared path, or they are accompanying children under 12 years of age.

[38] Provided that the ratio of *speed* (cycleway) to *speed* (non-cycleway) was 3.1, the actual speed values used were arbitrary, because travel time was not used as an attribute of the bicycle alternative during model estimation (only the bicycle distance was used). The only reason for assigning a *speed* to a link was to model bicycle routes, from which cycling distances were estimated.

cent of the value of travel time saving for roads with mixed traffic. Figure 5.3 illustrates the effect of this weighting on the shortest path calculation between an example origin-destination (OD) pair. The unweighted shortest path (a) is 2.4 km via a main road, while the weighted shortest path (b) is 2.8 km via a cycleway. Higher and lower weightings were tested, but had little effect on model outputs.

(a) Bicycle path in a road reserve (Bourke Street)



(b) Bicycle path not in a road reserve (Sydney Harbour Bridge)

(c) Good quality shared path classified as a cycleway (Moore Park)

(d) Poor quality shared path not classified as a cycleway (Victoria Road)

Figure 5.1: Categorisation of bicycle facilities

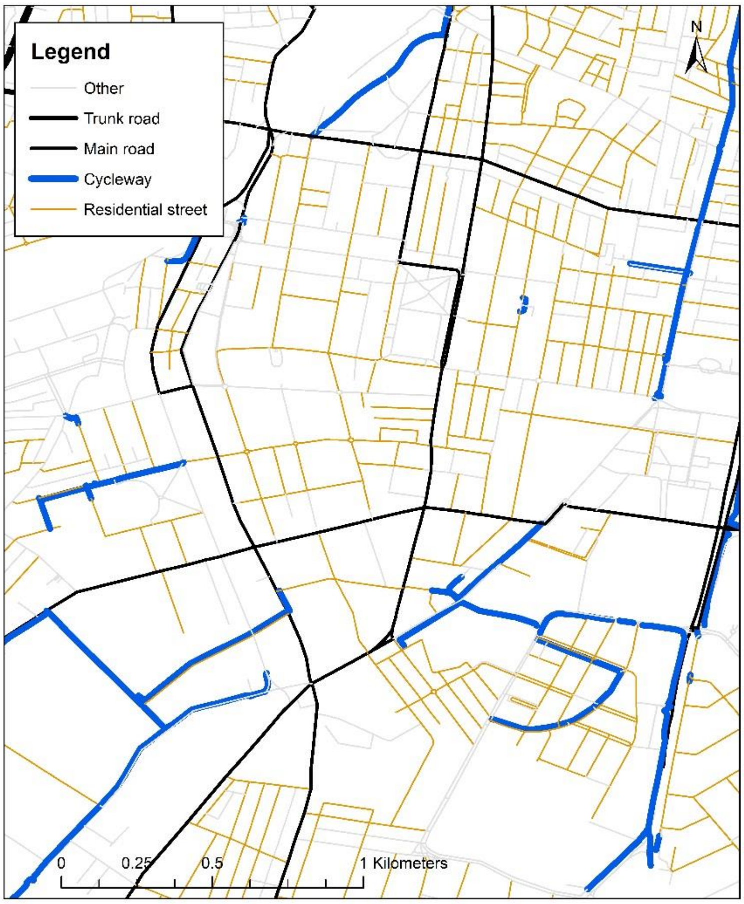


Figure 5.2: Bicycle network dataset detail

After the GIS-based bicycle demand model had been developed and tested, bicycle distances for all OD (trips) reported in the online travel diary were estimated using the following procedure:

1. The network dataset for the baseline bicycle network (2013) was loaded into ArcGIS.
2. Geocoded origin and destination coordinates for OD pairs were loaded into ArcGIS.
3. The ArcGIS Network Analyst Directions tool (ESRI, 2013c) was used to generate turn-by-turn directions for each OD pair, using Dijkstra's shortest path algorithm with *travel time* as the impedance variable (ESRI, 2017). Turn restrictions and one-way restrictions were ignored, given that in NSW bicycle riders are often exempted from them.

4. The turn-by-turn directions were parsed using a PHP[39] script to obtain the total cycling distance (*Distance*), distance on cycleway (*CW distance*), and non-cycleway distance (*Non-CW distance*) for each OD pair.

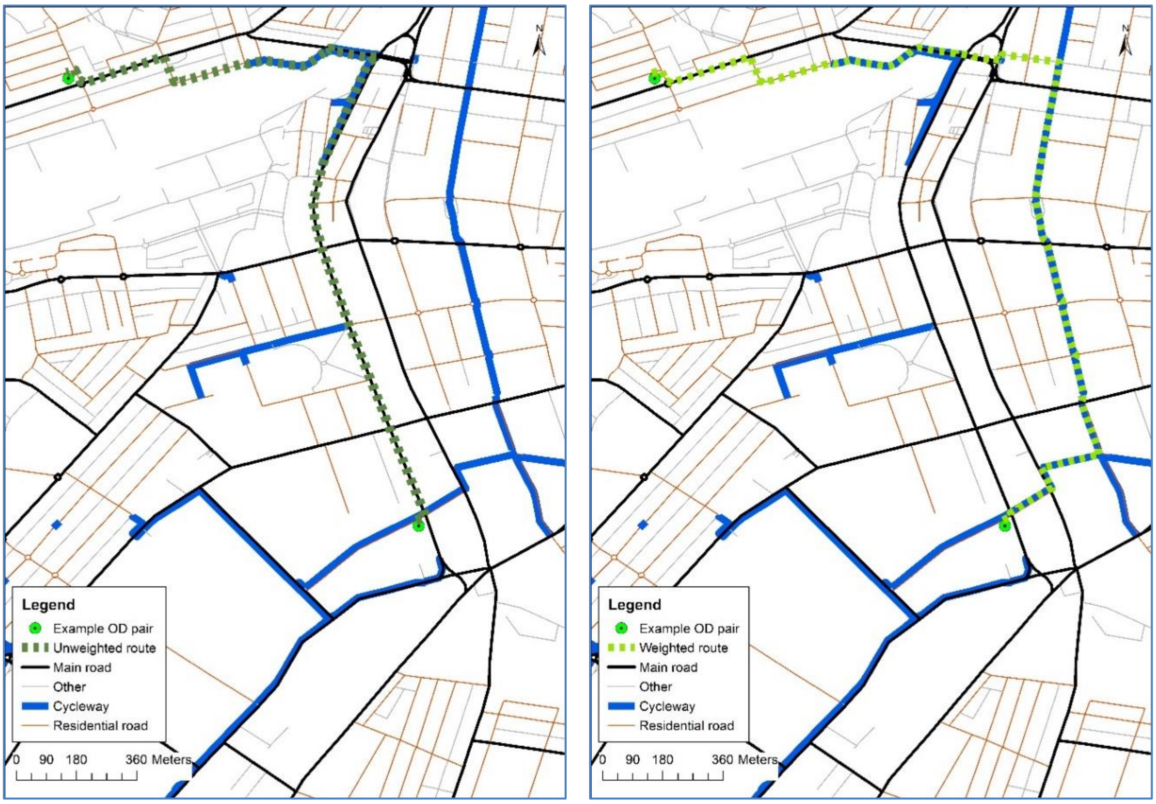


Figure 5.3: (a) Unweighted bicycle route; (b) Weighted bicycle route

This modelling approach facilitated the forecasting of changes in utility when new cycleways were added to the network. For many trips, adding a new cycleway to the network would result in *CW distance* increasing and *Non-CW distance* decreasing. If the parameter for *Non-CW distance* is significantly more negative than the parameter for *CW distance*, then it can be seen (from Equation 5.1) that bicycle utility can increase, even if the total *distance* increases (because people may take a longer route to use a cycleway).

It is acknowledged that the attributes of the routes generated using this (or any other) demand model will not always match those of the routes respondents would

[39] PHP is a widely-used general-purpose scripting language. More details can be found on the web page: http://php.net/manual/en/intro-whatis.php.

have used in practice. Nor does the model take into account inter-person and intra-person variation in route choice (some people may have greater preference for cycleways; some may prefer an indirect route via cycleways one day, and a more direct route using main roads the next).

To test whether the modelled routes were a reasonable approximation of the bicycle routes respondents actually used, modelled routes were compared with traces from those respondents who used the smartphone app or GPS device (see Sections 4.4.1.3 and 4.4.1.4). Although the exact routes tended to differ, the total trip distances were found to be similar. Dalton et al. (2014, p. 227) conducted a similar analysis in the United Kingdom, and concluded: "The use of GIS to model routes may be acceptable when an approximate estimate of travel distance is required or when estimates of the features of potential routes that could be taken are needed". They also examined trips made by other transport modes, and found that GIS-modelled bicycle routes are more accurate than GIS-modelled driving routes.

5.1.2.2 Imputation of walking, public transport and driving travel times

Travel times for walking, public transport and driving were estimated using the Google Maps Directions API (Google Inc., n.d.). This approach was previously employed by Ellison and Greaves (2011) for estimating bicycle travel times in Sydney, and by Wang and Xu (2011) for estimating driving times in Baton Rouge (United States). A PHP script was developed to (a) query the API with the parameters listed in Table 5.5, (b) parse the response, and (c) extract the travel time for each trip by walking, public transport and driving.

Table 5.5: Google Maps Directions API query parameters

Parameter	Description
Origin	Geocoded latitude/longitude of reported origin.
Destination	Geocoded latitude/longitude of reported destination.
Transport mode	Walking, transit (public transport) or driving.
Departure time	Departure time (for public transport only).

Google has published few details of how the Directions API calculates routes and travel times. Public transport travel times are based on published timetables, and access and egress by walking are assumed. Driving travel times assume free-flowing traffic.

Travel times for walking, public transport and driving for trips reported in the travel diary were imputed on 18 September 2015. There were no major changes to the walking, road and public transport networks between the time trips were reported, and the time travel times were imputed.

It is acknowledged that the travel times estimated with the Google Directions API are not likely to match actual or perceived travel times. Nor do they take into account population or temporal heterogeneity (some people walk faster than others; on some days road congestion is worse than on other days).

5.1.2.3 Other variables

Previous studies suggest that gradient (hilliness) is a significant factor in bicycle mode/route choice (see Section 3.2). However, the elevation data in the OpenStreetMap data were incomplete and unreliable. Therefore, the average elevation of a 400-metre buffer around each origin and destination was used in the mode choice model. This approach was previously used by Cole-Hunter et al. (2015) in a study of bicycle mode choice in Barcelona (Spain). Elevation data were extracted from the Geoscience Australia Digital Elevation Model with one arc second (~30 metre) resolution (Geoscience Australia, 2000),[40] and matched to origins and destinations using ArcGIS Spatial Analyst (ESRI, 2016).

Another consideration was whether a trip involved travel in Sydney's central business district (CBD). Riding a bicycle in the CBD can be particularly intimidating, due to heavy motor vehicle traffic throughout the day, a lack of bicycle paths or quiet laneways, and high traffic speeds (the posted speed limit is 40 to 50 km/h). Riding on footpaths is illegal, and otherwise generally impractical due to their narrowness and high pedestrian volumes. Whether a trip involved

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[40] The accuracy of the Digital Elevation Model is reported to be 90 percent of heights accurate to within 9.8 metres (Geoscience Australia, 2011).

travel in the CBD was determined in ArcGIS, using a spatial join of origin/destination coordinates with the area for postcode 2000.

To help account for the effect of peak-time road congestion on driving utility, an additional *Peak* variable was created, with its value based on the reported start and end times of each trip. If any part of a trip occurred during peak travel times (weekdays[41] 7:00 to 10:00 and 16:00 to 19:00), then the *Peak* variable for that trip was set to one (or zero otherwise).

Other variables were created to indicate whether the trip took place on a weekend or public holiday, and whether it had rained on the day of the trip. These variables, and the ways they were calculated, are summarised in Table 5.6.

Table 5.6: Other imputed variables

Variable	Type	Calculation
Origin elevation	Ratio	Average elevation of a 400-metre buffer around the trip origin.
Destination elevation	Ratio	Average elevation of a 400-metre buffer around the trip destination.
CBD	Dummy	True (1) if trip started or finished in Sydney's central business district (postcode 2000). False (0) otherwise.
Peak	Dummy	True (1) if departure or arrival was on a weekday (except public holidays) between 07:00 and 10:00 or between 16:00 and 19:00 (local time). False (0) otherwise.
Weekend/holiday	Dummy	True (1) if the trip departure was on a Saturday, Sunday or public holiday. False (0) otherwise.
Rain	Ratio	Millimetres of rain recorded at the Sydney Observatory Hill weather station (number 66062) on the day of the trip departure.
Rain 0mm	Dummy	True (1) if there was any rain on the day of the trip departure. False (0) otherwise.
Rain 3mm	Dummy	True (1) if there was more than 3 mm of rain on the day of the trip departure. False (0) otherwise.

5.1.3 Choice data formatting

Choice data were extracted from the database (see Section 4.4.1.5) using MySQL,[42] then formatted using a PHP script. Every trip reported in the travel diary was considered a discrete mode choice situation, with an alternative for each transport mode (walk, bicycle, public transport, car). A trip was discarded if it met one or more of the conditions listed in Table 5.7.

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[41] Excluding public holidays.

[42] Software for updating or querying relational databases.

Table 5.7: Excluded trips (Wave 1)

Reason for exclusion	Number of trips	% of trips
Round trip (origin and destination the same)	1322	8.26
Main transport mode was not walk, bicycle, public transport or drive	864	5.40
Destination address could not be geocoded	307	1.92
Origin address could not be geocoded	305	1.90
Origin or destination outside Greater Sydney metropolitan region[a]	16	0.10
Trip purpose was: Went for a walk/run	798	4.98
Trip purpose was: Went for a bike ride	75	0.47
Trip purpose was: Holiday/vacation	75	0.47
Trip purpose was: Filled up with fuel	26	0.16
Trip purpose was: None	8	0.05
Origin or destination was on an island not reachable by road	2	0.01
Pre-exclusion total	16,013	100
Total excluded[b]	3213	20.1
Post-exclusion total	12,800	79.9

[a] The area bounded by latitude -34.6 to -32.8 and longitude 149.9 to 151.9 in the WGS 84 coordinate system.
[b] Trips could be excluded for multiple reasons.

The individual characteristics for each choice situation were based on responses to the online questionnaire (Section 4.4.1.1). Trip attributes and contextual factors were imputed as described in Section 5.1.2. Categorical variables with more than two categories (e.g., age group) were dummy coded.

The number of alternative modes in each choice situation varied between two and four, depending on which modes were considered feasible for the trip. There were very few transport walking trips over 5 kilometres reported in the travel diary, so walking was assumed unfeasible for trips with an estimated network distance over 5 kilometres. Similarly, very few transport cycling trips over 15 kilometres were reported, so bicycle was assumed unfeasible for trips with an estimated network distance over 15 kilometres. Public transport or driving was assumed unfeasible only if a route could not be found using the Google Directions API (Section 5.1.2.2).

An example of the resulting choice data is presented in Table 5.8, showing four trips made by two respondents (100 and 101). A ‘1’ in the *Choice* column indicates which alternative the respondent actually chose. The number in the *Observations* column is the total number of choice situations (trips) for each respondent. This allows correlation between multiple trips by the same respondent to be accounted for during model estimation.

Table 5.8: Example choice data format

Respondent	Trip no.	Alternative	Choice	Alternatives	Observations	Weight	Independent variables
100	1	Walk	1	4	3		
100	1	Bicycle	0	4	3		
100	1	PT	0	4	3		
100	1	Car	0	4	3		
100	2	PT	1	2	3		
100	2	Car	0	2	3		
100	3	Bicycle	1	3	3		
100	3	PT	0	3	3		
100	3	Car	0	3	3		
101	4	Walk	0	4	1		
101	4	Bicycle	0	4	1		
101	4	PT	0	4	1		
101	4	Car	1	4	1		

The *Weight* variable was used for exogenous weighting during model estimation, to account for differences between the age and gender profiles of the sample and the population. The population age/gender profile for the study area was obtained from the 2011 Census (ABS 2015) and the resulting weights are shown in Table 5.9. A weight above 1.0 indicates a demographic that was under-represented in the sample, while a weight below 1.0 indicates a demographic that was over-represented.

Table 5.9: Sample weights

Age	Male	Female
18 to 19	1.65	0.61
20 to 24	1.36	0.84
25 to 29	1.78	1.39
30 to 34	1.79	1.02
35 to 39	1.57	1.09
40 to 44	1.16	0.75
45 to 49	0.96	0.68
50 to 55	0.64	0.41

5.1.4 Model estimation

Models were estimated using NLOGIT version 5 choice modelling software (Econometric Software Inc., 2009). Exploratory modelling was performed using a simple multinomial logit model (see Section 3.1.1). Subsequently, the mixed logit model was used, because it (a) can reveal random intra-sample preference heterogeneity, (b) allows flexible substitution patterns between alternatives, and (c) can account for panel data (i.e., correlation between multiple choice situations for one respondent).

Commuting and non-commuting trips were modelled separately, because the factors affecting bicycle mode choice have been found to differ with trip purpose (Börjesson & Eliasson, 2012).

For each trip (mode choice situation), it was assumed that the utility of transport mode alternative j to individual n in choice situation t is given by:

$$V_{njt} = \alpha_{nj} + \beta'_n x_{njt} + \theta_j E_{nj}, t = 1, \ldots, T_i, \tag{5.2}$$

where x_{njt} is a vector of individual characteristics, trip attributes and contextual factors, β' is a vector of parameters to be estimated, and α_{nj} are alternative specific constants. The alternative specific constant for the walk alternative was arbitrarily normalised to zero. E_{nj} are error components, which account for correlation between error terms of groupings of alternatives, while θ_j are the standard deviations of these error components.

The probability P_{njt} of individual n choosing mode j is then given by:

$$P_{njt} = \frac{exp(V_{njt})}{\sum_j^J exp(V_{njt})}. \tag{5.3}$$

To begin with, parameters for all variables were specified as random, and various distributions were tested. The lognormal distribution produced some erratic parameter estimates with long tails. There were sign issues with the normal distribution, i.e., positive cost parameters being estimated for a large proportion of respondents. The censored normal distribution produced erratic parameter estimates. Ultimately, it was found that a symmetric triangular distribution gave the best behavioural interpretation.

The spread of the triangular distribution was constrained to be half the mean, ensuring that all values in the distribution had the same sign, and were nonzero.

(As discussed in Section 3.3.1.1, calculation of a marginal rate of substitution is problematic if the parameter used as the denominator can take a value of zero.)

Parameters were changed to be non-random if doing so produced an improved model fit. Parameter values were constrained to be equal for all trips made by an individual respondent. Variables not significant at the 95 per cent confidence level were dropped.

To identify systematic sources of preference heterogeneity, attributes and contextual factors were interacted with individual characteristics, and interaction terms found to be statistically significant ($p < 0.05$) were retained.

Various error component structures were tested, to explore substitution patterns between alternatives. Error components with a statistically significant standard deviation ($p < 0.05$) were retained. Heteroscedasticity of error components was examined, by testing whether error component variance differed between demographic groups.

Halton intelligent random draws were used for simulation. For exploratory modelling, 20 draws per error component and 20 draws per random parameter were used. For the final models, 2,000 draws were used. Estimation time using an Intel Core i5 3.00 GHz processor was about two hours for the final commuting model, and four hours for the final non-commuting model.

Model fit was assessed in terms the McFadden pseudo-R^2 (where a higher value indicates a better fit) and the Akaike Information Criterion (AIC) (where a lower value indicates a better fit). Where two dependent variables were found to be correlated (e.g., *Gender* and *Bicycle rider type*), only one was included at a time, and the one that gave the best model fit was retained.

The means of the parameter estimates for cycleway distance (*CW distance*) and non-cycleway distance (*Non-CW distance*) were compared using t-tests. Cross elasticities were calculated to estimate the effect on mode share of a one per cent decrease in non-cycleway distance.

Marginal rates of substitution were calculated between cycleway distance and (a) non-cycleway distance, (b) walking travel time, (c) pubic transport travel time, and (c) driving travel time. Confidence intervals for these marginal rates of substitution were calculated using the Delta method (Equation 3.7). Individual marginal rates of substitution for each respondent were computed using conditional parameter estimates, i.e., respondent-specific parameter estimates, conditioned on the alternatives they actually chose (see Revelt & Train, 1999).

5.2 Forecasting changes in travel demand and consumer surplus

The baseline mode choice models and conditional parameter estimates were used to forecast the impacts of new cycleways being built in the City of Sydney. Forecasting was undertaken for the scenarios listed in Table 5.10. The 'Do nothing' Scenario A corresponded with the baseline (pre-intervention) data collection wave of the Sydney Travel and Health Study. Scenarios B and C corresponded with the two post-intervention data collection waves (2 and 3) of the Sydney Travel and Health Study. Scenario D assumed completion of all new cycleways proposed in City of Sydney's *Cycle Strategy and Action Plan* (City of Sydney, 2007). The cycleway networks for the four scenarios are shown in Figure 5.4.

Table 5.10: Scenarios

Scenario	Year	Corresponding data collection wave in the Sydney Travel and Health Study
A ('Do nothing')	2013	1
B (George St Cycleway)	2014	2
C (George St + CBD Cycleways)	2015	3
D (Complete Network)	2017	N/A

To model these scenarios, three additional versions of the bicycle network data were created, corresponding with Scenarios B, C and D. In each version, cycleway links were added or deleted to reflect the state of the bicycle network in the given scenario.

The travel demand in all four scenarios was based on that reported by intervention area respondents in Wave 1 of the Sydney Travel and Health Study, and was assumed the same for all scenarios. That is to say, it was assumed respondents would make the same number of trips, with the same origins and destinations, in all four scenarios. It was also assumed there was no change to walking, public transport or driving travel times. Thus, the only variables that could change between each scenario were cycleway distance (*CW distance*) and non-cycleway distance (*Non-CW distance*).

Figure 5.5 and Table 5.11 illustrate how the bicycle distance variables for an example trip could change after the addition of a new cycleway (the George Street Cycleway) to the network. In this example, cycleway distance increases, while non-cycleway distance decreases. If the parameter for the former is sufficiently more negative than that for the latter, then the utility of the bicycle alternative $V_{bicycle}$ for this trip increases (see Equation 5.1). Because the utility of the other alternatives does not change, then the probability of the respondent choosing bicycle increases – even though the total bicycle distance has increased (because of the diversion to use the cycleway).

Figure 5.4: Scenarios

(a) Pre-intervention **(b) Post-intervention**

Figure 5.5: Modelled bicycle routes

Table 5.11: Changes in bicycle distance variables for example trip

	Pre-intervention	Post-intervention	Change
Cycleway distance (km)	0.7	2.0	+1.3
Non-cycleway distance (km)	1.7	0.7	-1.0
Total distance (km)	2.4	2.7	+0.3

To estimate the transport mode shares, BKT and consumer surplus for each scenario, a simulation model was developed using Microsoft Excel and Visual Basic. In each iteration of the simulation, the probability of a respondent n choosing mode j for a trip t was calculated using the mixed logit model:

$$P_{njts} = \frac{exp\left(V_{ntj}^{s}\right)}{\sum_{j}^{J} exp\left(V_{ntj}^{s}\right)} \qquad 5.4$$

The systematic utility V_{ntj}^{s} of each mode j in scenario s was calculated based on the conditional parameter estimates obtained from the baseline (Wave 1) model estimation (see Section 5.1), and the variables (x_{ntj}^{s}) for the given scenario. It was assumed that individual characteristics and preferences did not change between scenarios, and the only trip attributes to change were cycleway distance and non-cycleway distance (due to changes to the bicycle network). It was also assumed there would be no congestion on cycleways.

Where the utility expression for an alternative included a daily rainfall variable, its value was simulated at random, based on rainfall data from the Sydney Observatory (station number 066062) (Bureau of Meteorology, 2017), averaged over the 10 years from 2007 to 2016 (Table 5.12).

Table 5.12: Daily rainfall at Sydney (Observatory Hill) 2007 to 2016

	> 0 mm	> 3 mm
Number of days	1,426	698
Probability	0.390	0.191

The mode choice for each trip was simulated using the estimated probabilities for each mode, using Halton pseudo-random draws from a uniform distribution. In each iteration of the simulation, mode shares were estimated by aggregating the simulated mode choices for all trips. BKT was calculated as the sum of bicycle distances, for all trips where the simulated mode choice was bicycle.

Following Train (2009) and de Jong et al. (2007), the expected consumer surplus $E(CS_{nts})$ for each trip t by respondent n in scenario s was calculated using Equation 5.5.

$$E(CS_{nts}) = (1/\alpha_n) \ln\left(\sum_j e^{V_{njt}^s}\right) + C \qquad 5.5$$

The natural log of the term in parentheses is the inclusive value, or logsum, of the choice situation, which gives the maximum expected utility to the decision maker. V_{njts} are the mode-specific utility functions, the form and parameters of which were previously estimated (Section 5.1), and α_n is the respondent's marginal utility of income. C is an unknown constant.

The marginal utility of income α_n is, by definition, the negative of the parameter of any price variable in the mode choice model, e.g., toll road cost or public transport fare (Train, 2009). Because there were no price variables in this particular model, a time variable with a well-established monetary valuation was chosen, namely the value of travel time savings for private car occupants, which the NSW Government values at an average of AUD 15.14 per hour (Transport for NSW, 2013a). $E(CS_{nts})$ was thus estimated in terms of hours of driving travel time savings, and converted to AUD by multiplying by AUD 15.14. The change in consumer surplus between two scenarios (s = 1 and s = 2) was calculated using Equation 5.6. The unknown constant C drops out.

$$\Delta E(CS_{nt}) = (1/\alpha_n) \ln\left(\sum_j e^{V_{ntj}^{s=2}}\right) - \left(\sum_j e^{V_{ntj}^{s=1}}\right) \quad 5.6$$

For each scenario, the mode shares, BKT and consumer surplus for the sample were averaged over 10,000 iterations of the simulation.

The estimated mode share, BKT and consumer surplus for the intervention area population (ages 18 to 55) were estimated by applying expansion factors, weighted as per Table 5.9. Population data were obtained from the 2011 Census (Australian Bureau of Statistics, 2011b).

5.3 Economic appraisal

Economic appraisals of Scenarios B and D (relative to the 'Do nothing' Scenario A) were performed following the NSW transport project appraisal guidelines (Transport for NSW, 2013a), with the following adjustments.

1. Public transport fare and motorway toll savings were not included, because these are transfer payments.
2. Reductions in congestion and other motor vehicle externalities were not included, for two reasons. First, the intervention area is a densely populated and congested inner-city area with high latent driving demand, so any mode shift from car to bicycle would be expected to induce more driving demand (see Section 2.4.4). Second, none of the scenarios involves a reduction in roadway capacity, or any other demand management measures.

3. Crash/injury costs were not included. Most injuries to people cycling for transport are caused by motor vehicle drivers (Lindsay, 2013), and including such spillover externalities in SCBA – while theoretically correct – biases it against cycling. To address this bias, Gössling & Choi (2015) suggest it is appropriate to exclude crash/injury costs in bicycle project appraisal.
4. Public health benefits (reduced mortality and morbidity) are valued at $1.21 per BKT, and $1.68 per walking kilometre, as recommended by Mulley et al. (2013) (adjusted from 2010 to 2013 prices). These valuations have been subjected to peer-review, whereas the value of $1.11 per bicycle or walking kilometre recommended in the NSW guidelines is based on a cursory review of grey literature.

Table 5.13 compares the appraisal parameters used in the present analysis, with those recommended in the NSW guidelines, and those used by consultants AECOM in their appraisal of the proposed Inner Sydney Regional Bicycle Network (AECOM, 2010; Yi et al., 2011).

The construction cost for Scenario B was obtained from City of Sydney. Construction cost for Scenario D was estimated based on the per-kilometre rate of Scenario B.[43] Annual maintenance costs were assumed to be 1 per cent of the construction cost.

The economic viability of Scenarios B and D, relative to the 'Do nothing' Scenario A, was expressed in terms of the following measures:

- Net present value (NPV): the 2013 value of net benefits.
- Benefit-cost ratio (BCR): the 2013 value of net benefits, divided by the 2013 value of investment and maintenance costs.

[43] In general, transport infrastructure costs are higher in Australia than in most high-income countries (Coultan, 2016). In the case of cycling infrastructure, over-engineering is a factor (Urban Movement & Phil Jones Associates, 2014).

Table 5.13: Economic appraisal parameters

	NSW guidelines (Transport for NSW, 2013a)	Appraisal of Inner Sydney Regional Bicycle Network (Yi et al., 2011)	Present analysis
Capital costs	Construction	$100,000 to $400,000 per kilometre	Construction
Recurring costs	1% of construction cost	1% of construction cost	1% of construction cost
Annual population growth	1.1%	Provided by Transport for NSW	1.1%
Trips included	Not specified	Commuting to work	Commuting to work/study, and non-commuting transport trips
Cost/benefit streams (AUD per kilometre, 2013 prices)			
Social costs/benefits			
Public health benefits (reduced mortality and morbidity) - bicycle	1.11	0.0649	1.21
Public health benefits (reduced mortality and morbidity) - walking	1.67		1.80
Absenteeism and productivity benefits	–	0.1730	–
Crash/injury costs	-0.19	-0.1769	–
Reduced motor vehicle externalities			
Congestion cost savings	0.32	0.2926	–
Vehicle operating cost savings	0.29	0.1343	–
Air pollution	0.0308	0.0300	–
Greenhouse gas emissions	0.024	0.0236	–
Noise	0.010	0.0097	–
Water pollution	0.0047	0.0045	–
Nature and landscape	0.00055		–
Urban separation	0.0071	0.0069	–
Roadway provision cost savings	0.05	0.0157	–
Parking cost saving	0.013	0.5738	–
User costs/benefits			
Public transport fare cost savings	0.12	–	–
Tolling cost savings	0.38	–	–
Travel time savings	0	0.1427	–
Journey ambience	–	0.1261	–
Improved accessibility and transport options (consumer surplus)	–	–	Valued as described in Section 5.2.
Discount rate	7% (±3%)	7%	7% (±3%)
Appraisal period	30 years	30 years	30 years

For comparison, economic appraisals of Scenarios B and D were also performed following the NSW appraisal guidelines (Transport for NSW, 2013a), using the Transport for NSW Bicycle Facility Cost benefit Analysis Tool (Transport for NSW, 2016),

5.4 Analysis of actual changes in travel behaviour/demand

5.4.1 Bicycle counts and intercept survey

Statistical analyses of the peak-time bicycle count data (described in Section 5.3) were performed using Microsoft Excel 2013 (Microsoft Corp., 2013).

Statistical analyses of the intercept survey data (described in Section 5.4) were performed using SPSS version 22 (IBM Corp., 2013). Data from both intercept sites were pooled for analysis. Logistic regression models were developed to identify factors associated with respondents who had (i) changed transport mode, and (ii) changed their usual bicycle route since the intervention. The initial models included as independent variables: observed gender, estimated age, trip purpose, length of time riding regularly (coded as 'two years and less' or 'more than two years'), and intercept site. In the final models, variables with $p > 0.20$ were omitted. In addition to pooled models for all trips, separate models were estimated for commuting and non-commuting trips.

The distance each respondent had diverted to use the cycleway was estimated as the difference between the shortest network distance between the stated origin and destination (see the example in Figure 5.6(a)), and the shortest network distance via the intercept site (see the example in Figure 5.6(b)).

To calculate these network distances, the GIS-based bicycle demand model was used (see Section 5.1.2.1 for details).

For every trip, the reported origin and destination were geocoded using the Google Maps Geocoding API (Google Inc., 2016), and the resulting geographic coordinates were loaded into the GIS model. Intercept site locations were added manually. The ArcGIS Network Analyst Directions tool (ESRI, 2013c) was used to generate turn-by-turn directions for each origin-destination pair, and each origin-intercept-destination triplet, using a Dijkstra shortest path algorithm, with travel time as the impedance variable (ESRI, 2017). Turn restrictions and one-way restrictions were ignored, given that in NSW bicycle riders are often exempted from them. The turn-by-turn directions were parsed using a PHP script to extract the network distances for each trip.

(a) Shortest path **(b) Shortest path via site 1**

Figure 5.6: Example shortest path calculations

Multiple linear regression was used to identify factors predicting the estimated distance respondents had diverted to use the cycleway. The initial models included as independent variables: observed gender, estimated age, trip purpose, shortest path network distance, length of time riding regularly, intercept site and attire as independent variables, plus interactions. Non-significant ($p > 0.05$) variables were removed from the model in a stepwise fashion. Again, separate models were estimated for commuting and non-commuting trips.

5.4.2 Longitudinal resident survey

Statistical analyses of the three waves of questionnaire and travel diary data (described in Sections 4.4.1.1 and 4.4.1.2) were conducted using STATA Version 13 (StataCorp, 2015).

5.4.2.1 Questionnaire

Characteristics of the baseline (Wave 1) and post-intervention (Wave 2) samples were compared using chi-square tests. Changes over time in travel behaviour reported in the questionnaire (weekly cycling frequency, usual commuting mode, bicycle ownership) were investigated using mixed effects logistic regression.

Logistic regression was used to examine differences between intervention and control area respondents in Wave 2. The model included, as independent variables, respondents' interaction with the cycleway (awareness, actual use, and future intention to use) and their neighbourhood perceptions, and was adjusted for differences in age, gender, income and education.

When it was found that some control area respondents reported having used the new cycleway at Wave 2, an alternative exposure variable was specified, namely residential proximity to the new cycleway. To estimate proximity, respondents' residential addresses were geocoded using the Google Maps Geocoding API (Google Inc., 2016). Then, the shortest network distance between each respondent's residential address, and the closest point along the cycleway, was estimated using ArcGIS Network Analyst (ESRI, 2013c), with OpenStreetMap network data downloaded on 20 December 2014 from the BBBike.org website. The resulting network distances were rescaled to increments of 500 metres and 100 metres, with the cycleway coded as zero, and every increment farther from the cycleway coded as a negative value.

This proximity variable was included in a logistic regression analysis of cycleway users versus non-users in Wave 2. The model included as covariates: age, gender, income, education, cycling frequency, and bicycle rider type.

5.4.2.2 Travel diary

Changes in cycling behaviour reported in the travel diary were assessed for those respondents who had satisfactorily completed all three waves of the diary. Non-transport trips (e.g., going for a walk) and trips starting or finishing outside the

Greater Sydney metropolitan region [44] were excluded. Cycling participation (whether respondents used a bicycle during the seven-day reporting period) in the intervention and control areas was compared across the three years using McNemar's test for binary outcomes. Changes in the average number of bicycle trips, and the average time spent cycling, were evaluated using paired sample t-tests. Differential effects in the intervention group versus the control group were assessed using differences-in-differences (balanced panel), which takes into account background factors that may have affected both groups (Angrist & Pischke, 2009). Finally, changes in weekly cycling minutes by proximity to the cycleway were examined using multilevel modelling for repeated measures, with proximity categorised into three groups (< 1.00 km, 1.00 to 2.99 km, and > 3.00 km) (full details in Crane, et al. 2017).

5.5 Analysis of temporal preference stability

To test for temporal preference stability, choice data for all three waves of the Sydney Travel and Health Study (2013, 2014 and 2015) were combined. These choice data were imputed and formatted in the same way as were the baseline choice data (Sections 5.1.2 and 5.1.3). Only trips reported by respondents who had satisfactorily completed the online travel diary in all three waves were included in this analysis.

For each wave, the bicycle distance variables were again estimated using the GIS-based bicycle demand model (described in Section 5.1.2.1), loaded with the corresponding bicycle network data for that wave. Travel time variables for walking, public transport and driving were again imputed using the Google Directions API (see Section 5.1.2.2). Travel times for trips reported in Wave 2 were generated on 18 September 2015. Travel times for trips reported in Wave 3 were generated on 23 March 2016.

[44] The area bounded by latitude -34.6 to -32.8 and longitude 149.9 to 151.9 in the WGS 84 coordinate system.

It is not recommended to directly compare parameter estimates between data sets collected at different times, because the variance of the unknown error term ε may have changed, resulting in a difference in scale between the data sets (Swait & Louviere, 1993). Therefore, other methods were used to test temporal preference stability:

- comparison of marginal rates of substitution between waves;
- joint estimation using nested logit and mixed logit; and
- joint estimation with interaction terms.

These methods are explained in more detail in Sections 5.5.1 to 5.5.3.

5.5.1 Changes in marginal rates of substitution

Marginal rates of substitution can be calculated by dividing one parameter estimate by another (Equation 3.6), meaning that scale parameters cancel out.

For each wave, two mixed logit mode choice models were estimated – one for commuting trips and another for non-commuting trips. Model specification was based on the final baseline models (Section 5.1), with random parameters to account for preference heterogeneity, and error components to allow for flexible substitution patterns. Estimation was by simulated maximum log likelihood, with 2,000 Halton draws.

Marginal rates of substitution were calculated between cycleway distance and non-cycleway distance, between non-cycleway distance and driving travel time, and between cycleway distance and driving travel time. Confidence intervals were calculated using the Delta method (Equation 3.7). Differences between waves were evaluated using t-tests.

5.5.2 Combined choice model

Data from all three waves were combined and estimated using both a nested logit model and a mixed logit model. In the nested logit model, a separate branch was specified for each wave, with the scale parameter for the Wave 1 branch normalised to a value of 1.0. In the mixed logit model, an error component was specified for each wave, and all parameters were specified as non-random. Estimation for the latter was performed using simulated maximum log likelihood, with 100 Halton draws.

In both models, parameters specific to the walking, public transport and driving alternatives were specified to be generic across waves (assumed stable). After accounting for any scale differences, parameters for the bicycle alternative were compared across waves using the t-test formula given in Equation 5.6. This formula tests the null hypothesis that the mean parameter estimate in Wave A ($\hat{\beta}_A$) is equal to the mean parameter estimate in Wave B ($\hat{\beta}_B$). The null hypothesis can be rejected with 95 per cent confidence if the t-statistic (t_A) is greater than 1.96. $Cov(\hat{\beta}_A, \hat{\beta}_B)$ is the covariance between $\hat{\beta}_A$ and $\hat{\beta}_B$.

$$t_A = \frac{\hat{\beta}_A - \hat{\beta}_B}{\sqrt{Var(\hat{\beta}_A) + Var(\hat{\beta}_B) - 2Cov(\hat{\beta}_A, \hat{\beta}_B)}} \quad 5.7$$

5.5.3 Interaction of variables with wave

Again, data from all three waves were combined. New dummy variables were created to identify trips made in Waves 2 and 3, and these were interacted with bicycle trip attributes, to test whether the wave had any systematic influence on bicycle preferences. A mixed logit model with error components was used, with all parameters specified as non-random. Estimation was by simulation, with 100 Halton draws.

5.6 Summary

This chapter has described the methods used for forecasting and valuing the transport impacts and user benefits of new bicycle infrastructure using discrete choice analysis, and for testing the assumption of preference stability on which such forecasts depend.

Central to this analysis was the development of a transport mode choice model, in which utility functions for four transport modes (walk, bicycle, public transport and private car) were estimated from baseline travel diary data.

For each trip reported in the baseline travel diary, the attributes of the four alternative modes were imputed using two transport models: a GIS-based model with open source network data for bicycle; and the Google Maps Directions API for other modes.

To forecast the transport impacts of new bicycle infrastructure, the bicycle distance attributes (cycleway distance and non-cycleway distance) were recalculated for each scenario using the GIS-based bicycle demand model. Resulting improvements in accessibility and transport choice were then monetised for the purposes of economic appraisal.

Actual changes in travel behaviour were assessed by analysing post-intervention travel diary data, data from an intercept survey of users of the new infrastructure, and bicycle traffic counts.

The assumption of temporal preference stability – on which demand forecasting and resulting economic appraisals depend – was tested by modelling travel diary data obtained before and after the intervention.

6 RESULTS

This chapter begins with the results of the mode choice analysis performed on the baseline (pre-intervention) data from the Sydney Travel and Health Study (Section 6.1). The outputs of this analysis were used to forecast the transport (Section 6.2) and economic (Section 6.3) impacts of a new cycleway in the City of Sydney local government area.

Following the opening of the new cycleway, actual changes in travel behaviour/demand were assessed using data from bicycle traffic counts, a post-project intercept survey, and subsequent waves of the Sydney Travel and Health Study (Section 6.4).

An inherent assumption of the forecasting/valuation approach is that preferences underlying personal transport choices (i.e., mode choice model parameters) remain stable over time. The results of various analyses used to test this hypothesis are presented in Section 6.5.

6.1 Baseline mode choice analysis

6.1.1 Sample characteristics

A total of 608 respondents satisfactorily completed the baseline (Wave 1) travel diary. The age and gender profile of this sample is compared with that of the study area population in Table 6.1. The population profile is based on the 2011 Census (ABS 2015). The proportion of females in the sample is significantly larger than that in the population (59.9 per cent versus 49.4 per cent; $p < 0.01$), and significantly larger in the control group than in the intervention group (64.2 per cent versus 54.3 per cent; $p < 0.01$). The age profile of the baseline sample is skewed towards older age groups, relative to the population; this is mostly due to the large number of respondents aged 45 to 55 in the control group. The age profile of the intervention group is reasonably representative of the population. To account for these differences between the sample and population characteristics, appropriate weightings were used for the baseline choice analysis, demand assessment and economic appraisal.

Table 6.1: Age and gender profile of baseline sample versus study area population

Gender	Age group	Study area population ages 18 to 55) (N = 74,618[a]) (%)	Intervention sample (n = 267) (%)	Control sample (n = 341) (%)	Intervention + control samples (n = 608) (%)
Male	18 to 24	7.2	4.9	5.3	5.1
Male	25 to 34	17.3	14.6	5.9	9.7
Male	35 to 44	15.1	14.2	8.8	11.2
Male	45 to 55	11.0	12.0	15.8	14.1
Male	18 to 55	50.6	45.7	35.8	40.1
Female	18 to 24	7.5	10.1	9.1	9.5
Female	25 to 34	17.8	20.2	11.1	15.1
Female	35 to 44	13.8	10.5	18.8	15.1
Female	45 to 55	10.3	13.5	25.2	20.1
Female	18 to 55	49.4	54.3	64.2	59.9
Both	18 to 24	14.7	15.0	14.4	14.6
Both	25 to 34	35.1	34.8	17.0	24.8
Both	35 to 44	28.9	24.7	27.6	26.3
Both	45 to 55	21.2	25.5	41.1	34.2
Both	18 to 55	100.0	100.0	100.0	100.0

[a] Population statistics for the study area are based on the 2011 Census (ABS 2015).

Bicycle users are over-represented in the baseline sample (see Figure 6.1), because they were specifically targeted during recruitment for the Sydney Travel and Health Study. The travel demand forecasts were calibrated against actual transport mode shares for the study area.

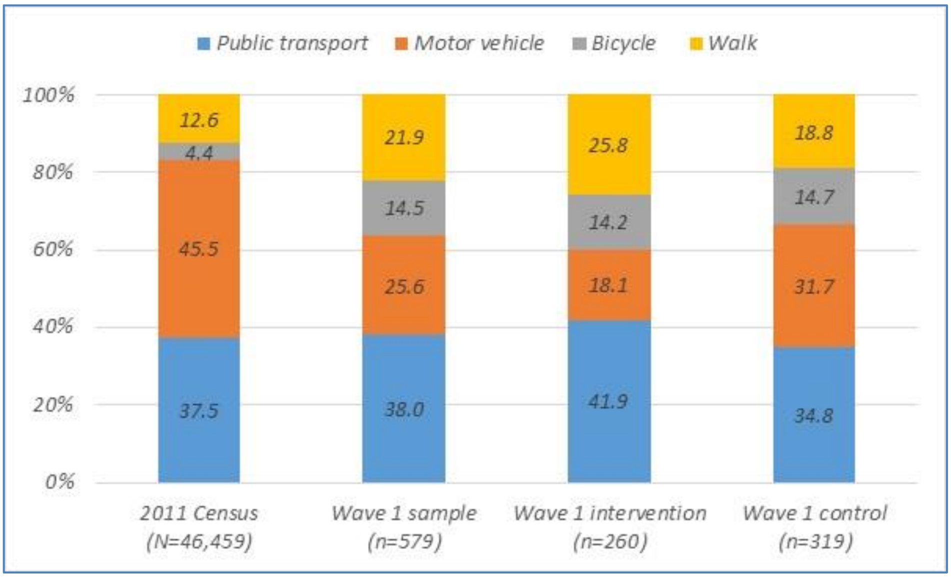


Figure 6.1: Commuting mode[45] of sample versus population

[45] Usual commute mode reported by respondents in the baseline questionnaire. Excludes respondents who did not commute to work or study.

6.1.2 Final mode choice models

6.1.2.1 Commuting trips

Of the 608 respondents who completed the travel diary in Wave 1, 504 reported some commuting travel, and they made 3,763 trips between them. The final mode choice model for these trips is presented in Table 6.2. The model is a significant improvement on a constants only model (chi-square 6221.671, 16 degrees of freedom, $p < 0.01$), and fits the data well (pseudo-R^2 0.57).

The two bicycle distance parameters have the expected negative sign, and specifying them as random improves model fit, indicating non-systematic preference heterogeneity among the sample. The parameter for cycleway distance (*CW distance*) is significantly smaller than that for non-cycleway distance (*Non-CW distance*) (t-statistic 2.36; marginal rate of substitution 1.41, 95% CI 1.01 to 1.80), suggesting that commuters will, on average, cycle for 1.41 km on cycleways instead of riding for 1 km in mixed traffic.

The parameters for the daily rainfall and CBD dummy variables (*Rain 3mm-bicycle* and *CBD-bicycle*) are negative and have statistically significant spreads, indicating differing levels of aversion to bicycle commuting on days with more than 3 mm of rain, or to/from the CBD.

Self-reported rider type has a significant influence on sensitivity to non-cycleway distance, with low-intensity riders having a higher sensitivity (*Non-cycleway distance x Low intensity*). In an alternative model specification, gender had a similar influence on sensitivity to non-cycleway distance, with women having a higher sensitivity. Because the gender and rider type variables are strongly correlated (women are more likely to identify as low-intensity riders), only rider type is retained in the final model, as it gives a marginally better model fit.

Table 6.2: Mixed logit model of mode choice for Wave 1 commuting trips (3,763 trips, 504 respondents, 2,000 Halton draws)

	Coefficient	t-statistic	95% CI	Distribution	Spread	t-statistic	95% CI
Constants							
Bicycle	-5.768	**-15.600**	-6.492 to -5.043				
PT	-4.634	**-13.240**	-5.320 to -3.948				
Car	-3.660	**-18.910**	-4.039 to -3.280				
Random parameters							
CW distance	-0.952	**-13.390**	-1.092 to -0.813	Triangular	0.476	**13.390**	0.406 to 0.546
Non-CW distance	-1.340	**-11.400**	-1.570 to -1.109	Triangular	0.670	**11.400**	0.555 to 0.785
Rain 3mm-bicycle	-0.590	**-2.950**	-0.982 to -0.198	Triangular	0.295	**2.950**	0.099 to 0.491
CBD-bicycle	-2.966	**-12.320**	-3.438 to 2.494	Triangular	1.483	**12.320**	1.247 to 1.719
Time-walk	-0.342	**-32.280**	-0.362 to -0.321	Triangular	0.171	**32.280**	0.160 to 0.181
Time-PT	-0.304	**-38.760**	-0.319 to -0.288	Triangular	0.152	**38.760**	0.144 to 0.160
Time-car	-0.782	**-41.290**	-0.819 to -0.744	Triangular	0.391	**41.290**	0.372 to 0.409
CBD-car	-5.448	**-15.440**	6.139 to 4.756	Triangular	2.724	**15.440**	2.378 to 3.070
Non-random parameters							
Non-CW distance x Low intensity	-1.259	**-13.930**	1.435 to 1.081				
CBD-bicycle x Low intensity	1.988	**8.520**	1.530 to 2.445				
Children-car	1.417	**7.900**	1.065 to 1.768				
Age 45-55-car	1.078	**5.310**	0.680 to 1.475				
Error component					**Std. deviation**		
E1 (Bicycle, PT)				Normal	3.684	**12.140**	3.089 to 4.278
Model fit statistics							
Log likelihood	-2350.499						
Chi-square	6221.671						
Degrees of freedom	16						
Pseudo-R^2	0.57						
AIC	4733.0						

The travel time parameters for other modes (*Time-walk*, *Time-PT* and *Time-car*) are, as expected, negative. T-test comparisons of the travel time parameters for walk, public transport and car indicate they are statistically different from each other (**Error! Not a valid bookmark self-reference.**). Sensitivity to travel time is lowest for public transport, and highest for car. All have statistically significant spreads, indicating that preferences are heterogeneous

Table 6.3: Comparison of parameters for distance and time – commuting

Variable A	β_A	Variable B	β_B	t-statistic
Non-CW distance	-1.340	CW distance	-0.952	**2.36**
Time-walk	-0.342	Time-PT	-0.304	**-3.05**
Time-walk	-0.342	Time-car	-0.782	**23.49**
Time-PT	-0.304	Time-car	-0.782	**27.53**

The constants for bicycle, public transport and car are all negative; this implies that, after the observed variables are accounted for, there are unobserved effects that reduce the utility of all these modes, relative to walking. Respondents aged 45 to 55, or with children under 18 years of age living at home, have a greater preference for car travel.

The parameters for area (intervention/control), household income, education level, end of trip facilities, origin elevation, and destination elevation are not statistically significant; these variables are omitted in the final model.

The error component for bicycle and public transport has a significant standard deviation ($p < 0.01$), indicating that commuters are more likely to substitute between these two modes than between others, i.e., the Independence of Irrelevant Alternatives (IIA) assumption is relaxed. There is no evidence of heteroscedasticity in this error component, i.e., its magnitude is not affected by individual characteristics.

The utility functions for the four modes are as follows:

$$U_{Walk} = (-0.342 + 0.171 \times t) \times \text{'Time'} \\ + \varepsilon_{j=Walk} \qquad 6.1$$

$$\begin{gathered} U_{Bicycle} = -5.768 \\ +(-1.340 + 0.670 \times t) \times \text{'Non-CW Distance'} \\ +(-0.952 + 0.476 \times t) \times \text{'CW distance'} \\ +(-0.590 + 0.295 \times t) \times \text{'Rain 3mm'} \\ +(-2.966 + 1.483 \times t) \times \text{'CBD'} \\ -1.259 \times \text{'Non CW distance'} \times \text{'Low intensity'} \\ +1.988 \times \text{' CBD'} \times \text{'Low intensity'} \\ +3.684 \times N_{E1} \\ +\varepsilon_{j=Bike} \end{gathered} \qquad 6.2$$

$$\begin{gathered} U_{PT} = -4.634 \\ +(-0.304 + 0.152 \times t) \times \text{'Time'} \\ +3.684 \times N_{E1} \\ +\varepsilon_{j=PT} \end{gathered} \qquad 6.3$$

$$\begin{gathered} U_{Car} = -3.660 \\ +(-0.782 + 0.391 \times t) \times \text{'Time'} \\ +(-5.448 + 2.724 \times t) \times \text{'CBD'} \\ +1.417 \times \text{'Children'} \\ +1.078 \times \text{'Age 45-55'} \\ +\varepsilon_{j=Car}, \end{gathered} \qquad 6.4$$

where t has a triangular distribution, N_{E1} has a normal distribution, and ε_j have a Generalized Extreme Value Type I distribution.

6.1.2.2 Non-commuting trips

Of the 608 respondents who completed the travel diary in Wave 1, 600 reported some non-commuting travel, and they made 8,716 trips between them. The final mode choice model for these trips is presented in Table 6.4. The model is a significant improvement on a constants only model (chi-square 14844.335, 20 degrees of freedom, $p < 0.01$), and fits the data well (pseudo-R^2 0.61).

Table 6.4: Mixed logit model of mode choice for Wave 1 non-commuting trips (8,716 trips, 600 respondents, 2,000 Halton draws)

	Coefficient	t-statistic	95% CI	Distribution	Spread	t-statistic	95% CI
Constants							
Bicycle	-6.413	**-24.29**	-6.931 to -5.896				
PT	-6.831	**-29.51**	-7.285 to -6.377				
Car	-4.347	**-22.85**	-4.72 to -3.974				
Random parameters							
CW distance	-0.251	**-4.18**	-0.369 to -0.134	Triangular	0.126	**4.18**	0.067 to 0.184
Non-CW distance	-0.662	**-6.62**	-0.858 to -0.466	Triangular	0.331	**6.62**	0.233 to 0.429
Rain 3mm-bicycle	-0.735	**-4.09**	-1.087 to -0.383	Triangular	0.368	**4.09**	0.192 to 0.544
CBD-bicycle	-2.187	**-6.63**	-2.834 to -1.54	Triangular	1.093	**6.63**	0.77 to 1.417
Time-walk	-0.229	**-36.71**	-0.241 to -0.217	Triangular	0.114	**36.71**	0.108 to 0.121
Rain 0mm-walk	-0.545	**-6.06**	-0.721 to -0.369	Triangular	0.272	**6.06**	0.184 to 0.36
Time-PT	-0.049	**-8.37**	-0.06 to -0.037	Triangular	0.024	**8.37**	0.019 to 0.03
Time-car	-0.111	**-11.07**	-0.131 to -0.092	Triangular	0.056	**11.07**	0.046 to 0.065
CBD-car	-4.412	**-26.16**	-4.742 to -4.081	Triangular	2.206	**26.16**	2.041 to 2.371
Non-random parameters							
Non-CW distance x Low intensity	-0.487	**-5.69**	-0.655 to -0.319				
CBD-bicycle x Low intensity	-1.201	**-2.59**	-2.109 to -0.293				
Children-car	1.177	**4.59**	0.674 to 1.680				
Error components					**Std. deviation**		
E1 (Bicycle, PT)				Normal	1.718	**12.58**	1.45 to 1.985
E2 (Transit, Car)				Normal	1.611	**14.30**	1.39 to 1.832
E3 (Walk, PT)				Normal	2.467	**16.26**	2.17 to 2.764
Heteroscedastic effects							
E1 x Children	0.369	**3.50**	0.163 to 0.576				
E3 x Children	-0.393	**-3.24**	-0.631 to -0.155				
Model fit statistics							
Log likelihood	-4706.320						
Chi-square	14844.335						
Degrees of freedom	20						
Pseudo-R2	0.61						
AIC	9452.6						

The two bicycle distance parameters have the expected negative sign, and specifying them as random improves model fit, indicating non-systematic preference heterogeneity among the sample. The parameter for cycleway distance is significantly smaller than that for non-cycleway distance (t-statistic 3.02; marginal rate of substitution of 2.64, 95% CI 0.89 to 4.38), suggesting that non-commuters will, on average, cycle for 2.64 km on cycleways instead of riding for 1 km in mixed traffic. This is almost twice the substitution rate estimated for commuting trips (1.41, 95% CI 1.01 to 1.80)

The parameters for the daily rainfall and CBD dummy variables are negative and have statistically significant spreads, indicating differing levels of aversion to riding on days with more than 3 mm of rain, or to/from the CBD.

Again, self-reported rider type has a significant influence on sensitivity to non-cycleway distance, with low-intensity riders having a higher sensitivity (*Non-cycleway distance x Low intensity*). In an alternative model specification, gender had a similar influence on sensitivity to non-cycleway distance, with women having a higher sensitivity. Because the gender and rider type variables are strongly correlated (women are more likely to identify as low-intensity riders), only rider type is retained in the final model, as it gives a marginally better model fit.

The travel time parameters for the other modes are, as expected, negative. T-test comparisons of the travel time parameters for walk, public transport and car indicate they are statistically different form each other (Table 6.5). Sensitivity to travel time is lowest for public transport, and highest for walking. All have statistically significant spreads, indicating that preferences are heterogeneous.

Table 6.5: Comparison of parameters for distance and time – non-commuting

Variable A	β_A	Variable B	β_B	t-statistic
Distance non-CW	-0.662	Distance CW	-0.251	**3.01**
Time-walk	-0.229	Time-PT	-0.049	**-26.64**
Time-walk	-0.229	Time-car	-0.111	**-12.78**
Time-PT	-0.049	Time-car	-0.111	**10.75**

The constants for bicycle, public transport and car are all negative; this implies that, after the observed variables are accounted for, there are unobserved effects that reduce the utility of all these modes, relative to walking. Respondents with children under 18 years of age living at home have a greater preference for car travel. Daily rainfall above 0 mm reduces the utility of walking.

The parameters for area (intervention/control), age, income, education level, origin elevation, and destination elevation are not statistically significant; these variables are omitted in the final model.

The error components for public transport and car, bicycle and public transport, and walk and public transport all have statistically significant standard deviations ($p < 0.01$), suggesting that non-commuters are more likely to substitute between these pairs of modes than between others, i.e., the Independence of Irrelevant Alternatives (IIA) assumption is relaxed. Substitution is most likely between walk and public transport. Examination of the heteroscedastic effects suggests respondents with children under 18 years of age are more likely to substitute between bicycle and public transport, and less likely to substitute between walk and public transport.

The utility functions for the four modes are as follows:

$$\begin{aligned} U_{Walk} &= (-0.229 + 0.114 \times t) \times \text{'Time'} \\ &+ (-0.545 + 0.272 \times t) \times \text{'Rain 0mm'} \\ &+ 2.467 \times N_{E3} \\ &+ \varepsilon_{j=Walk} \end{aligned} \tag{6.5}$$

$$\begin{aligned} U_{Bicycle} &= -6.413 \\ &+ (-0.662 + 0.331 \times t) \times \text{'Non-CW distance'} \\ &+ (-0.251 + 0.126 \times t) \times \text{'CW distance'} \\ &+ (-0.735 + 0.368 \times t) \times \text{'Rain 3mm'} \\ &+ (-2.187 + 1.093 \times t) \times \text{'CBD'} \\ &- 0.487 \times \text{' Non CW distance'} \times \text{'Low intensity'} \\ &- 1.201 \times \text{' CBD'} \times \text{'Low intensity'} \\ &+ 1.718 \times N_{E1} \\ &+ \varepsilon_{j=Bicycle} \end{aligned} \tag{6.6}$$

$$U_{PT} = -6.831 + (-0.049 + 0.024 \times t) \times '\mathrm{Time}' + 1.718 \times N_{E1} + 1.611 \times N_{E2} + 2.467 \times N_{E3} + \varepsilon_{j=PT} \quad 6.7$$

$$U_{Car} = -4.347 + (-0.111 + 0.056 \times t) \times '\mathrm{Time}' + (-4.412 + 2.206 \times t) \times '\mathrm{CBD}' + 1.177 \times '\mathrm{Children}' + 1.611 \times N_{E2} + \varepsilon_{j=Car}, \quad 6.8$$

where t has a triangular distribution, N_{E1}, N_{E2} and N_{E3} have a normal distribution, and ε_j have a Generalized Extreme Value Type I distribution.

6.1.3 Model outputs

6.1.3.1 Elasticities

Table 6.6 shows the forecast effect on mode choice probabilities of decreasing the non-cycleway distance for all trips by 1 per cent. For both commuting and non-commuting trips, the probability of bicycle being chosen increases with relative elasticity, while the probability of other modes being chosen decreases with relative cross-elasticity. Commuters are more likely to switch to bicycle from walking, while non-commuters are more likely to switch to bicycle from public transport.

Table 6.6: Elasticity with respect to a 1 per cent decrease in non-cycleway distance

	Walk	Bicycle	Public transport	Car
Commuting	-0.252	0.901	-0.229	-0.134
Non-commuting	-0.021	0.621	-0.037	-0.026

Table 6.7 shows the forecast impact on mode shares of a 10 per cent increase in cycleway distance, together with a 10 per cent decrease in non-cycleway distance, for all trips. For commuting, 45 per cent of new cycling trips are forecast to replace public transport trips. For non-commuting, 60 per cent of new cycling trips are

forecast to replace car trips. This flexible substitution pattern is facilitated by the specification of error components in the mixed logit models.

6.1.3.2 Marginal rates of substitution

Marginal rates of substitution between the unconditional parameter estimates for travel time and distance are shown in Table 6.8, with confidence intervals calculated using the Delta method (Equation 3.7). Based on these estimates, commuters, on average, will ride 1.0 km on a cycleway in exchange for: riding 0.7 km not on a cycleway; walking for 2.8 minutes; or driving for 1.2 minutes. Non-commuters, on average, will ride 1.0 km on a cycleway in exchange for: riding 0.38 km not on a cycleway; walking for 1.1 minutes; or driving for 2.3 minutes.

Table 6.7: Forecast effect of a 10 per cent increase in cycleway distance and a 10 per cent decrease in non-cycleway distance

	Walk	Bicycle	Public transport	Car	Total
Commuting					
Baseline mode share (%)	19.753	13.190	36.795	30.262	100
Baseline trips	743	496	1,385	1,139	3,763
Forecast mode share (%)	19.623	13.757	36.534	30.085	100
Forecast trips	738	518	1,375	1,132	3,763
Change in mode share (pp)	-0.13	+0.57	-0.26	-0.18	0.00
Change in trips	-5	+22	-10	-7	0
Non-commuting					
Baseline mode share (%)	37.669	3.843	13.528	44.960	100
Baseline trips	3,283	335	1,179	3,919	8,716
Forecast mode share (%)	37.632	4.01	13.493	44.866	100
Forecast trips	3,280	350	1,176	3,910	8,716
Change in mode share (pp)	-0.04	+0.17	-0.04	-0.09	0.00
Change in trips	-3	+15	-3	-9	0

pp: percentage points

Table 6.8: Marginal rates of substitution between unconditional parameter estimates

Variable A	Variable B	Marginal rate of substitution (95% CI)	
		Commuting	**Non-commuting**
Non-CW distance	CW distance	1.41 (1.01 to 1.8)	2.64 (0.89 to 4.38)
Non-CW distance	Time-walk	3.92 (3.19 to 4.65)	2.89 (2.02 to 3.76)
Non-CW distance	Time PT	4.41 (3.58 to 5.24)	13.64 (8.86 to 18.41)
Non-CW distance	Time-car	1.71 (1.4 to 2.03)	5.95 (4.09 to 7.81)
CW distance	Non-CW distance	0.71 (0.51 to 0.91)	0.38 (0.13 to 0.63)
CW distance	Time-walk	2.79 (2.36 to 3.22)	1.1 (0.58 to 1.61)
CW distance	Time-PT	3.14 (2.69 to 3.58)	5.18 (2.75 to 7.6)
CW distance	Time-car	1.22 (1.04 to 1.4)	2.26 (1.22 to 3.29)
Time-walk	Time-PT	1.13 (1.04 to 1.21)	4.72 (3.66 to 5.78)
Time-walk	Time-car	0.44 (0.41 to 0.47)	2.06 (1.72 to 2.39)
Time-PT	Time-car	0.39 (0.37 to 0.41)	0.44 (0.38 to 0.49)

Marginal rates of substitution between the parameter estimates for non-cycleway distance and cycleway distance for individual respondents (conditioned on their actual choices) are plotted in Figure 6.2 (for commuting) and Figure 6.3 (for non-commuting). For most respondents, their marginal rate of substitution is close to the unconditional rate. For commuting, there are three respondents whose conditional rate is outside the 95 per cent confidence interval of the unconditional rate. There are no obvious relationships between these respondents, in terms of their sociodemographic characteristics, or their reported travel behaviour.

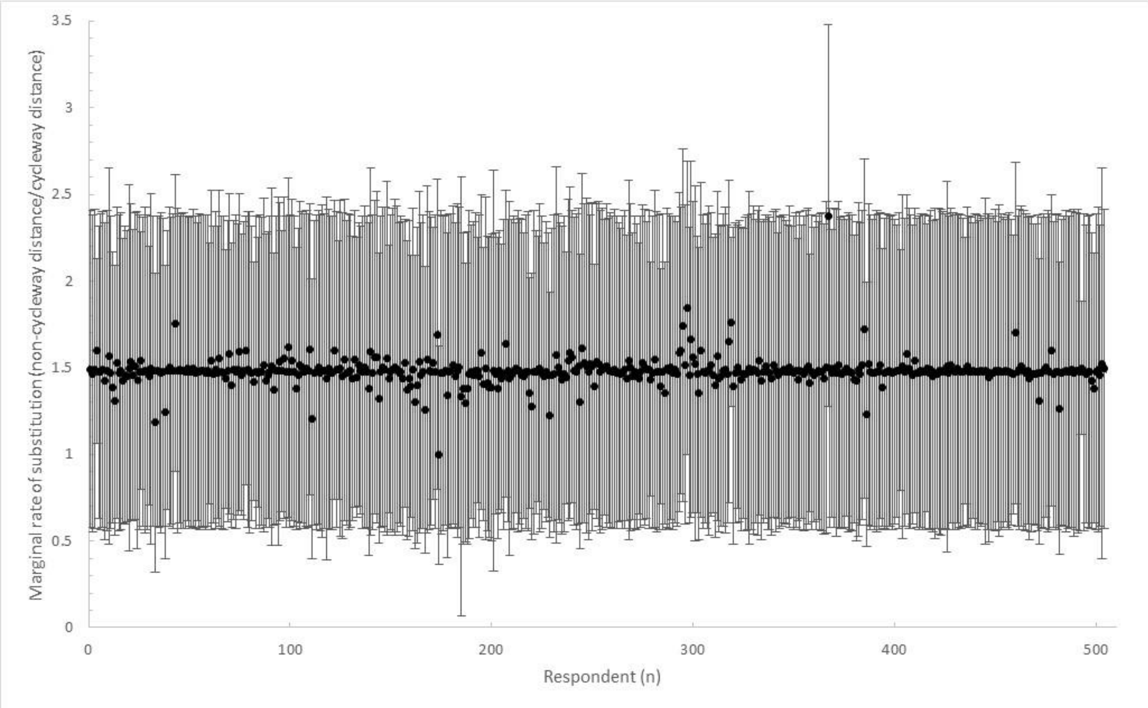


Figure 6.2: Individual marginal rates of substitution for commuting trips (n = 504)

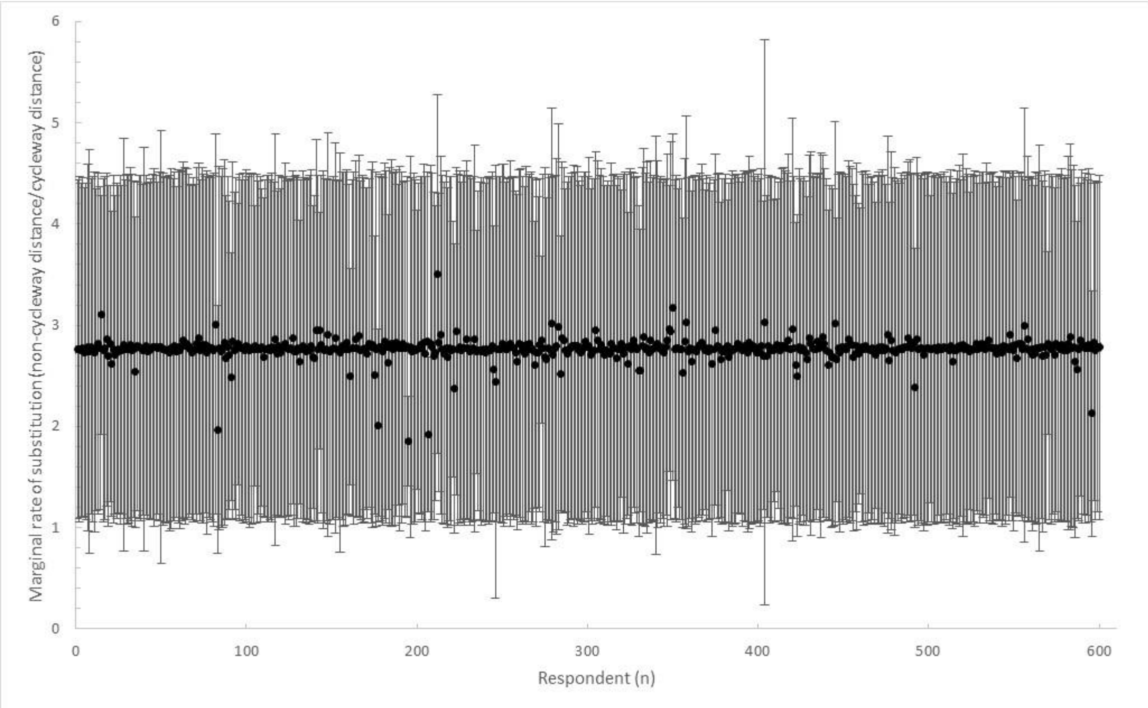


Figure 6.3: Individual marginal rates of substitution for non-commuting trips (n = 600)

6.2 Forecast changes in travel behaviour/demand

This section presents the travel demand forecasts for the four bicycle network scenarios (Table 5.10 and Figure 5.4), which were simulated using the parameter estimates obtained from the baseline mode choice models (Section 6.1).

6.2.1 Mode shares

Forecast transport mode shares for the intervention group in each scenario are shown in Table 6.9. The forecast 'Do nothing' (2013) mode shares differ slightly from the actual 2013 mode shares for two reasons. First, actual rainfall during the baseline data collection was higher than the 10-year average value used in the simulation. Second, prediction success for both baseline choice models is less than 100 per cent – as is generally the case with regression-type modelling.

Table 6.9: Forecast mode shares (sample)

		Mode shares (%)				Versus 'Do nothing' (percentage points)			
Scenario	**Year**	**Walk**	**Bicycle**	**PT**	**Car**	**Walk**	**Bicycle**	**PT**	**Car**
Commuting									
Actual mode shares	2013	24.0	12.5	43.1	20.4	-	-	-	-
'Do nothing' (A)	2013	21.8	14.3	40.8	23.0	-	-	-	-
George St Cycleway (B)	2014	21.4	18.1	38.3	22.2	-0.4	+3.7	-2.6	-0.7
George St + CBD Cycleways (C)	2015	21.0	21.2	36.0	21.8	-0.8	+6.9	-4.9	-1.2
Complete Network (D)	2017	18.6	34.5	28.0	18.9	-3.2	+20.2	-12.9	-4.1
Non-commuting									
Actual mode shares	2013	43.8	5.7	10.6	40.0	-	-	-	-
'Do nothing' (A)	2013	44.8	4.2	12.3	38.7	-	-	-	-
George St Cycleway (B)	2014	44.7	4.7	12.2	38.4	-0.1	+0.5	-0.1	-0.3
George St + CBD Cycleways (C)	2015	44.7	4.9	12.1	38.3	-0.1	+0.6	-0.2	-0.4
Complete Network (D)	2017	44.1	7.3	11.7	36.9	-0.7	+3.1	-0.7	-1.7

To correct for the over-representation of bicycle users in the sample, the 2013 'Do nothing' forecast was calibrated to the actual 2013 mode shares for the intervention area adult population (ages 18 to 55). The resulting mode shares for each scenario are as shown in Table 6.10. The bicycle mode share is predicted to increase, largely at the expense of public transport in the case of commuting, and largely at the expense of car trips in the case of non-commuting. Again, this flexible substitution pattern is facilitated by the inclusion of error components in the mixed logit models. The bicycle mode share increase is greater for commuting trips than for non-commuting trips, in terms of both percentage points and percentage change. This is intuitive, given the proposed cycleways are primarily designed to connect residential areas with the employment-rich CBD.

Table 6.10: Forecast mode shares (calibrated)

		Mode shares (%)				Versus 'Do nothing' (percentage points)			
Scenario	**Year**	**Walk**	**Bicycle**	**PT**	**Car**	**Walk**	**Bicycle**	**PT**	**Car**
Commuting									
'Do nothing' (A)	2013	12.9	4.5	40.9	38.8	-	-	-	-
George St Cycleway (B)	2014	12.6	5.6	38.3	37.5	-0.2	+1.2	-2.6	-1.2
George St + CBD Cycleways (C)	2015	12.4	6.6	36.0	36.8	-0.5	+2.1	-4.9	-2.0
Complete Network (D)	2017	11.0	10.7	28.0	31.9	-1.9	+6.3	-12.9	-6.9
Non-commuting									
'Do nothing' (A)	2013	51.1	2.7	14.2	34.4	-	-	-	-
George St Cycleway (B)	2014	51.0	3.0	14.1	34.2	-0.1	+0.3	-0.1	-0.2
George St + CBD Cycleways (C)	2015	51.0	3.1	14.0	34.1	-0.1	+0.4	-0.2	-0.3
Complete Network (D)	2017	50.3	4.6	13.4	32.9	-0.8	+2.0	-0.8	-1.6

6.2.2 Bicycle kilometres travelled

Forecast BKT for the intervention area population (ages 18 to 55) for each scenario are shown in Table 6.11. The forecast BKT increases are due to a combination of (a) people changing mode to bicycle, and (b) existing bicycle users diverting from their previous route to use cycleways. Most of the change in BKT is forecast to be from commuting travel.

Table 6.11: Forecast annual BKT

		Commuting (N = 18,742)		Non-commuting (N = 30,388)		Total	
Scenario	**Year**	**BKT (km)**	**Versus 'Do nothing'**	**BKT (km)**	**Versus 'Do nothing'**	**BKT (km)**	**Versus 'Do nothing'**
'Do nothing' (A)	2013	1,301,765	-	1,224,215	-	2,525,980	-
George St Cycleway (B)	2014	1,702,996	401,231 (+31%)	1,446,985	222,770 (+18%)	3,149,981	624,001 (+25%)
George St + CBD Cycleways (C)	2015	2,097,039	795,273 (+61%)	1,558,456	334,241 (+27%)	3,655,495	1,129,514 (+45%)
Complete Network (D)	2017	2,986,654	1,684,889 (+129%)	2,204,799	980,584 (+80%)	5,191,454	2,665,473 (+182%)

6.3 Economic appraisal

6.3.1 User benefits

Consumer surplus estimates for each scenario are presented in Table 6.12 (for commuting) and Table 6.13 (for non-commuting). The inclusive value (second column) is a measure of the disutility of travel in each scenario – an increase can be interpreted as an improvement in accessibility and transport options.

In the third column, these inclusive values are converted into average hours of driving travel time per respondent. Thus, the average disutility of commuting over seven days is equivalent to 1.88 hours of driving in the 'Do nothing' scenario (A), decreasing to 1.77 hours in the 'Complete Network' scenario (D). The average disutility of non-commuting travel over seven days is equivalent to 6.85 hours of driving in Scenario A, decreasing to 6.82 hours in Scenario D.

In the fourth column, hours of travel time are monetised using the NSW Government's 2013 value of travel time savings for private car occupants (AUD 15.14) (Transport for NSW, 2013a). Expansion factors are applied to give a weighted estimate for the intervention area's adult population (ages 18 to 55).

The improved accessibility and transport options afforded to the intervention area adult population (ages 18 to 55) by the George Street Cycleway (Scenario B) are valued at almost $300,000 per annum. The improved accessibility and transport options afforded by the Complete Network (Scenario D) are valued at over $2.3 million per annum. However, the Complete Network covers the whole City of Sydney local government area (population aged 18 to 55: 129,755), not just the intervention area for the Sydney Travel and Health Study (population aged 18 to 55: 30,388). Assuming the benefit of the Complete Network to the average intervention area resident is representative of the benefit to the average City of Sydney resident, then the improved accessibility and transport options can be valued at almost $10 million per annum.[46] The user benefit per kilometre for the single George Street Cycleway is $124,782, whereas for the Complete Network it is $219,883. This suggests the user benefits of individual cycleway links are amplified when they are connected into a network.

Table 6.12: Forecast change in consumer surplus – commuting trips

	Sample (n = 229)	Average respondent	Intervention area commuters ages 18 to 55 (N = 18,742)		City of Sydney commuters ages 18 to 55 (N = 80,027)
Scenario	**Inclusive value (logsum)**	**Hours of driving time (7 days)**	**Consumer surplus valuation (48 weeks)**	**Change in annual consumer surplus versus 'Do nothing'**	**Change in annual consumer surplus versus 'Do nothing'**
'Do nothing' (A)	-20,202	1.88	-$26,218,204	-	-
George St Cycleway (B)	-20,045	1.87	-$26,019,879	+$198,325	-
Complete Network (D)	-18,990	1.77	-$24,660,114	+$1,558,090	+$6,652,952

Table 6.13: Forecast change in consumer surplus – non-commuting trips

	Sample (n = 259)	Individual respondent (n = 1)	Intervention area residents ages 18 to 55 (N = 30,338)		City of Sydney residents ages 18 to 55 (N = 129,755)
Scenario	**Inclusive value (logsum)**	**Hours of driving time (7 days)**	**Consumer surplus valuation (48 weeks)**	**Change in annual consumer surplus versus 'Do nothing'**	**Change in annual consumer surplus versus 'Do nothing'**
'Do nothing' (A)	-11,847	6.85	-$157,145,700	-	-
George St Cycleway (B)	-11,840	6.85	-$157,052,449	+$93,251	-
Complete Network (D)	-11,790	6.82	-$156,386,493	+$759,207	+$3,241,770

6.3.2 Social cost benefit analysis

The economic appraisals of the George Street Cycleway (Scenario B) and the Complete Network (Scenario D) are presented in Table 6.14, with discount rates of 4, 7 and 10 per cent. For Scenario B, all construction costs are assumed to be incurred in the base year (2013). For Scenario D, construction costs are phased

[46] In addition, people living outside the City of Sydney local government area would also benefit, if they travel to or through the City if Sydney.

over five years (2013 to 2017 inclusive), with future costs discounted at the applicable rate. The annual maintenance cost in both scenarios is assumed to be 1 per cent of the construction cost.

Annual public health benefits are estimated by multiplying forecast BKT increases (Section 6.2.2) by the Mulley et al. (2013) valuation of $1.21 per BKT. From this is subtracted the value of diverted walking trips, using the Mulley at al. (2013) valuation of $1.80 per walking kilometre. Annual user benefits are valued as described in Section 6.3.1. Public health and user benefits accrue from the time a cycleway opens, until the end of the 30-year appraisal period (2042), and are discounted at the applicable rate.

At the discount rate of 7 per cent recommended by Transport for NSW, the George Street Cycleway has a benefit-cost ratio of 2.61, indicating this project is very worthwhile from a welfare economic perspective. Almost one third (32 per cent) of the benefit stream comprises user benefits. The Complete Network has a higher benefit-cost ratio (3.42), with 43 per cent of the benefit stream comprising user benefits.

Due to data restrictions, this economic appraisal does not include potential benefits accruing to residents aged under 18 or over 55, nor to people living outside the City of Sydney local government area who may derive a benefit from the new infrastructure. As such, these economic indicators are conservative estimates.

However, three key observations can be made. First, the user benefits are of a similar order of magnitude to the public health benefits. Second, investment in cycleways is much more worthwhile from a welfare economic perspective if they are developed as part of a connected network, i.e., the value of a cycleway network is greater than the sum of its parts – and the user benefits increase at a greater rate than the public health benefits. Third, the welfare economic benefit of the proposed cycleways derives mostly from residents having improved accessibility to work/study (as opposed to access to other activities).

Table 6.14: Economic appraisal of George Street Cycleway – user benefits estimated using DCA

Scenario	George Street Cycleway (B)			Complete Network (D)		
Discount rate	4%	7%	10%	4%	7%	10%
Present value of investment	$4,673,365	$4,673,365	$4,673,365	$95,012,503	$89,196,038	$83,925,743
Present value of maintenance costs	$793,711	$573,781	$437,876	$16,570,392	$12,043,119	$9,187,177
Present value of welfare costs/benefits						
Public health benefits accruing from increased BKT	$15,054,002	$10,578,193	$7,894,455	$306,943,364	$220,811,544	$167,321,056
Public health costs from reduced walking	-$2,687,326	-$1,888,339	-$1,409,258	-$54,793,196	-$39,417,598	-$29,868,883
Net public health benefits	$12,366,676	$8,689,854	$6,485,197	$252,150,169	$181,393,946	$137,452,173
User benefits	$5,813,434	$4,085,002	$3,048,618	$190,674,173	$137,386,314	$104,211,313
Total	$18,180,110	$12,774,856	$9,533,815	$442,824,342	$318,780,260	$241,663,487
Decision criteria						
NPV	$12,923,306	$7,870,982	$4,887,232	$336,623,777	$225,457,875	$158,332,330
NPVI	$2.77	$1.68	$1.05	$3.54	$2.53	$1.89
BCR	3.46	2.61	2.05	4.17	3.42	2.90

Pricing year: 2013
Appraisal period: 30 years (2013-2042)
Population growth: 1.1% per annum

For comparison, an economic appraisal of the George Street Cycleway (Scenario B), undertaken following the Transport for NSW guidelines (Transport for NSW, 2013a), is presented in Table 6.15.

Again, the appraisal includes only adults aged 18 to 55 living in the intervention area, with the change in bicycle demand as previously estimated (see Section 6.2).

As discussed in Section 2.3, Transport for NSW includes road tolling and public transport fare savings, which are (by definition) transfer payments and, therefore, do not belong in a social cost benefit analysis. Transport for NSW also includes reduced motor vehicle externalities, despite there being no clear empirical evidence that a marginal increase in bicycle use will result in a sustained decrease in motor vehicle use.

Benefits are offset by an increase in bicycle rider injuries; though it could be argued much of this cost should be attributed to motor vehicles (see Section 2.4.1).

Excluding injury costs, the public health benefits account for 80 per cent of all benefits. There are no benefits to users of the new infrastructure, unless it is assumed some portion of the public health benefit accrues to users. However, the guidelines imply people choose to cycle for altruistic reasons, stating that "choosing to ride a [bicycle] is aimed at improving health and gaining *other social benefits* but not to reach a destination faster" (Transport for NSW, 2013a, p. 157). In this appraisal, the estimated benefits of the project do not justify the cost, whichever discount rate is used.

Table 6.15: Economic appraisal of George Street Cycleway – NSW guidelines

Costs and benefits	Value over project life	Present Value over project life (discounted at 7%)	Percentage of Present Value costs and benefits
Costs			
Construction cost	-$4,673,365	-$4,673,365	89%
Maintenance cost	-$1,402,020	-$579,924	11%
Operating costs	$0	$0	0%
Other costs	$0	$0	0%
Total cost	-$6,075,385	-$5,253,289	100%
Benefits			
Parking cost savings	$1,771	$695	0%
Congestion cost savings	$44,272	$17,372	7%
Reduction in motor vehicle operating costs (incl. fuel)	$44,272	$17,372	7%
Roadway provision cost savings	$6,325	$2,482	1%
Public transport fare cost savings (bus)	$29,816	$11,700	5%
Public transport fare cost savings (train)	$3,329	$1,306	1%
Tolling cost savings	$4,933	$1,936	1%
Bicycle accident cost savings	-$103,156	-$40,479	-17%
Reduced noise from cars	$1,265	$496	0%
Reduced air pollution from cars	$3,997	$1,568	1%
Reduced greenhouse gas emissions from cars	$3,162	$1,241	1%
Reduced water pollution from cars	$607	$238	0%
Improved health	$561,616	$220,379	93%
Total benefits	$602,207	$236,307	100%
Decision criteria			
Discount rate	**4%**	**7%**	**10%**
Present value of costs	-$5,481,491	-$5,253,289	-$5,113,922
Present value of benefits	$336,293	$236,307	$176,355
NPV	-$5,145,198	-$5,016,982	-$4,937,567
BCR	0.1	0.0	0.0
NPVI	-1.10	-1.07	-1.06
FYRR	0%	0%	0%

6.4 Actual changes in travel behaviour/demand

6.4.1 Bicycle traffic counts

Changes in peak-time bicycle traffic counts along the George Street corridor are presented in Table 6.16. At Site A (closest to the CBD), there was a 23 per cent increase in bicycle traffic at the time of Wave 2, falling back to 9 per cent at the time of Wave 3 (relative to Wave 1). At Site B, there was a 102 per cent increase at the time of Wave 2, increasing to 124 per cent at the time of Wave 3 (relative to Wave 1).

Table 6.16: Changes in bicycle counts 2012 to 2016

			Wave 1		Wave 2		Wave 3	
	October 2012	**March 2013**	**October 2013**	**March 2014**	**October 2014**	**March 2015**	**October 2015**	**March 2016**
George Street: Site A (North)	774	713	812	972	1001	923	886	888
Change from Wave 1					+23%		+9%	
Population increase since Wave 1[a]					+4.5%		+10.2%	
George Street: Site B (South)	242	237	201	369	406	450	450	588
Change since Wave 1					+102%		+124%	
Population increase since Wave 1[b]					+7.7%		+19.5%	
Other 98 count sites (average)	488	553	552	600	566	519	472	464
Change since Wave 1					+3%		-14%	
Population increase since Wave 1[c]					+3.3%		+10.0%	

[a] For the suburb of Redfern (Australian Bureau of Statistics, 2017).
[b] For suburb of Green Square (Australian Bureau of Statistics, 2017).
[c] For the City of Sydney local government area (Australian Bureau of Statistics, 2017).

Comparing the traffic counts at these sites with the average for the other 98 count sites in the City of Sydney local government area (Figure 6.4), it appears that bicycle traffic along the George Street corridor increased after the cycleway opened, despite a general decline in peak-time bicycle use in the City of Sydney.

It should be noted that the residential population increased more in the suburbs through which the cycleway passes than in the City of Sydney as a whole. Furthermore, it is possible some new residents chose to move to these suburbs because of the new cycleway (i.e., residential self-selection). However, in the March 2015 intercept survey, only 2.3 per cent of intercepted riders stated they had moved to the area after the cycleway opened (Table 6.17), suggesting population growth and residential self-selection had little effect on the bicycle counts.

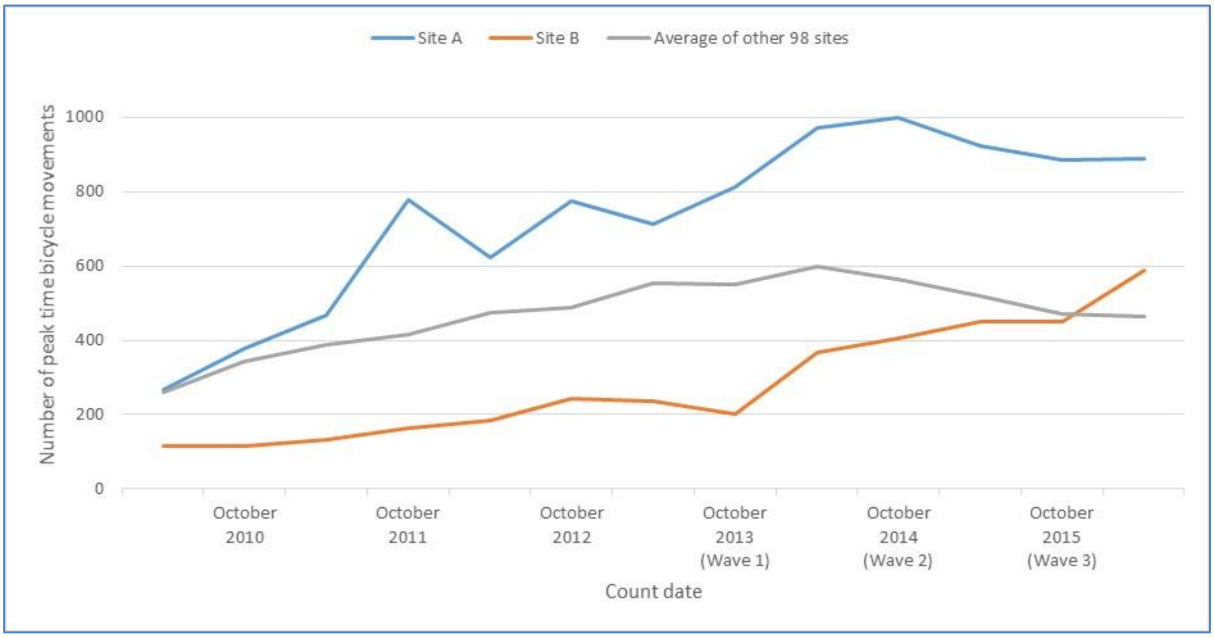


Figure 6.4: Change in peak-time bicycle traffic

6.4.2 Intercept survey

6.4.2.1 Sample characteristics

In total, 1,079 bicycle riders were intercepted at the two sites over the two-week survey in March 2015. Of these, 783 (73 per cent) agreed to being surveyed, 127 (12 per cent) advised they had been surveyed previously doing the same trip (so were not re-surveyed), and 169 (16 per cent) declined. The characteristics and responses of the final sample (n = 783) are summarised in Table 6.17. The majority of respondents appeared to be male (71 per cent), and more than half (56 per cent) had an estimated age of between 30 and 60 years. The majority were dressed in casual clothing (60 per cent); fewer were wearing cycling-specific attire (31 per cent) or business attire (8 per cent). The majority (61 per cent) reported they had been riding regularly for more than two years. The purpose of most trips (59 per cent) was commuting to work. The majority of respondents (63 per cent) lived or worked in the suburbs through which the George Street Cycleway passes.

Table 6.17: Sample summary statistics (n = 783)

Variable	Category	Frequency[a]	%
Trip purpose	Commuting to work	465	59.4
	Shopping/personal business	82	10.5
	Other	225	28.7
Transport mode used before cycleway opened	Bicycle	433	55.3
	Train	105	13.4
	Other	180	23.0
	Would not have made trip	32	4.1
	Moved to area after cycleway opened	18	2.3
Changed bicycle route after the cycleway opened	Yes	336	42.9
	No	228	29.1
	N/A[c]	168	21.4
Length of time riding regularly (years)	≤ 2	308	36.1
	> 2	475	60.7
Observed attire	Cycling-specific	240	30.7
	Causal	469	59.9
	Business	66	8.4
Observed gender	Male	553	70.6
	Female	218	27.8
Estimated age (years)	18 to 29	296	37.8
	30 to 60	436	55.7
	> 60	43	5.5

[a] Some totals do not add up to 783 due to missing observations.
[b] Would not have made trip, or recently moved.
[c] Did not use bicycle before cycleway opened, or recently moved.

6.4.2.2 Changes in transport mode

For the mode change analysis, complete data were available for 691 (88 per cent) of the 783 respondents. Of these, 40 per cent said they had switched from another mode of travel to bicycle since the cycleway opened. Of those who had previously used another mode, 21 per cent stated they had previously driven, 59 per cent said they had used public transport, and 20 per cent had walked.

The logistic regression model of mode change for all trip purposes (Table 6.18) shows that those who had changed mode to bicycle were more likely to have been riding regularly for two years or less (adjusted odds ratio (AOR) 8.73, 95% confidence interval (CI) 5.86 to 13.00) and have an estimated age of 30 years or more (AOR 1.75, 95% CI 1.17 to 2.62). A chi-square test of the full model against a constant only model is statistically significant ($p < 0.01$), indicating that the independent variables as a set reliably distinguish between mode switchers and non-switchers. Prediction success is also better in the full model (73.8 per cent versus 60.0 per cent). Nagelkerke's R^2 of 0.27 indicates a moderate relationship between prediction and grouping.

The model for commuting trips shows that mode changers were more likely to be female (AOR 1.68, 95% CI 1.10 to 2.77), have been riding regularly for two years or less (AOR 8.45, 95% CI 5.38 to 13.27), and have an estimated age of 30 years or more (AOR 1.74, 95% CI 1.10 to 2.77). In the model for non-commuting trips, mode changers are again more likely to have been riding regularly for two years or less (AOR 9.80, 95% CI 3.81 to 25.19). Model fit statistics for the partitioned models are similar to those for the pooled model.

6.4.2.3 Changes in bicycle route

Overall, 48 per cent of the 415 existing riders said they had changed route since the cycleway opened, with the proportion higher at Site 1 (further from the city centre) than at Site 2 (61 per cent versus 45 per cent).

The logistic regression model of route change for all trip purposes (Table 6.19) shows that route changers were most likely to have been intercepted at Site 1 (AOR 2.07, 95% CI 1.19 to 3.62). There is also some indication that route changers were more likely to be male and not commuting. A chi-square test of the full model against a constant only model is statistically significant ($p = 0.01$). Prediction success is also better in the full model (55.9 per cent versus 51.8 per cent). Nagelkerke's R^2 of 0.05 indicates a poor relationship between prediction and grouping.

Table 6.18: Logistic regression model of cycleway users who had changed mode compared with those who had not

	All trips (n = 618)			Commuting trips (n = 462)			Non-commuting trips (n = 156)		
	AOR	**95% CI**	**p value**	**AOR**	**95% CI**	**p value**	**AOR**	**95% CI**	**p value**
Observed gender									
Female				**1.68**	**1.10 to 2.77**	**0.02**	0.547	0.22 to 1.35	0.19
Male (reference)				1.00					
Estimated age									
≥ 30 years	**1.75**	**1.17 to 2.62**	**< 0.01**	**1.74**	**1.10 to 2.77**	**0.02**	1.95	0.79 to 4.84	0.15
< 30 years (reference)	1.00			1.00			1.00		
Length of time riding regularly									
≤ 2 years	**8.73**	**5.86 to 13.00**	**< 0.01**	**8.45**	**5.38 to 13.27**	**< 0.01**	**9.80**	**3.81 to 25.19**	**< 0.01**
> 2 years (reference)	1.00			1.00			1.00		
Intercept site									
Site 1							2.53	0.93 to 6.91	0.07
Site 2 (reference)							1.00		
Model fit statistics									
Chi-square	$p < 0.01$			$p < 0.01$			$p < 0.01$		
Nagelkerke's R^2	0.27			0.28			0.27		
Prediction success (full model)	73.8%			73.2%			76.9%		
Prediction success (constant only)	60.0%			56.7%			69.9%		

The model for commuting trips is similar to the pooled model, with route changers most likely to have been intercepted at Site 1 (AOR 2.65, 95% CI 1.41 to 4.98), and a similar model fit. The model for non-commuting trips is not significantly different from a constant only model (p = 0.77).

Table 6.19: Logistic regression model of cycleway users who had changed route compared with those who had not

	All trips (n = 371)			**Commuting trips (n = 262)**		
	AOR	**95% CI**	**p value**	**AOR**	**95% CI**	**p value**
Observed gender						
Female	0.70	0.44 to 1.13	0.14	0.60	0.34 to 1.09	0.09
Male (reference)	1.00			1.00		
Estimated age						
≥ 30 years	1.43	0.92 to 2.21	0.11	1.45	0.86 to 2.47	0.17
< 30 years (reference)	1.00			1.00		
Intercept site						
Site 1	**2.07**	**1.19 to 3.62**	**0.01**	**2.65**	**1.41 to 4.98**	**< 0.01**
Site 2 (reference)	1.00			1.00		
Trip purpose						
Commuting to work or study	0.70	0.44 to 1.10	0.12			
Other (reference)	1.00					
Model fit statistics						
Chi-square	p = 0.01			p < 0.01		
Nagelkerke's R^2	0.05			0.07		
Prediction success (full model)	57.4%			59.5%		
Prediction success (constant only)	52.8%			53.8%		

6.4.2.4 Diversion to use cycleway

Of the 783 respondents, 643 (82 per cent) were riding for transport purposes and gave sufficient information about their trip origins and destinations for network distances to be estimated in the GIS model. The average estimated distance respondents had diverted to use the cycleway was 351 metres (σ = 870), with commuters diverting by 252 metres on average (σ = 411), and non-commuters by 544 metres on average (σ = 1372). Descriptive statistics for the estimated diversion distance are provided in Table 6.20.

Table 6.20: Descriptive statistics for estimated diversion distance (metres)

	Commuting trips (n = 485)	Non-commuting trips (n = 246)	All trips (n = 643)
Mean	252	505	315
Standard deviation	411	1481	822
First quartile	26	40	26
Median	140	197	150
Third quartile	283	428	333

The final multiple linear regression model to predict diversion distance suggests that only trip purpose ($p < 0.01$) and shortest path network distance ($p < 0.01$) are significant, with observed gender, estimated age, length of time riding regularly, and intercept site not significant. The regression equation is:

$$\text{Diversion distance (km)} = 0.295 + 0.050 \times \text{Network distance (km)} - 0.321 \times \text{Commute}, \quad R^2 = 0.08, p < 0.01. \tag{6.9}$$

In the model for commuters, only shortest path network distance ($p < 0.01$) is significant. The regression equation is:

$$\text{Diversion distance (km)} = 0.171 + 0.015 \times \text{Network distance (km)}, \quad R^2 = 0.02, p < 0.01. \tag{6.10}$$

In the model for non-commuters, shortest path network distance ($p < 0.01$) and intercept location ($p = 0.01$) are significant, with predicted diversion distance greater for respondents intercepted at Site 1 (furthest from the CBD). The regression equation is:

$$\text{Diversion distance (km)} = -0.622 + 0.240 \times \text{Network distance (km)} + 0.746 \times \text{Site 1}, \quad R^2 = 0.32, p < 0.01. \tag{6.11}$$

6.4.3 Longitudinal resident survey

6.4.3.1 Sample characteristics

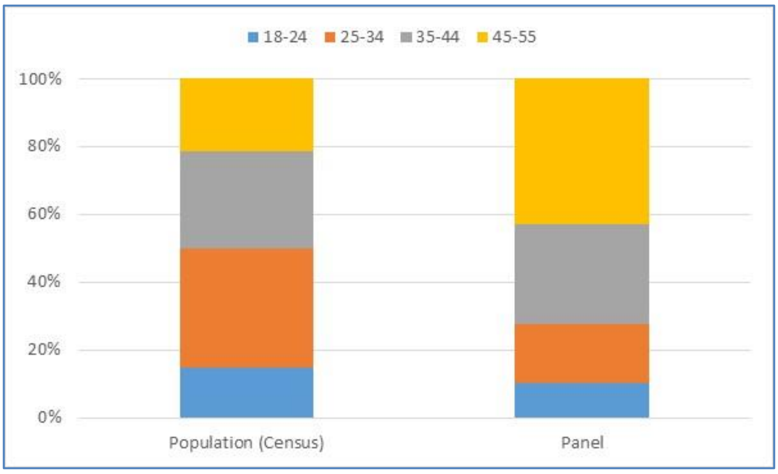
In total, 363 respondents satisfactorily completed the seven-day travel diary in all three waves of the Sydney Travel and Health Study (148 from the intervention area and 215 from the control area), allowing changes in their travel behaviour following the opening of the George Street Cycleway to be assessed. The demographic profile of this panel is summarised, and compared with that of the study area population, in Table 6.21 and Figure 6.5.

Table 6.21: Characteristics of resident panel

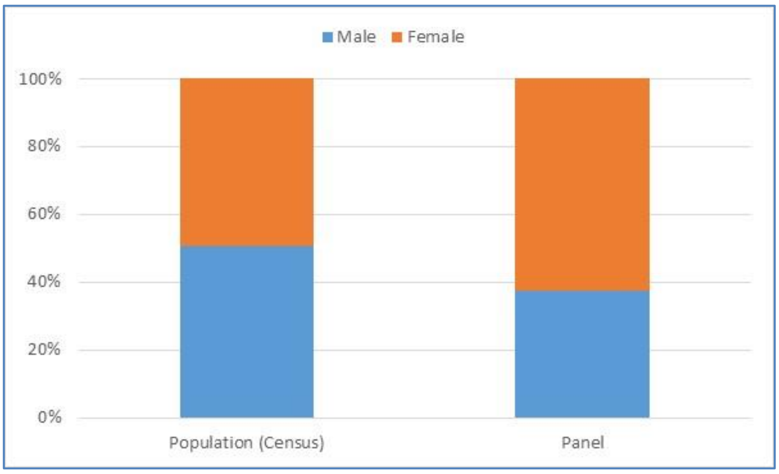
	Panel n = 363 (%)	Baseline sample n = 604 (%)	Population (Census) N = 46,459 (%)
Gender			
Male	37.5	40.1	50.6
Female	62.5	59.9	49.4
Age			
18 to 24	10.2	14.6	14.7
25 to 34	17.4	24.8	35.1
35 to 44	29.5	26.3	28.9
45 to 55	43.0	34.2	21.2
Commuting mode			
Walk	22.4	21.3	12.6
Bicycle	12.2	14.2	4.4
Public transport	36.4	37.5	37.5
Car	28.9	27.0	45.5

Compared to the population, the panel has fewer males and more people aged 45 to 55. These differences must be noted, but are not a major concern for panel analysis, because they are constant over time. In terms of usual commuting mode, walking and cycling is more prevalent in the panel than the population.

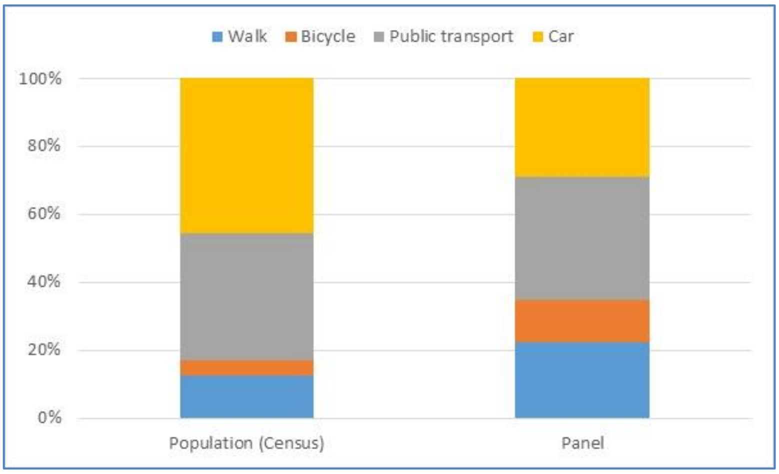
The final logistic regression model comparing the intervention and control groups in Wave 2 (Table 6.22) shows that awareness, use of, and intention to use the new cycleway were significantly higher in the intervention group compared with the control group. Of respondents who reported having used the cycleway, 75 per cent lived in the intervention area. Three times as many respondents in the intervention group were aware of the new cycleway (60 per cent) compared with the control group (19 per cent) (adjusted odds ratio (AOR) = 5.99, 95% CI 3.87 to 9.27). Use of the cycleway was significantly higher in the intervention group (24 per cent) than in the control group (7 per cent) (AOR = 3.58, 95% CI 2.01 to 6.40). Intention to use the cycleway among the intervention group (36 per cent) was more than double that among the control group (16 per cent) (AOR = 2.77, 95% CI 1.76 to 4.37).



(a) Age profile of panel versus population



(b) Gender profile of panel versus population



(c) Commuting mode shares of panel versus population

Figure 6.5: Characteristics of resident panel (at Wave 1)

Respondents in the intervention group were significantly more likely than respondents in the control group to agree/strongly agree that, compared to 12 months previously: their neighbourhood was more pleasant (48 per cent versus 30 per cent) (AOR = 2.44, 95% CI 1.63 to 3.66); there were more people walking in their local area (54 per cent versus 38 per cent) (AOR = 2.04, 95% CI 1.37 to 3.03); and there were more people cycling in their local area (75 per cent versus 59 per cent) (AOR = 2.48, 95% CI 1.62 to 3.79) (see Table 6.22). There was no significant difference in respondents reporting they felt more connected to their neighbours.

In the Wave 2 questionnaire, 15 per cent of respondents reported they had used the new cycleway since it opened six months previously. However, 24 per cent of these lived in the control area, suggesting the binary exposure measure (intervention/control) is not ideal (or the control area was too close to the intervention).

Therefore, in the logistic regression model of cycleway use for Wave 2 (Table 6.23), residential proximity to the cycleway was used as the exposure variable instead. As distance from the cycleway decreases (500 metre increments), likelihood of using the cycleway increases significantly (AOR = 1.24, 95% CI 1.13 to 1.37). In addition, those who reported having used the cycleway were most likely to identify as a high-intensity recreational rider (AOR = 4.38, 95% CI 1.53 to 12.59) or as a low-intensity transport rider (AOR = 2.42, 95% to 1.17–5.04), and to have ridden a bicycle in the past week (AOR = 7.50, 95% CI 3.93 to 14.31).

Table 6.22: Comparison between intervention and control groups in Wave 2 (n = 512)

	Control (%)	Intervention (%)	Odds ratio (intervention vs. control)	Adjusted odds ratio (95% CI)[a]	p value
Bicycle path interaction					
Awareness	18.8	60.0	6.49	**5.99 (3.87 to 9.27)**	**< 0.001**
Use of bicycle path	7.0	23.8	4.15	**3.58 (2.01 to 6.40)**	**0.001**
Intention to use (Very likely/likely)	15.8	35.8	2.97	**2.77 (1.76 to 4.37)**	**< 0.001**
Neighbourhood factors					
Compared with 12 months ago (agree/strongly agree):					
I feel more connected with my neighbours	40.2	37.6	0.88	1.09 (0.72 to 1.58)	0.612
My neighbourhood is more pleasant	29.5	47.5	2.14	**2.44 (1.63 to 3.66)**	**< 0.001**
There are more people walking in my local area	37.6	53.7	1.94	**2.04 (1.37 to 3.03)**	**< 0.001**
There are more people cycling in my local area	58.7	74.8	2.04	**2.48 (1.62 to 3.79)**	**< 0.001**
Agree/strongly agree that:					
It is easy to ride a bicycle around your local area	64.0	71.3	1.39	1.37 (0.90 to 2.08)	0.201
There are bicycle facilities in my local area	74.6	85.4	2.12	**2.08 (1.26 to 3.42)**	**< 0.001**
Cycling frequency					
Bicycled in past week	23.2	25.8	1.16	1.07 (0.67 to 1.69)	0.767

[a] Adjusts for age, gender, income and education.

Table 6.23: Factors associated with respondents who used new cycleway in Wave 2 versus those who had not

	%	Odds ratio (95% CI)	Adjusted odds ratio (95% CI)[a]	p value
Age				
18 to 24	15.5	1.0	1.0	
25 to 34	20.9	1.44 (0.62 to 3.36)	0.54 (0.18 to 1.57)	0.890
35 to 44	18.4	1.23 (0.53 to 2.85)	0.73 (0.25 to 2.15)	0.953
45 to 55	9.6	0.58 (0.25 to 1.34)	0.42 (0.14 to 1.24)	0.192
Gender				
Female	13.9	1.0	1.0	
Male	16.3	1.21 (0.74 to 1.99)	0.64 (0.34 to 1.21)	0.306
Education				
Less than tertiary	13.0	1.0	1.0	
Tertiary or higher	15.5	1.23 (0.69 to 2.20)	0.83 (0.39 to 1.77)	0.908
Income				
Less than AUD 80K	13.2	1.0	1.0	
AUD 80K or more	17.0	1.34 (0.75 to 2.39)	1.26 (0.63 to 2.54)	0.551
Weekly cycling frequency				
Less than weekly		1.0	1.0	
At least weekly		**7.44 (4.41 to 12.56)**	**7.50 (3.93 to 14.31**)	**< 0.001**
Bicycle rider type				
Low-intensity recreational	7.0	1.0	1.0	
High-intensity recreational	30.3	**5.79 (2.45 to 13.68)**	**4.38 (1.53 to 12.59)**	**0.026**
Low-intensity transport	25.4	**4.54 (2.50 to 8.22)**	**2.42 (1.17 to 5.04)**	**0.032**
High-intensity transport	31.0	**5.97 (2.72 to 13.09)**	2.40 (0.90 to 6.44)	0.598
Residential proximity to cycleway				
500m intervals[b]		**1.21 (1.12 to 1.31)**	**1.24 (1.13 to 1.37)**	**< 0.001**
100m intervals[b]		**1.04 (1.02 to 1.05)**	**1.04 (1.02 to 1.06)**	**< 0.001**

[a] Adjusted for all other variables in the model.

[b] One or the other included in the model at one time.

6.4.3.2 Travel diary

Of the 29,168 valid trips reported in the three waves of the travel diary, 26,983 (92.5 per cent) were for transport purposes and fully within the Greater Sydney metropolitan region. At the aggregate level, there was little change in travel behaviour. The average daily trip rate remained stable, and was higher in the intervention area than the control area (see Table 6.24).

Table 6.24: Aggregate changes in travel behaviour

	Intervention (n = 148)			Control (n = 215)			
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3	Total
Total transport trips within Sydney	3,379	3,385	3,375	5,666	5,576	5,602	26,983
Trips per respondent per day	3.26	3.27	3.26	3.76	3.70	3.72	3.54

Overall, the number of respondents who reported at least one bicycle trip increased marginally, from 79 (21.8 per cent) in Wave 1, to 81 (22.3 per cent) in Wave 3. In the intervention group, 14 respondents who did not use a bicycle for transport in Wave 1 did so in Wave 2 and/or Wave 3. One respondent who did use a bicycle in Wave 1 did not do so in Wave 2 or Wave 3. Overall, the number of intervention group respondents who used a bicycle for transport increased from 35 to 39. However, changes over time in cycling participation, bicycle trips and cycling minutes are not statistically significant in either the intervention group or the control group (see Table 6.25). Similarly, the differences-in-differences estimators, which isolate the effect of the intervention from trend or background effects present in both the intervention and control groups, are not statistically significant. Overall, the intervention had no measurable effect on bicycle use among the resident panel, when assessed using a binary exposure variable (intervention/control group).

Table 6.25: Changes in reported bicycle use

	Intervention (n = 148)			**Control (n = 215)**		
	Wave 1	**Wave 2**	**Wave 3**	**Wave 1**	**Wave 2**	**Wave 3**
Cycling participation						
Respondents who used a bicycle	35 (23.6%)	37 (25.0%)	39 (26.4%)	44 (20.5%)	43 (20.0%)	42 (19.5%)
McNemar's repeated measures test (vs. Wave 1)	---	p = 0.80	p = 0.42	---	p = 1.00	p = 0.84
Differences-in-differences estimator for intervention group (vs. Wave 1)	---	+1.8pp (p = 0.60)	+3.6pp (0.29)	---	---	---
Bicycle trips per respondent						
Average	1.65	1.56	1.67	1.34	1.26	1.49
Paired sample t-test (vs. Wave 1)	---	p = 0.68	p = 0.51	---	p = 0.59	p = 0.37
Differences-in-differences estimator for intervention group (vs. Wave 1)	---	0.00 (p = 0.99)	-0.32 (p = 0.29)	---	---	---
Cycling time per respondent (minutes)						
Average	41.6	48.6	50.35	33.8	30.9	44.0
Paired sample t-test (vs. Wave 1)	---	p = 0.24	p = 0.20	---	p = 0.54	p = 0.12
Differences-in-differences estimator for intervention group (vs. Wave 1)	---	+9.99 (p = 0.20)	-1.43 (p = 0.88)	---	---	---
pp = percentage points						

Using the shortest network distance between a respondent's home and the cycleway as the exposure variable, those who lived between 1.00 and 2.99 km from the cycleway were more likely to have increased the time they spent cycling in

Waves 2 and 3, compared to those who lived more than 2.99 km away (see Table 6.26 and Figure 6.6). For those who lived less than 1.00 km from the cycleway, there was no significant change in cycling duration.

Table 6.26: Multilevel linear regression analysis of cycling duration associated with exposure to cycling infrastructure

		Δ Cycling (minutes per week)[a]		
		n	**β (95% CI)**	**p value**
Distance from cycleway	< 1.00 km			
Wave	1	43	9.1 (-48.3 to 66.4)	0.007
	2	33	30.5 (-36.6 to 97.6)	
	3	30	-37.1 (-105.9 to 31.7)	
Distance from cycleway	1.00 to 2.99 km			
Wave	1	37	-2.8 (-63.0 to 57.4)	
	2	25	**76.8 (4.8 to 148.9)**	
	3	18	**96.2 (19.0 to 173.4)**	

[a] Reference category is > 3.00 km from the cycleway.
Adjusts for age and gender and previous waves in the model.

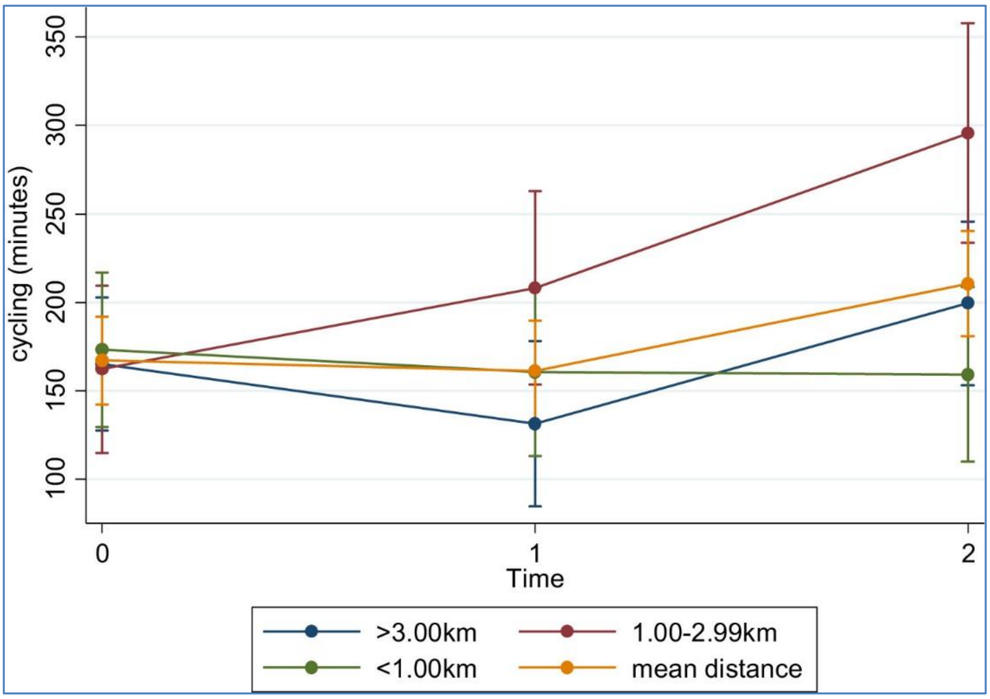


Figure 6.6: Changes in weekly cycling (minutes) by distance from the cycleway

Changes in transport mode shares are shown in Table 6.27. In the intervention group, there were some significant changes in mode shares. The bicycle mode share fell over the three waves. The walking mode share initially increased in Wave 2, but then fell markedly in Wave 3 (see Figure 6.7). The public transport mode share increased. There was no significant change in the mode shares in the control group.

Table 6.27: Changes in mode shares (trips)

	Intervention			Control		
	Wave 1	**Wave 2**	**Wave 3**	**Wave 1**	**Wave 2**	**Wave 3**
Car	34.9	31.6	34.6	52.6	52.9	51.8
Walk	33.8	35.3	31.3	27.6	28.6	28.0
Public transport	19.1	22.3	23.5	13.0	12.5	13.0
Bicycle	8.2	7.9	6.8	4.3	3.9	4.9
Other[a]	3.9	2.9	3.8	2.2	2.4	2.5
Pearson's chi-square (vs. Wave 1)	---	$p < 0.01$	$p < 0.01$	---	$p = 0.35$	$p = 0.61$

[a] Includes motorcycle, taxi, other.

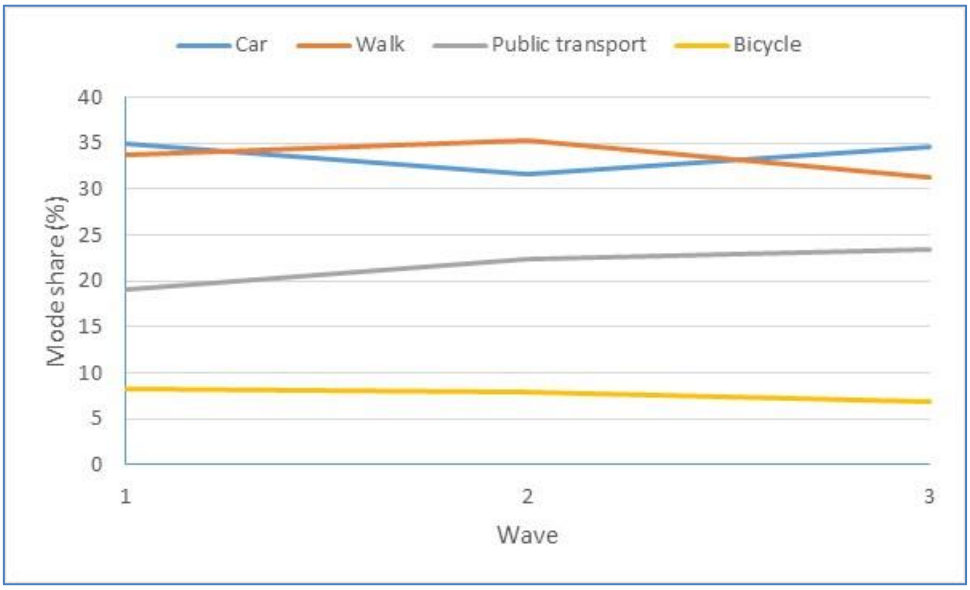


Figure 6.7: Changes in intervention group mode shares

6.5 Temporal preference stability

The travel demand forecasts and economic appraisals for the future scenarios use parameters estimated from the baseline (Wave 1) travel diary data (Section 6.1), and assume these parameters will not change over the 30-year lifetime of the assessed projects. This section presents the results of the temporal preference stability tests, used to test this assumption.

The characteristics of the sample used for these analyses are described in Section 6.4.3.1.

6.5.1 Interaction with wave

Final models of the pooled (Waves 1 to 3) data, with bicycle-specific variables interacted with the wave, are presented in Table 6.28 (commuting) and Table 6.29 (non-commuting). The models are a significant improvement on constants only ones ($p < 0.01$) and fit the data well (pseudo-$R^2 > 0.48$). All parameters have the expected sign. Error components are significant ($p < 0.01$), indicating flexible substitution patterns.

Table 6.28: Error components logit model with wave interactions – commuting

	Coefficient	t-statistic	95% CI
Constants			
Bicycle	-4.193	**-23.250**	-4.546 to -3.839
PT	-3.544	**-19.240**	-3.905 to -3.183
Car	-2.553	**-68.660**	-2.626 to -2.48
Non-random parameters			
CW distance	-0.128	**-5.260**	-0.176 to -0.08
CW distance x Wave 2	-0.060	-1.660	-0.13 to 0.011
CW distance x Wave 3	-0.009	-0.300	-0.065 to 0.048
Non-CW distance	-0.378	**-13.560**	-0.432 to -0.323
Non-CW distance x Wave 2	-0.125	**-3.350**	-0.199 to -0.052
Non-CW distance x Wave 3	-0.146	**-4.870**	-0.204 to -0.087
Rain 3mm-bicycle	-0.357	**-3.460**	-0.559 to -0.155
CBD-bicycle	0.751	**6.070**	0.508 to 0.993
CBD-bicycle x Wave 2	0.079	0.380	-0.326 to 0.484
CBD-bicycle x Wave 3	0.514	**3.290**	0.208 to 0.821
CBD-bicycle x Low intensity	-2.717	**-50.270**	-2.823 to -2.611
Time-walk	-0.122	**-74.660**	-0.125 to -0.118
Time-PT	-0.048	**-19.850**	-0.053 to -0.043
Time-car	-0.143	**-25.900**	-0.154 to -0.132
CBD-car	-2.728	**-54.670**	-2.825 to -2.63
Children-car	0.768	**24.710**	0.707 to 0.829
Age 45-55-car	0.264	**8.270**	0.202 to 0.327
Error component	**Std. deviation**	**t-statistic**	**95% CI**
E1 (Bicycle, PT)	3.431	**17.070**	3.037 to 3.824
Model fit statistics			
Log likelihood	-4770.066		
Chi-square	9937.304		
Degrees of freedom	21		
Pseudo-R^2	0.51		
AIC	9582.1		

None of the parameters for the interactions of cycleway distance and wave is statistically significant, suggesting no change over time in preference for using cycleways. However, some of the parameters for the interaction of non-cycleway distance and wave are significant, suggesting greater aversion to mixed traffic in Waves 2 and 3 for commuting, and lower aversion to mixed traffic in Wave 3 for non-commuting (relative to Wave 1). Preference for commuting by bicycle to the CBD increases in Wave 3, perhaps due to the opening of new cycleways in the CBD between Waves 2 and 3.

Table 6.29: Error components logit model with wave interactions – non-commuting

	Coefficient	t-statistic	95% CI
Constants			
Bicycle	-5.787	**-45.230**	-6.038 to -5.536
PT	-5.880	**-59.840**	-6.072 to -5.687
Car	-3.444	**-42.840**	-3.601 to -3.286
Non-random parameters			
CW distance	-0.194	**-2.380**	-0.353 to -0.034
CW distance x Wave 2	0.014	0.140	-0.174 to 0.202
CW distance x Wave 3	-0.019	-0.200	-0.205 to 0.167
Non-CW distance	-0.699	**-12.060**	-0.813 to -0.585
Non-CW distance x Wave 2	-0.003	-0.030	-0.157 to 0.152
Non-CW distance x Wave 3	0.206	**2.970**	0.07 to 0.342
Rain 3mm-bicycle	-0.263	**-1.990**	-0.523 to -0.004
CBD-bicycle	-2.381	**-5.000**	-3.314 to -1.447
CBD-bicycle x Wave 2	0.441	1.100	-0.345 to 1.228
CBD-bicycle x Wave 3	-0.488	-1.140	-1.328 to 0.352
CBD-bicycle x Low intensity	0.120	0.290	-0.69 to 0.93
Time-walk	-0.192	**-79.330**	-0.197 to -0.187
Time-PT	-0.025	**-6.900**	-0.032 to -0.018
Time-car	-0.056	**-8.310**	-0.069 to -0.043
CBD-car	-3.785	**-57.290**	-3.914 to -3.655
Children-car	0.311	**3.620**	0.142 to 0.479
Error components	**Std. deviation**	**t-statistic**	**95% CI**
E1 (Bicycle, PT)	1.786	**26.190**	1.653 to 1.92
E2 (Transit, Car)	1.545	**25.700**	1.427 to 1.663
E3 (Walk, PT)	-1.836	**-35.650**	-1.937 to -1.735
Model fit statistics			
Log likelihood	-8340.749		
Chi-square	28215.032		
Degrees of freedom	23		
Pseudo-R^2	0.63		
AIC	16727.5		

6.5.2 Nested logit

The final nested logit models of the pooled data (Waves 1 to 3), with a branch for each wave, are presented in Table 6.30 (for commuting) and Table 6.31 (for non-commuting). The models are a significant improvement over constant only ones ($p < 0.01$) and fit the data well (pseudo-$R^2 > 0.62$). All parameters have the expected sign. Scale parameters are relatively stable across branches/waves, except for a significant difference between Waves 1 and 3 (t-ratio -2.55) in the non-commuting model, meaning choices in Wave 3 are less deterministic.[47]

Commuting model parameters and constants are compared within and between waves (model branches) in Table 6.32. As in the baseline model, the parameter for non-cycleway distance is larger than that for cycleway distance in all three waves. There are no significant changes between Waves 1 and 2. In Wave 3, preference for cycleway, and for cycling to/from the CBD, increases.

Non-commuting model parameters and constants are compared within and between waves (model branches) in Table 6.33. As in the baseline model, the parameter for non-cycleway distance is larger than that for cycleway distance in all three waves. Between Waves 1 and 2, preference for riding to/from the CBD increases. Preference for non-cycleway distance appears to be higher in Waves 2 and 3. There is no change in preference for cycleway distance.

[47] However, parameter estimates in a nested logit model account for scale differences, meaning parameters can be directly compared between branches.

Table 6.30: Joint nested logit model – commuting

	Wave 1			**Wave 2**			**Wave 3**		
	Coefficient	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**
Constants									
Bicycle	-2.959	**-14.380**	-3.362 to -2.556	-3.244	**-12.630**	-3.747 to -2.741	-3.381	**-15.380**	-3.812 to -2.95
PT	-2.666	**-17.410**	-2.966 to -2.366	-2.499	**-16.800**	-2.791 to -2.207	-2.143	**-14.910**	-2.425 to -1.862
Car	-2.870	**-20.620**	-3.143 to -2.597	-2.855	**-19.770**	-3.139 to -2.572	-2.436	**-18.020**	-2.7 to -2.171
Non-random parameters									
CW distance	-0.162	**-4.080**	-0.24 to -0.084	-0.203	**-4.500**	-0.291 to -0.115	-0.097	**-2.860**	-0.163 to -0.031
Non-CW distance	-0.471	**-7.010**	-0.603 to -0.34	-0.523	**-6.150**	-0.689 to -0.356	-0.433	**-7.190**	-0.55 to -0.315
Rain 3mm-bicycle	-0.121	-0.980	-0.362 to 0.121	-0.121	-0.980	-0.362 to 0.121	-0.121	-0.980	-0.362 to 0.121
CBD-bicycle	-1.277	**-8.160**	-1.584 to -0.97	-0.917	**-5.180**	-1.265 to -0.57	-0.655	**-4.050**	-0.973 to -0.338
Time-walk	-0.115	**-26.330**	-0.123 to -0.106	-0.115	**-26.330**	-0.123 to -0.106	-0.115	**-26.330**	-0.123 to -0.106
Time-PT	-0.051	**-13.600**	-0.059 to -0.044	-0.051	**-13.600**	-0.059 to -0.044	-0.051	**-13.600**	-0.059 to -0.044
Time-car	-0.099	**-13.910**	-0.113 to -0.085	-0.099	**-13.910**	-0.113 to -0.085	-0.099	**-13.910**	-0.113 to -0.085
CBD-car	-2.375	**-20.370**	-2.603 to -2.146	-2.375	**-20.370**	-2.603 to -2.146	-2.375	**-20.370**	-2.603 to -2.146
Children-car	0.640	**9.710**	0.511 to 0.769	0.640	**9.710**	0.511 to 0.769	0.640	**9.710**	0.511 to 0.769
Age 45-55-car	0.423	**6.610**	0.298 to 0.549	0.423	**6.610**	0.298 to 0.549	0.423	**6.610**	0.298 to 0.549
IV parameter	1.000	**-**	**-**	1.084	**19.080**	0.973 to 1.195	1.047	**18.710**	0.937 to 1.157
Std. deviation	1.283	**-**	**-**	1.183	**19.080**	1.062 to 1.305	1.225	**18.710**	1.097 to 1.353
Wald test vs. Wave 1					1.480			0.842	
Model fit statistics									
Log likelihood	-6542.599								
Chi-square	21827.741								
Degrees of freedom	27								
Pseudo-R^2	0.63								
AIC	13139.2								

Table 6.31: Joint nested logit model – non-commuting

	Wave 1			Wave 2			Wave 3		
	Coefficient	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**
Constants									
Bicycle	-3.48307	**-27.93**	-3.728 to -3.239	-3.4135	**-23.85**	-3.694 to -3.133	-3.6413	**-25.69**	-3.919 to -3.363
PT	-4.17551	**-38.99**	-4.385 to -3.966	-4.1778	**-31.13**	-4.441 to -3.915	-4.0052	**-30.73**	-4.261 to -3.75
Car	-2.47443	**-32.32**	-2.624 to -2.324	-2.5746	**-31.86**	-2.733 to -2.416	-2.4931	**-29.96**	-2.656 to -2.33
Non-random parameters									
CW distance	-0.23524	**-3.21**	-0.379 to -0.092	-0.1921	**-3.7**	-0.294 to -0.09	-0.2192	**-6.12**	-0.289 to -0.149
Non-CW distance	-0.64893	**-8.3**	-0.802 to -0.496	-0.6797	**-8.9**	-0.829 to -0.53	-0.406	**-7.87**	-0.507 to -0.305
Rain 3mm-bicycle	-0.13118	-1.07	-0.371 to 0.109	-0.1312	-1.07	-0.371 to 0.109	-0.1312	-1.07	-0.371 to 0.109
CBD-bicycle	-2.3919	**-7.93**	-2.983 to -1.801	-1.5268	**-7.32**	-1.936 to -1.118	-1.9922	**-8.99**	-2.427 to -1.558
Time-walk	-0.14452	**-37.92**	-0.152 to -0.137	-0.1445	**-37.92**	-0.152 to -0.137	-0.1445	**-37.92**	-0.152 to -0.137
Rain 0mm-walk	-0.03124	-0.63	-0.129 to 0.067	-0.0312	-0.63	-0.129 to 0.067	-0.0312	-0.63	-0.129 to 0.067
Time-PT	-0.02955	**-9.63**	-0.036 to -0.024	-0.0296	**-9.63**	-0.036 to -0.024	-0.0296	**-9.63**	-0.036 to -0.024
Time-car	-0.06349	**-10.86**	-0.075 to -0.052	-0.0635	**-10.86**	-0.075 to -0.052	-0.0635	**-10.86**	-0.075 to -0.052
CBD-car	-2.71558	**-31.5**	-2.885 to -2.547	-2.7156	**-31.5**	-2.885 to -2.547	-2.7156	**-31.5**	-2.885 to -2.547
Children-car	0.78233	**18.51**	0.699 to 0.865	0.78233	**18.51**	0.699 to 0.865	0.78233	**18.51**	0.699 to 0.865
IV parameter	1	**-**	-	0.951	**29.17**	0.887 to 1.015	0.91974	**29.22**	0.858 to 0.981
Std. deviation	1.28255	**-**	-	1.34864	**29.17**	1.258 to 1.439	1.39447	**29.22**	1.301 to 1.488
Wald test vs. Wave 1					-1.503			**-2.550**	
Model fit statistics									
Log likelihood	-10925.705								
Chi-square	58624.777								
Degrees of freedom	27								
Pseudo-R^2	0.73								
AIC	21905.4								

Table 6.32: Comparison of parameter estimates – commuting

Parameter/constant A	Coefficient A	Parameter/constant B	Coefficient B	t-statistic
Wave 1				
CW distance	-0.16	Non-CW distance	-0.47	**-3.60**
Wave 2				
CW distance	-0.20	Non-CW distance	-0.52	**-3.50**
Wave 3				
CW distance	-0.10	Non-CW distance	-0.43	**-4.50**
Wave 1 versus Wave 2				
Bicycle (constant)	-2.96	Bicycle (constant)	-3.24	-0.99
CW distance	-0.16	CW distance	-0.20	-0.70
Non-CW distance	-0.47	Non-CW distance	-0.52	-0.49
CBD-bicycle	-1.28	CBD-bicycle	-0.92	1.55
PT (constant)	-2.67	PT (constant)	-2.50	1.48
Car (constant)	-2.87	Car (constant)	-2.86	0.13
Wave 1 versus Wave 3				
Bicycle (constant)	-2.96	Bicycle (constant)	-3.38	**-1.67**
CW distance	-0.16	CW distance	-0.10	1.29
Non-CW distance	-0.47	Non-CW distance	-0.43	0.45
CBD-bicycle	-1.28	CBD-bicycle	-0.66	**2.81**
PT (constant)	-2.67	PT (constant)	-2.14	**4.52**
Car (constant)	-2.87	Car (constant)	-2.44	**3.90**
Wave 2 versus Wave 3				
Bicycle (constant)	-3.24	Bicycle (constant)	-3.38	-0.48
CW distance	-0.20	CW distance	-0.10	**1.94**
Non-CW distance	-0.52	Non-CW distance	-0.43	0.90
CBD-bicycle	-0.92	CBD-bicycle	-0.66	1.11
PT (constant)	-2.50	PT (constant)	-2.14	**3.00**
Car (constant)	-2.86	Car (constant)	-2.44	**3.62**

Table 6.33: Comparison of parameter estimates – non-commuting

Parameter/constant A	Coefficient A	Parameter/constant B	Coefficient B	t-statistic
Wave 1				
CW distance	-0.24	Non-CW distance	-0.65	**-3.16**
Wave 2				
CW distance	-0.19	Non-CW distance	-0.68	**-4.47**
Wave 3				
CW distance	-0.22	Non-CW distance	-0.41	**-2.60**
Wave 1 versus Wave 2				
Bicycle (constant)	-3.48	Bicycle (constant)	-3.41	0.41
CW distance	-0.24	CW distance	-0.19	0.49
Non-CW distance	-0.65	Non-CW distance	-0.68	-0.29
CBD-bicycle	-2.39	CBD-bicycle	-1.53	**2.38**
PT (constant)	-4.18	PT (constant)	-4.18	-0.02
Car (constant)	-2.47	Car (constant)	-2.57	**-1.71**
Wave 1 versus Wave 3				
Bicycle (constant)	-3.48	Bicycle (constant)	-3.64	-0.95
CW distance	-0.24	CW distance	-0.22	0.20
Non-CW distance	-0.65	Non-CW distance	-0.41	**2.68**
CBD-bicycle	-2.39	CBD-bicycle	-1.99	1.08
PT (constant)	-4.18	PT (constant)	-4.01	**1.75**
Car (constant)	-2.47	Car (constant)	-2.49	-0.31
Wave 2 versus Wave 3				
Bicycle (constant)	-3.41	Bicycle (constant)	-3.64	-1.46
CW distance	-0.19	CW distance	-0.22	-0.44
Non-CW distance	-0.68	Non-CW distance	-0.41	**3.09**
CBD-bicycle	-1.53	CBD-bicycle	-1.99	-1.56
PT (constant)	-4.18	PT (constant)	-4.01	**1.74**
Car (constant)	-2.57	Car (constant)	-2.49	1.36

6.5.3 Marginal rates of substitution

Separate mode choice models for all three waves are presented in Table 6.34 (for commuting) and Table 6.35 (for non-commuting). All six models are a significant improvement over constants only ones ($p < 0.01$) and fit the data well (pseudo-R^2 > 0.57). All parameters have the expected sign, and random parameters have statistically significant spreads, indicating intra-sample preference heterogeneity. The bicycle-specific parameter for the rainfall dummy variable is not significant in Waves 2 and 3. There was less rainfall during these data collection waves than in Wave 1, making it more difficult to estimate a parameter for this variable. The error components are significant ($p < 0.01$), indicating a flexible substitution pattern.

Table 6.34: Mixed logit model partitioned by wave – commuting

	Wave 1			Wave 2			Wave 3		
	Coefficient	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**
Constants									
Bicycle	-5.815	**-11.060**	-6.845 to -4.784	-6.917	**-12.060**	-8.04 to -5.793	-5.807	**-10.950**	-6.847 to -4.768
PT	-5.627	**-10.670**	-6.661 to -4.594	-5.744	**-10.200**	-6.848 to -4.641	-3.298	**-6.550**	-4.286 to -2.311
Car	-3.255	**-12.750**	-3.755 to -2.755	-3.529	**-9.550**	-4.254 to -2.804	-3.084	**-10.210**	-3.676 to -2.492
Non-random parameters									
Children-car	1.516	**6.610**	1.067 to 1.966	1.033	**3.280**	0.416 to 1.651	0.564	**2.290**	0.08 to 1.047
Age 45-55-car	0.543	**2.620**	0.136 to 0.949	0.685	**2.200**	0.073 to 1.296	-0.046	-0.190	-0.532 to 0.44
Random parameters[a]									
CW distance	-0.816	**-8.000**	-1.016 to -0.616	-1.673	**-11.030**	-1.971 to -1.376	-1.285	**-11.120**	-1.511 to -1.058
Non-CW distance	-2.789	**-11.790**	-3.253 to -2.325	-2.793	**-9.920**	-3.345 to -2.241	-2.328	**-9.760**	-2.796 to -1.861
Rain 3mm-bicycle	-0.995	**-3.350**	-1.576 to -0.413	-0.197	-0.200	-2.12 to 1.727	0.211	0.810	-0.301 to 0.724
CBD-bicycle	-2.402	**-7.270**	-3.05 to -1.754	-0.802	**-3.130**	-1.305 to -0.3	-2.285	**-5.910**	-3.044 to -1.527
Time-walk	-0.344	**-24.320**	-0.371 to -0.316	-0.387	**-22.270**	-0.421 to -0.353	-0.360	**-23.090**	-0.39 to -0.329
Time-PT	-0.298	**-27.180**	-0.319 to -0.276	-0.360	**-33.530**	-0.381 to -0.339	-0.347	**-26.920**	-0.372 to -0.322
Time-car	-0.813	**-31.460**	-0.864 to -0.763	-0.980	**-30.830**	-1.042 to -0.918	-0.717	**-30.150**	-0.764 to -0.671
CBD-car	-5.300	**-10.780**	-6.263 to -4.337	-4.790	**-8.520**	-5.891 to -3.688	-5.586	**-10.900**	-6.591 to -4.582
Error component									
E1 (Bicycle, PT)	4.309	**10.570**	3.51 to 5.108	4.615	**9.440**	3.657 to 5.573	4.866	**9.810**	3.893 to 5.838
Model fit statistics									
Log likelihood	-1301.199			-1241.416			-1259.716		
Chi-square	3685.833			4127.020			4059.920		
Degrees of freedom	14			14			14		
Pseudo-R^2	0.59			0.62			0.62		
AIC	2630.4			2510.8			2547.4		

[a] Triangular distribution with spread equal to half the mean. Spreads of random parameters not shown.

Table 6.35: Mixed logit model partitioned by wave – non-commuting

	Wave 1			Wave 2			Wave 3		
	Coefficient	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**	**Coefficient**	**t-statistic**	**95% CI**
Constants									
Bicycle	**-6.355**	**-19.060**	**-7.009 to -5.702**	**-6.773**	**-21.080**	**-7.403 to -6.143**	**-6.967**	**-21.020**	**-7.617 to -6.317**
PT	**-7.316**	**-23.990**	**-7.914 to -6.718**	**-7.092**	**-20.780**	**-7.76 to -6.423**	**-6.965**	**-23.710**	**-7.541 to -6.389**
Car	**-4.246**	**-18.250**	**-4.702 to -3.79**	**-4.878**	**-18.020**	**-5.409 to -4.347**	**-4.645**	**-17.910**	**-5.154 to -4.137**
Non-random parameter									
Children-car	**1.012**	**3.140**	**0.381 to 1.642**	**1.703**	**5.520**	**1.099 to 2.308**	**1.509**	**5.040**	**0.922 to 2.097**
Random parameters[a]									
CW distance	**-0.284**	**-3.170**	**-0.46 to -0.108**	**-0.364**	**-5.360**	**-0.497 to -0.231**	**-0.289**	**-4.320**	**-0.421 to -0.158**
Non-CW distance	**-1.072**	**-7.630**	**-1.347 to -0.796**	**-1.336**	**-9.750**	**-1.604 to -1.067**	**-0.825**	**-8.750**	**-1.01 to -0.64**
Rain 3mm-bicycle	**-1.298**	**-3.240**	**-2.082 to -0.514**	0.080	0.160	-0.873 to 1.032	0.326	1.600	-0.073 to 0.726
CBD-bicycle	**-3.806**	**-7.320**	**-4.825 to -2.787**	**-2.230**	**-5.650**	**-3.004 to -1.457**	**-3.386**	**-8.380**	**-4.178 to -2.595**
Time-walk	**-0.258**	**-30.540**	**-0.275 to -0.242**	**-0.271**	**-32.600**	**-0.287 to -0.255**	**-0.242**	**-28.490**	**-0.258 to -0.225**
Rain 0mm-walk	**-0.316**	**-2.810**	**-0.536 to -0.096**	**0.416**	**4.270**	**0.225 to 0.607**	-0.138	-1.470	-0.322 to 0.046
Time-PT	**-0.039**	**-5.600**	**-0.053 to -0.025**	**-0.075**	**-8.550**	**-0.092 to -0.058**	**-0.043**	**-6.260**	**-0.057 to -0.03**
Time-car	**-0.095**	**-7.680**	**-0.119 to -0.071**	**-0.141**	**-11.170**	**-0.166 to -0.117**	**-0.086**	**-6.960**	**-0.11 to -0.062**
CBD-car	**-4.636**	**-22.190**	**-5.046 to -4.227**	**-4.831**	**-16.770**	**-5.395 to -4.266**	**-4.775**	**-18.310**	**-5.286 to -4.264**
Error components									
E1 (Bicycle, PT)	**2.080**	**9.830**	**1.665 to 2.495**	**2.264**	**9.810**	**1.811 to 2.716**	**2.091**	**8.010**	**1.579 to 2.603**
E2 (Transit, Car)	**1.442**	**9.310**	**1.138 to 1.745**	**2.042**	**11.090**	**1.681 to 2.402**	**1.858**	**11.420**	**1.539 to 2.177**
E3 (Walk, PT)	**2.654**	**12.540**	**2.239 to 3.069**	**2.178**	**10.430**	**1.769 to 2.588**	**2.177**	**10.570**	**1.773 to 2.581**
Heteroscedastic effects									
E3 x Children	**-0.385**	**-2.900**	**-0.646 to -0.125**	**-0.572**	**-3.960**	**-0.855 to -0.288**	-0.208	-1.400	-0.5 to 0.084
Model fit statistics									
Log likelihood	-2790.558			-2570.958			-2756.252		
Chi-square	9837.251			9483.489			9340.254		
Degrees of freedom	18			18			18		
Pseudo-R^2	0.64			0.65			0.63		
AIC	5617.1			5177.9			5548.5		

[a] Triangular distribution with spread equal to half the mean. Spreads of random parameters not shown.

Parameter values cannot be compared directly between waves, because of possible scale differences between the datasets. However, marginal rates of substitution can be compared between waves, as they are free of scale.

For commuting trips, marginal rates of substitution for all three waves are shown in Table 6.36. The ratio of the non-cycleway distance and cycleway distance parameters declines from 3.42 (95% CI 2.19 to 4.64) in Wave 1 to 1.67 (95% CI 1.18 to 2.16) in Wave 2, and the difference is significant (t-ratio -2.65). The non-cycleway distance parameter remains stable – relative to the time parameters for other modes – while the cycleway distance parameter increases. This suggests that preference for using a cycleway for commuting declined between Waves 1 and 2; however, cycleway distance was still preferred over non-cycleway distance. A possible explanation for this decline is that some respondents were not aware of the new George Street Cycleway in Wave 2, and chose not to cycle believing they would have to mix with traffic while riding along the George Street corridor – whereas the imputed distance variables took the new cycleway into account. For non-commuting trips, marginal rates of substitution for all three waves are shown in Table 6.37. Marginal rates of substitution did not change, indicating preferences were stable for non-commuting travel.

Additional models were estimated with data partitioned by area (intervention/control); however, the smaller sample sizes meant parameter values had large standard errors, making it difficult to compare them across waves.

Table 6.36: Changes in marginal rates of substitution – commuting

Parameter A	Coefficient A	Parameter B	Coefficient B	MRS	t-ratio	95% CI	t-test vs. Wave 1
Wave 1							
Non-CW distance	-2.79	CW distance	-0.82	3.42	**5.58**	2.191 to 4.643	-
Non-CW distance	-2.79	Time-walk	-0.34	8.12	**10.75**	6.606 to 9.625	-
Non-CW distance	-2.79	Time-PT	-0.30	9.37	**11.28**	7.712 to 11.037	-
Non-CW distance	-2.79	Time-car	-0.81	3.43	**11.34**	2.825 to 4.035	-
CW distance	-0.82	Time-walk	-0.34	2.37	**7.90**	1.774 to 2.976	-
CW distance	-0.82	Time-PT	-0.30	2.74	**7.86**	2.046 to 3.441	-
CW distance	-0.82	Time-car	-0.81	1.00	**8.01**	0.753 to 1.254	-
Wave 2							
Non-CW distance	-2.79	CW distance	-1.67	1.67	**6.78**	1.177 to 2.161	**-2.65**
Non-CW distance	-2.79	Time-walk	-0.39	7.23	**9.36**	5.682 to 8.768	-0.82
Non-CW distance	-2.79	Time-PT	-0.36	7.75	**9.48**	6.115 to 9.385	-1.39
Non-CW distance	-2.79	Time-car	-0.98	2.85	**9.95**	2.277 to 3.422	-1.39
CW distance	-1.67	TIMEW	-0.39	4.33	**10.26**	3.486 to 5.173	**3.77**
CW distance	-1.67	Time-PT	-0.36	4.64	**11.48**	3.835 to 5.452	**3.56**
CW distance	-1.67	Time-car	-0.98	1.71	**10.85**	1.393 to 2.022	**3.50**
Wave 3							
Non-CW distance	-2.33	CW distance	-1.28	1.81	**6.24**	1.231 to 2.394	**-2.37**
Non-CW distance	-2.33	Time-walk	-0.36	6.47	**8.94**	5.026 to 7.923	-1.57
Non-CW distance	-2.33	Time-PT	-0.35	6.71	**9.49**	5.298 to 8.128	**-2.44**
Non-CW distance	-2.33	Time-car	-0.72	3.25	**10.03**	2.598 to 3.893	-0.42
CW distance	-1.28	Time-walk	-0.36	3.57	**10.36**	2.883 to 4.262	**2.62**
CW distance	-1.28	Time-PT	-0.35	3.70	**11.23**	3.044 to 4.363	**2.00**
CW distance	-1.28	Time-car	-0.72	1.79	**11.22**	1.471 to 2.11	**3.88**

Table 6.37: Changes in marginal rates of substitution – non-commuting

Parameter A	Coefficient A	Parameter B	Coefficient B	MRS	t-ratio	95% CI	t-test vs. Wave 1
Wave 1							
Non-CW distance	-1.07	CW distance	-0.28	3.77	2.67	0.948 to 6.594	-
Non-CW distance	-1.07	Time-walk	-0.26	4.15	7.84	3.09 to 5.206	-
Non-CW distance	-1.07	Time-PT	-0.04	27.35	5.16	16.758 to 37.938	-
Non-CW distance	-1.07	Time-car	-0.10	11.27	6.55	7.83 to 14.717	-
CW distance	-0.28	Time-walk	-0.26	1.10	3.18	0.409 to 1.792	-
CW distance	-0.28	Time-PT	-0.04	7.25	3.10	2.573 to 11.932	-
CW distance	-0.28	Time-car	-0.10	2.99	3.22	1.135 to 4.845	-
Wave 2							
Non-CW distance	-1.34	CW distance	-0.36	3.67	4.22	1.931 to 5.404	-0.06
Non-CW distance	-1.34	Time-walk	-0.27	4.93	10.16	3.957 to 5.896	1.08
Non-CW distance	-1.34	Time-PT	-0.08	17.77	8.41	13.545 to 22.004	-1.68
Non-CW distance	-1.34	Time-car	-0.14	9.44	10.26	7.603 to 11.284	-0.94
CW distance	-0.36	TIMEW	-0.27	1.34	5.24	0.83 to 1.856	0.56
CW distance	-0.36	Time-PT	-0.08	4.85	4.60	2.738 to 6.954	-0.94
CW distance	-0.36	Time-car	-0.14	2.57	4.88	1.519 to 3.631	-0.39
Wave 3							
Non-CW distance	-0.83	CW distance	-0.29	2.85	3.56	1.251 to 4.45	-0.57
Non-CW distance	-0.83	Time-walk	-0.24	3.41	9.09	2.662 to 4.163	-1.13
Non-CW distance	-0.83	Time-PT	-0.04	19.10	5.93	12.653 to 25.542	-1.33
Non-CW distance	-0.83	Time-car	-0.09	9.60	6.22	6.513 to 12.686	-0.72
CW distance	-0.29	Time-walk	-0.24	1.20	4.42	0.655 to 1.739	0.22
CW distance	-0.29	Time-PT	-0.04	6.70	4.51	3.73 to 9.668	-0.20
CW distance	-0.29	Time-car	-0.09	3.37	5.11	2.05 to 4.685	0.33

6.5.4 Comparison of preference stability tests

In the commuting models, the non-cycleway distance parameter remained larger than the cycleway distance parameter in all three waves. However, the ratio between them changed. The MRS models suggest the ratio contracted (owing to a more negative cycleway distance parameter), while the nested logit model suggests it enlarged (owing to a more positive cycleway distance parameter). The interaction model also suggests the ratio enlarged, but owing to a more negative non-cycleway distance parameter.

In the non-commuting models, the non-cycleway distance parameter remained larger than the cycleway distance parameter in all three waves. Both the interaction and nested logit models suggest the ratio contracted, due to a more positive non-cycleway distance parameter. However, the MRS models suggest there was no significant change in the ratio.

6.6 Summary

In the mode choice analysis of the Wave 1 (baseline) travel diary data, it was found that respondents prefer riding on cycleways to riding in mixed traffic, but to a lesser extent when they are commuting to work or study. On average, women and low-intensity riders are more averse to riding in mixed traffic than are men and high-intensity riders, and aversion to cycling increases on rainy days, or when the trip involves travel to/from the CBD. However, there was notable variation in preferences among the sample.

From the baseline models, it was forecast that the new George Street Cycleway would result in bicycle mode share for the intervention area increasing by 1.1 percentage points for commuting trips, and by 0.3 percentage points for non-commuting trips. Annual bicycle kilometres travelled were forecast to increase by 25 per cent. The resulting public health benefits were valued at AUD 12.5m over 30 years, and the user benefits (improvements in accessibility and transport choice) were valued at AUD 4.1m, leading to a benefit-cost ratio of 3.4.

In terms of how travel behaviour/demand changed in practice, the bicycle traffic counts showed a significant increase in peak-time bicycle traffic along the cycleway, and a decline elsewhere in the City of Sydney LGA. In the intercept survey, 40 per cent of cycleway users reported having changed mode to bicycle since it opened, while 48 per cent of those who had cycled previously had changed their route. However, there was little change in bicycle use among the resident panel after the cycleway opened, in either the intervention group or the control group.

In analysing how the preferences of the resident panel changed over the three data collections waves, it was found that sensitivity to non-cycleway distance remained higher than sensitivity to cycleway distance. However, the ratio between these parameters did change, though in different ways depending on the modelling method used.

7 DISCUSSION AND CONCLUSION

This chapter discusses the results presented in Chapter 6, in terms of (a) answering the research questions and testing the hypotheses stated in Chapter 1, and (b) implications for future research, policy and practice. For the benefit of the reader, the purpose and aims of the research are restated (Section 7.1). Next, each research question and hypothesis is addressed in turn (Section 7.2). Contributions and limitations of the research are acknowledged in Sections 7.3 and 7.4 respectively. Potential directions for future research are outlined in Section 7.5, followed by implications for practice and policy (Section 7.6). Finally, some concluding remarks are made in Section 7.7.

7.1 Purpose and aims

By way of recall, this research was funded by an Australian Research Council Linkage Project grant, with the broad remit of making major contributions to the assessment of the transport, health and economic impacts of bicycle infrastructure.

Various methods for assessing and valuing the social impacts (externalities) of bicycle infrastructure, particularly the public health benefits, are described in the literature, and have been adopted in practice. However, the user benefits have received less attention – perhaps because user benefits of transport infrastructure are typically assessed in terms of potential travel speed increases, and new bicycle infrastructure can sometimes result in *slower* journeys.

However, empirical observation shows some people willingly choose to travel by bicycle when there are faster alternatives available, and will choose a longer, low-stress bicycle route when there are options that are more direct. For them to make these choices, there must be some *benefit* or *utility* to these individuals. It has also been suggested that people value having more transport options available to them, even if they do not intend to use them (option value) (K. Geurs et al., 2006).

The primary aim of this thesis, therefore, was to develop a framework for forecasting and valuing the user benefits of low-stress, separated cycleways, by analysing the trade-offs people make when choosing which transport mode to use for their journeys. This assessment framework was applied to a new cycleway being built in inner-city Sydney, using travel survey data obtained from local residents before it opened. The assessment framework was evaluated by (a) re-surveying the same residents after the cycleway opened, and (b) analysing bicycle traffic counts and data from a post-intervention intercept survey of cycleway users.

7.2 Research questions and hypotheses

7.2.1 Research Question 1

Which trip attributes, individual characteristics and contextual factors affect people's decisions to travel by bicycle or not, in a car-oriented Australian city?

Variables found to be statistically significant in the mode choice model of the pre-intervention travel diary data (Section 6.1) are listed in Table 7.1 (with their parameter signs). It was found that the utility of cycling decreases with increasing trip distance, consistent with previous mode choice studies (e.g., Rodríguez & Joo, 2004).

Table 7.1: Factors affecting cycling mode choice

Variable	Commuting	Non-commuting
Variables		
Cycleway distance	-	-
Non-cycleway distance	-	-
Daily rainfall > 3 mm	-	-
Trip starts or ends in CBD	-	-
Interaction terms		
Non-cycleway distance x low intensity rider	-	-
Trip starts or ends in CBD x low intensity rider	-	-

Previous choice studies have shown that bicycle riders, in general, prefer separated cycleways to mixed traffic, implying they will take a longer route to use them. From a mode choice study in the United Kingdom, Wardman et al. (2007) estimated that commuters, on average, will ride for up to 3 km on cycleways to avoid riding 1 km in mixed traffic. Using stated preference data from commuters in Stockholm (Sweden), Börjesson and Eliasson (2012) estimated that commuters will ride for up to 1.4 km (1.9 km for trips of 40 minutes and above) to avoid riding 1 km in mixed traffic. (Neither study looked at non-commuting travel.)

In the present mode choice analysis, it was found that commuters will ride for up to 1.4 km to avoid riding 1 km in mixed traffic. In a separate model, it was estimated that non-commuters would ride for up to 2.6 km to avoid riding 1 km in mixed traffic.

These findings were mirrored in the post-intervention intercept survey (Section 6.4.2). More than one third (38 per cent) of cycleway users had diverted by more than 5 per cent from the shortest path to use the new cycleway, which is at the upper end of the 6 to 42 per cent range estimated by Monsere et al. (2014) across eight cycleways in the United States. The average diversion of 351 metres was somewhat more than the 277 metres estimated by Krenn et al. (2014, p. 2) in a similar study undertaken in the "bike-friendly city" of Graz (Austria). There was a significant relationship between the estimated distance users had diverted, and both trip distance and trip purpose. On average, non-commuters had diverted further to use the cycleway than had commuters.

It has previously been established that car and public transport commuters place a higher value on travel time savings than non-commuters (Li et al., 2010) – possibly due to the need to arrive for work on time, and the monotony of making the same trip multiple times per week. These results indicate this is true of bicycle commuters also – however, commuters are still willing to divert from the shortest path to use a lower-stress route.

The mode choice model parameters for origin and destination elevation were not found to be statistically significant. Previous bicycle choice studies (e.g., Broach et al., 2012, 2009; Sener et al., 2009; Stinson & Bhat, 2003; Zimmermann et al., 2017) have shown that hilliness is a deterrent to cycling; and inner-city Sydney is certainly hilly. However, using origin and destination elevation is a somewhat coarse approach to measuring the effect of gradient. A better approach may have been to use the total elevation gain along the modelled bicycle route.

In terms of gender, it was found that men and women have the same sensitivity to cycleway distance. However, women are significantly more sensitive than are men to non-cycleway distance, consistent with previous studies that have found women are more averse than men to riding in mixed traffic (Garrard, Rose, & Lo, 2008). This may explain why previous mode choice studies undertaken in countries with limited bicycle facilities (e.g., United Kingdom and United States) have shown women are less likely to cycle (Sener et al., 2009; Wardman et al., 2007); whereas those undertaken in cities with extensive bicycle facilities (e.g., Stockholm (Sweden)), have found that gender is not significant (Börjesson & Eliasson, 2012).

Interestingly, using self-reported rider type instead of gender gave a slightly improved model fit, with low-intensity riders more sensitive to non-cycleway distance than high-intensity riders. This seems intuitive: a high-intensity sport cyclist may feel more confident riding in traffic than a low-intensity transport rider, irrespective of their gender. However, there was a strong positive correlation between respondents identifying as a low-intensity rider and identifying as female, and the differences in model fit were marginal. Furthermore, the self-reported rider type variable is prone to scale perception bias, whereby respondents may have interpreted low- and high-intensity differently.

Otherwise, the choice model parameters and their signs were largely as expected, e.g., rain is a deterrent to cycling.

7.2.2 Research Question 2

How can discrete choice analysis be used to measure and value the user benefits of new bicycle facilities, in a way that fits into existing infrastructure appraisal frameworks?

How do these benefits compare in magnitude to other benefits normally attributed to cycling projects (e.g., public health benefits)?

Are there any implementation issues?

What are the implications for the economic assessment of future cycling projects?

The user benefits of transport project proposals are typically valued in terms of potential travel speed increases or time savings. The post-intervention intercept survey (Section 6.4.2) confirmed some people willingly change mode or route to use a new cycleway, even if doing so results in a *slower* journey. For them to make such a choice, the cycleway must offer them other benefits, such as greater enjoyment, reduced fear and intimidation from motor vehicle drivers, or an opportunity for exercise. While it may be possible to measure and value all these user benefits individually, discrete choice analysis provides a convenient methodology for estimating and valuing the total increase in utility resulting from new cycling infrastructure – without needing to know the exact reasons for it.

As demonstrated in this thesis, if discrete choice analysis is used for demand forecasting, then the user benefits are relatively straightforward to estimate from the resulting inclusive value (logsum) parameters. The key is to include, in the choice models, variables that vary sufficiently because of the intervention. In the present analysis, the bicycle distance was divided into 'cycleway distance' and 'non-cycleway distance' variables – such that the former increases (and the latter decreases) for many trips as more cycleways are added to the network. If the choice model includes a cost parameter, then the inclusive value parameter can be converted to a monetary value (consumer surplus).

From the pre-intervention (2013) mode choice models (Section 6.1), it was estimated the George Street Cycleway would have a benefit-cost ratio (BCR) of 2.6 (range: 2.1 at a 10 per cent discount rate to 3.5 at a 4 per cent discount rate). Excluding the user benefits, the BCR would be only 1.8 (range: 1.4 to 2.4).[48] For the Complete Network scenario, a BCR of 3.4 (range: 2.9 to 4.2) was estimated. These BCRs are likely to be conservative because, due to data limitations, they do not account for benefits accruing to people aged under 18 or over 55. However, it is notable that the BCR for the Complete Network is higher than that for the single cycleway. This suggests the benefits of cycleways can be maximised when they are connected into networks providing low-stress cycling options between multiple origin/destination pairs (a case of the whole being greater than the sum of its parts). In addition, the user benefits appear to become increasingly important as

[48] An investment is generally considered worthwhile if the BCR is greater than 1.0.

the network grows (32 per cent of total benefits in the single cycleway scenario; 43 per cent of total benefits in the Complete Network scenario).

For comparison, Table 7.2 lists the High Priority Projects and Priority Projects[49] listed in the Australian Government's July 2017 Infrastructure Priority List (Infrastructure Australia, 2017). As discussed in Chapter 2, the economic benefits comprise mostly user benefits – predominantly forecast increases in travel speeds and travel time reliability. The relatively high discount rate of 7 per cent discriminates against passenger rail projects, which tend to have longer design and construction timeframes than road projects. The European Commission (2014) recommends a discount rate of 3 per cent for infrastructure appraisal.

In their systematic review of economic assessments of walking and cycling projects, Brown et al. (2016) found the estimated BCRs ranged from -31.9 to 59 (see Figure 7.1). However, it should be noted there was considerable variation in assessment methodology, including between the three bicycle project assessments undertaken in Australia (AECOM, 2010; PricewaterhouseCoopers, 2009; Sinclair Knight Merz & PricewaterhouseCoopers, 2011).

[49] High Priority Projects and Priority Projects are defined as "potential infrastructure solutions for which a full business case has been completed and been positively assessed by the Infrastructure Australia Board" (Infrastructure Australia, 2017, p. 3).

Table 7.2: Passenger transport projects on the Australian Government's Infrastructure Priority List (Infrastructure Australia, 2017)

Mode	Project	Location	Capital cost ($AUD million)	BCR[a]
Road	M1 Pacific Motorway – Gateway Motorway merge upgrade	Queensland	208	6.3
	M4 motorway upgrade	NSW	853	5.3
	Armadale Road upgrade	Western Australia	Undisclosed	4.2
	Ipswich Motorway Rocklea–Darra Stage 1c	Queensland	400	3.8
	M1 Pacific Motorway upgrade – Mudgeeraba to Varsity Lakes	Queensland	221	3.5
	Bruce Highway Upgrade – Mackay Ring Road Stage 1	Queensland	497	3.3
	Bringelly Road Upgrade Stage 2	NSW	180	2.8
	Bruce Highway Upgrade – Cooroy to Curra Section C	Queensland	273	2.4
	Perth Freight Link	Western Australia	1,742	2.2
	M80 Ring Road upgrade	Victoria	515	2.0
	WestConnex	NSW	16,800	1.7
	The Northern Road Upgrade	NSW	1,752	1.3
Passenger rail	Sydney Metro: City and Southwest	NSW	Undisclosed	1.3
	Melbourne Metro Rail	Victoria	10,900	1.1

[a] 7% discount rate. Excluding Wider Economic Benefits (e.g., agglomeration economies, increased competition, and improved labour supply).

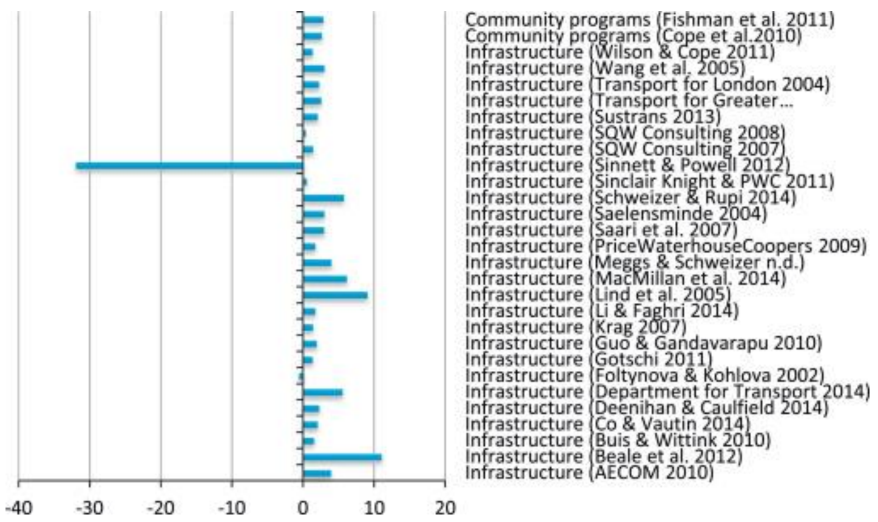


Figure 7.1: Benefit-cost ratios for active transport projects (Brown et al., 2016)[50]

For the proposed Inner Sydney Regional Bicycle Network – covering the City of Sydney LGA and surrounding municipalities – AECOM (2010) estimated a BCR of 3.88 and a present value of benefits totalling AUD 682.3 million (in 2010 prices), broken down as shown in Figure 7.2. The methodology for this appraisal is

[50] Where more than one BCR was reported, only the smallest is presented in this figure.

critiqued in Chapter 2. Many of the benefits derive from a forecast reduction in car use, even though the project involves no reduction in road capacity, nor any increase in driving or parking costs. Morbidity benefits are not included; however, user benefits are – in the form of travel time savings and "journey ambiance" (essentially an estimate of travellers' willingness to pay to use a low-stress bicycle facility – see Section 3.3.1).

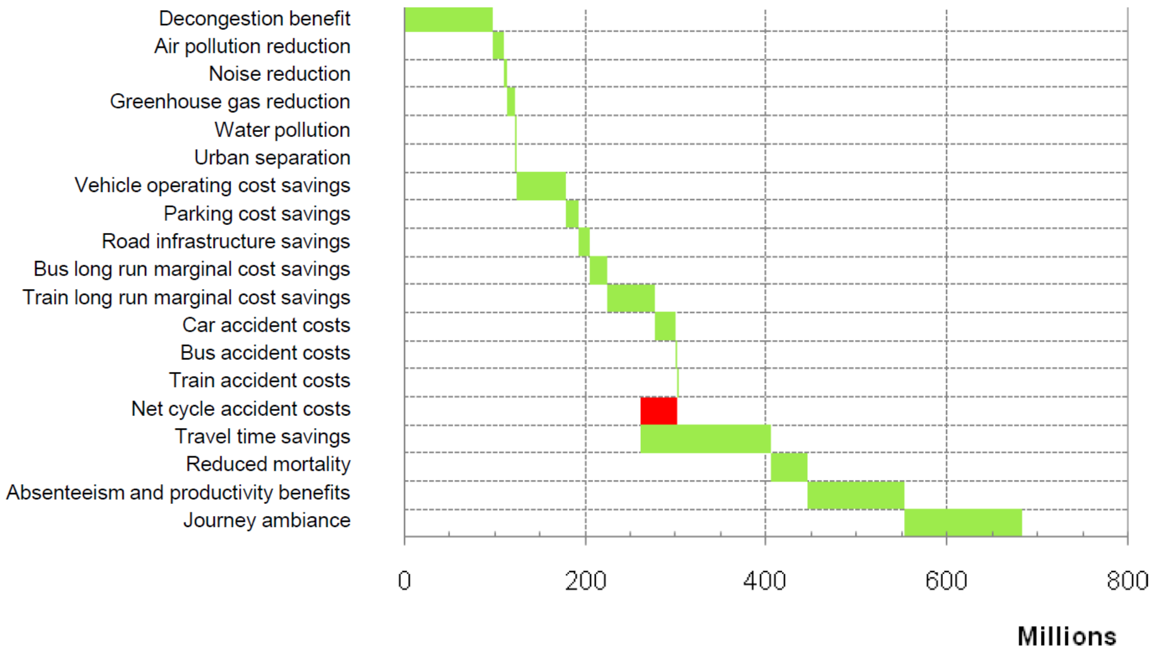


Figure 7.2: Breakdown of discounted benefits of Inner Sydney Regional Bicycle Network, in 2010 prices (AUD) (Yi et al., 2011)

In summary, the three components of this research question are answered as follows.

1. This thesis has demonstrated that discrete choice analysis can be used to measure and value the user benefits of new bicycle facilities. The present value of these user benefits can then be added to the net present value for the project, provided no user benefits (e.g., travel time savings) have already been included (to avoid double-counting). The method is appealing from the analyst's perspective, because the inclusive value is a by-product of discrete choice-based demand assessment.
2. In the case of the George Street Cycleway, the estimated value of the user benefits is of a similar order of magnitude to the estimated value of the public health benefits.

3. Implementing this appraisal methodology in practice requires good quality bicycle network data and an appropriate source of revealed preference travel data (e.g., Household Travel Survey).

There remains, however, the question of communicability. While 'travel time savings' may sound compelling and have meaning for decision makers and stakeholders, 'inclusive values', 'logsums' or 'consumer surpluses' likely would not.

7.2.3 Hypothesis 1 (Null)

Following the construction of a new bicycle path, measured changes in bicycle travel are no different from those that are forecast using a discrete mode choice model.

In their review of four previous validation studies, Fox and Hess (2010, p. 79) concluded that "mode choice models were able to predict the impact of often substantial changes in level of service on mode share with reasonable accuracy". However, there was one notable exception (Silman, 1981), in which the future shares for the major modes (car driver and bus) were accurately predicted, but the future share for the minor mode (car passenger) was not. Furthermore, these studies considered only commuting travel, while none of the models included a bicycle alternative.

In the present analysis, it was predicted (Section 6.2) that the George Street Cycleway would increase the utility of cycling for many trips, and therefore the probability of bicycle being chosen. Consequently, it was forecast that the bicycle mode share in the intervention area population would increase from 4.5 per cent to 5.6 per cent for commuting trips, and from 2.7 per cent to 3.0 per cent for non-commuting trips. Annual BKT were forecast to increase by 25 per cent, from 1.73 to 2.16 km per person (as a result of the bicycle mode share increasing, and people taking longer routes to use the cycleway).

Actual changes in travel demand (Section 6.4) were assessed by analysing changes in peak-time bicycle traffic counts, data from the post-intervention (March 2015) intercept study, and data from the post-intervention (2014 and 2015) resident panel surveys.

The bicycle traffic counts showed the number of bicycle riders using George Street during peak times increased by 90 per cent at the southern end (from 237 to 450 per day), and by 29 per cent at the northern end (from 713 to 923 per day), after the cycleway opened.

These increases occurred against the backdrop of an average 5 per cent decline in the bicycle count over the same period across the other 98 count sites in the City of Sydney LGA. Possible explanations for this decrease include: the introduction of the Opal smartcard ticketing system for public transport, which made public transport more attractive; the state government blocking the construction of more cycleways, and demolishing existing ones, in the City of Sydney LGA (O'Reilly, 2014); and increased police enforcement of cycling infringements, primarily not wearing a helmet (Gorman, 2015). The state government also announced significantly increased fines for cycling infringements, and plans to force residents and visitors to carry government-issued photo identification when cycling (Saulwick, 2015a).

The bicycle count data suggest the opening of the cycleway prompted an increase in bicycle traffic along the George Street corridor. However, it is not possible to tell, from the count data alone, whether this increase was due to people changing mode to bicycle, making more trips, changing destination, or changing route.

The post-intervention intercept survey made it possible to estimate the proportion of cycleway users who had changed mode and route since it opened. The finding that 40 per cent of intercepted bicycle riders had changed mode to bicycle is much greater than the 6 to 21 per cent range (average 10 per cent) recorded by Monsere et al. (2014) in similar surveys across eight new cycleways in five cities in the United States. A possible explanation for this difference is that a greater number of people in inner-city Sydney were in what Marshall and Biddle (2001) describe as the 'preparation' stage of behaviour change, and the opening of the cycleway facilitated their progress to the 'action' stage.

No statistically significant changes in cycling frequency or distance were observed in the resident panel, in either the intervention group or the control group. This may be because the sample was simply too small for the forecast changes to be detected. Furthermore, it is known that some people in a population will have no interest in cycling, and will not consider switching no matter how convenient or comfortable it is made. Dill and McNeil (2012) describe these as the 'no way, no how' group in their typology of four types of cyclists, and estimate they comprise 25 per cent of the population in the City of Portland (United States).[51] Taverner Research (2007) estimate the proportion for Sydney is 20.8 per cent. Considering these so-called 'non-traders', the expected change in demand would be even smaller, requiring an even larger sample size to be able to detect it.

However, using residential proximity as the exposure variable (instead of intervention/control area), there was found to be a statistically significant increase in weekly cycling minutes among respondents who lived between 1.00 and 2.99 km from the cycleway. There was, however, no change in weekly cycling minutes among respondents who lived less than 1.00 km from the cycleway. These respondents were clustered around the northern end of the intervention area, close to the CBD, and would have had less reason to use the cycleway than those living further south.

Previous before-after studies of the impacts of single bicycle paths have also found little or no change in bicycle use (Burbidge & Goulias, 2008; Scheepers et al., 2014). Generally, it is only in cases where an intervention comprises multiple new facilities, that a statistically significant increase in bicycle travel amongst residents has been detected – for example, an assessment of town-wide cycling initiatives in the United Kingdom by Goodman et al. (2013).

In terms of the impact on the demand for other transport modes, the majority (59 per cent) of intercept survey respondents who had changed mode to bicycle had previously used public transport. This is consistent with previous studies, which have found the cross-elasticity between driving and cycling to be low, and that

[51] The other groups are 'the strong and the fearless' (6 per cent), 'the enthused and confident' (9 per cent), and 'the interested but concerned' (60 per cent).

bicycle competes mostly with public transport (Börjesson & Eliasson, 2012). From the pre-intervention mode choice models, it was predicted most switching to bicycle for commuting would be from public transport, but most switching to bicycle for other trip purposes would be from car. Sydney's public transport systems are oriented towards commuting travel, so this difference is not unexpected.

Among the resident panel, however, the cycling mode share in the intervention group fell from 8.2 per cent pre-intervention (2013), to 6.8 per cent post-intervention (2015). Over the same period, the public transport mode share increased from 19.1 per cent to 23.5 per cent. This unexpected increase in the public transport mode share might be attributed to the roll-out of smartcard ticketing in 2014, along with pricing incentives, e.g., cheaper fares, free travel after eight trips in a week, and unlimited travel on Sundays for AUD 2.50. Ideally, a variable for public transport fare would have been incorporated into the pre-intervention mode choice models, and the fare reductions modelled in the future scenarios. However, Sydney's public transport fare structure is very complex, making it difficult to impute the fare for a given choice situation (trip). In the temporal preference stability models (Section 6.5), the alternative specific constants for public transport did increase between 2013 and 2015. These constants capture sources of utility/disutility not accounted for by specified variables, and the increase in their values may, in part, be attributable to the ticketing and fare changes.

This being the case, a similar increase in the public transport mode share would be expected among the control group. However, there was no statistically significant change in mode shares of this group. This might be due to differences in the way public transport services improved between the intervention and control areas. While the intervention area is well served by swift and frequent heavy rail services connecting to destinations throughout the Greater Sydney metropolitan region, the control area is largely served by buses – which are slow, indirect and often full – as is the single light rail line. Furthermore, control area residents travelling to a rail interchange by bus or light rail, and then transferring to a heavy rail service, must pay an additional fare to change mode – whereas intervention area residents travelling by heavy rail only are not penalised for changing train line.

From the pre-intervention mode choice models, it was predicted that women would be more likely than men to change mode to bicycle (because the provision of a low-stress bicycle route is expected to offer greater utility gains for women than for men). There was no statistically significant difference between men and women taking up cycling among the resident panel – again, the sample size may have been too small to detect any difference. However, intercept survey respondents who reported having changed commuting mode to bicycle were more likely to be female.

In summary, the bicycle count and intercept survey data support the rejection of the null hypothesis. The picture from the resident panel is less clear. There is some indication that cycling time increased among those living on the fringes of the intervention area, which may have been because they took longer routes to use the new cycleway. However, the cycling mode share among the intervention group decreased at the expense of public transport, contrary to what was forecast. This finding could be attributed to background factors, such as public transport changes, which were not modelled in the original forecasts, and affected intervention and control areas differently.

7.2.4 Hypothesis 2 (Null)

Preferences underlying bicycle mode choice are stable over time.

In the preference stability tests for commuting, respondents preferred cycleway distance to non-cycleway distance in all three years (2013 to 2015). However, the ratio between the preference parameters changed. The marginal rate of substitution (MRS) model suggested the ratio contracted (owing to a greater aversion to cycleway distance across the waves), while the nested logit model suggested it enlarged (owing to a lower aversion to cycleway distance). The interactions model also suggested the ratio enlarged, but owing to a greater aversion to non-cycleway distance.

In the preference stability tests for non-commuting, respondents again preferred cycleway distance to non-cycleway distance in all three years. Both the interaction and nested logit models suggested the ratio contracted, due to lower aversion to non-cycleway distance. However, the MRS models suggested there was no significant change in the ratio.

These findings do not necessarily mean respondents' preferences changed. There may have been differences in the way they completed the travel diary in each wave (e.g., due to survey fatigue). Alternatively, there may have been differences in the way the diary data were cleaned (this task was undertaken by different analysts in each wave, albeit following a consistent set of rules). The models may have been mis-specified or over-specified (Badoe and Miller (1995) found that a simpler model gave better prediction success, even though it fitted the data less well than one with more variables). As such, the hypothesis cannot be rejected with confidence.

Whatever the reasons for the changes in preference parameters, they highlight the issue with making travel demand forecasts, and estimating economic benefits/costs of a project proposal, based on parameters estimated at one point in time.

7.3 Thesis contributions

Social cost benefit analysis (SCBA) is the principal deicsion support tool used to justify and prioritise transport investments in Australia, and many other jurisdictions worldwide. However, SCBA typically values user benefits in terms of travel speed increases or time savings, which discriminates against transport modes where the travel time is enjoyable, or can be used for other activities.

Notwithstanding these and other concerns, van Wee and Börjesson (2015) argued that SCBA can still be a useful tool for informing decision-making for cycling projects and policies. However, they highlighted some areas where additional research is needed.

They identified the need for "a better understanding of the key variables determining cycling volumes and how they affect the utility and disutility of cycling" (van Wee & Börjesson, 2015, p. 123). The mode choice analyses undertaken for this thesis largely confirm previous models used to predict bicycle demand. People prefer low-stress bicycle routes to high-stress ones, do not like to cycle in the rain, etc. However, whereas previous models for car-centric cities suggest men are generally more inclined to cycle than women, the present analysis shows there is no preference difference between the genders for distance ridden on protected cycleways. In other words, women like cycling just as much as men do, as long as they do not have to ride with traffic. Furthermore, by modelling commuting and non-commuting travel separately, notable differences in preferences between trip purposes have been identified. In particular, the willingness to travel farther/longer to use a cycleway diminishes when the trip purpose is commuting. Finally, by using mixed logit, as opposed to the more commonly used MNL model, it was possible to identify preference heterogeneity, and to allow flexible substitution patterns.

Van Wee and Börjesson (2015, p. 123) also call for more research to "improve the possibilities of evaluating all the accessibility-related impacts of cycling policies", including "option value". This thesis has demonstrated how changes in consumer surplus for a cycling project can be estimated from a discrete choice model, capturing improvements in accessibility and option value,[52] as well as other user benefits – in a way that can be incorporated into existing SCBA frameworks.

Demand forecasts for a transport intervention are often not validated. When they are, they often prove to be inaccurate – possible reasons for this are that travellers' preferences change over time, or they are affected by experience of the intervention itself. In this study, travel data were collected both before and after the intervention. This enabled forecasts to be validated, and the hypothesis of temporal preference stability to be tested. The use of additional survey methods (traffic counts and an intercept survey) provided a broader picture of changes in

[52] Refer to Section 3.3.2.1. In the present analysis, the value of improvements to transport mode options is captured. The value of improvements to destination and other options could be captured by incorporating these choices into the model.

travel behaviour and preferences, than would have been possible using travel diary data alone.

Previous temporal preference stability studies in the transport field have used repeat cross-sectional data. This is the first known study to use panel data, and the first to investigate changes in cycling preferences following a bicycle infrastructure intervention.

7.4 Limitations

7.4.1 Recruitment for resident survey

A number of challenges were experienced during recruitment for the Sydney Travel and Health Study. Originally, it had been anticipated that an intervention sample representative of the population and living within roughly 500 metres of the new cycleway, and a control sample from a similar area, would be recruited through online consumer panels. When it became clear that the target sample size (343 respondents from each area) would not be met, the following steps were taken.

- The size of the intervention area was expanded to cover the expected catchment area of the new cycleway. The size of the control area was also increased (see Figure 4.10).
- Quotas for age and gender were relaxed, resulting in a convenience sample not representative of the population. Notably, the pre-intervention sample was skewed towards older age groups. Where possible, these differences have been accounted for through weighting.
- Additional recruitment methods were employed, including random digit dialling letterbox drops, social media, electronic mailing lists (primarily aimed at tertiary students) and two Ride2Work Day breakfast events (see Section 4.4.3). These recruitment methods resulted in bicycle users being oversampled. Where possible, this has been accounted for in the analysis.

People under 18 and over 55 were excluded from the study, as may have been people who do not identify as male or female (because no other gender options could be selected). The recruitment and survey methods used may have excluded other groups, e.g., people without Internet access.

To mask the purpose of the study, it was advertised as a 'travel and health survey'. This may have attracted people with an interest in healthy and active living – analysis of reported physical activity showed the sample was more physically active to begin with than the general population. The specific purpose of the study may have become obvious to respondents during the post-intervention questionnaires, when they were asked a number of questions about the new cycleway.

The respondent attrition rate was higher than the anticipated 15 per cent, resulting in a smaller than expected sample for the Wave 2 (post-intervention) data collection, and making it more difficult to detect statistically significant changes in travel behaviour. To minimise further attrition in Wave 3, the financial incentive was increased, and respondents who had completed Wave 1 but not Wave 2 were contacted by telephone and invited to re-join he study.

7.4.2 Mode choice analysis

Modelling and forecasting human travel behaviour is both an art and a science, and results can be sensitive to decisions and assumptions made by the analyst.

For this thesis, a decision was taken to use a quantitative approach, namely discrete choice analysis, in which it is assumed humans, when faced with choosing from a finite set of alternatives (a) have complete information about those alternatives, (b) aim to maximise their utility, and (c) act rationally. As discussed in Chapter 3, there are many criticisms of this approach, and the underlying theory. However, discrete choice analysis was considered an appealing and pragmatic method for gauging the user benefits of new cycling infrastructure, in a way that fits in with existing appraisal frameworks, and that can exploit existing data sources (e.g., household travel surveys).

Next, a decision was made to focus on trip mode choice, and to assume destinations are fixed. The mode choice situations were constructed by modelling likely journeys by different modes; the attributes of these modelled journeys are unlikely to have exactly matched those perceived by the respondents when making their choices. Another approach could have been to model the bicycle route choice for each trip, and then feed the estimated inclusive values (representing bicycle utility/accessibility) into a mode choice model, as described by Hood et al. (2011). However, this approach would involve collecting and processing a large amount of route choice data, e.g., GPS traces, so would be costly to replicate.

Driving travel times estimated with the Google Maps Directions API assumed free-flow traffic conditions. To account for road congestion, a 'peak time' dummy variable was included in the models. However, this is unlikely to have fully captured the influence of congestion on mode choice. More realistic travel times could be obtained using a strategic transport model, e.g., the Sydney Strategic Travel Model (Bureau of Transport Statistics, 2011).

Origins and destinations were assumed to be fixed; this may be a reasonable assumption for commuting travel, because home, work and study destinations tend to be fixed – in the short term at least. However, destination choice can be affected by mode choice (and vice versa) (Ortúzar & Willumsen, 2011).

A major failing of road and public transport appraisal, and one reason why forecast travel time savings have not been demonstrated to materialise in full, is that modellers often assume people will not change home location in response to a transport intervention – when it is known some people will move farther from work and other destinations, if new infrastructure gives them the opportunity to do so while staying within their travel time budget (Metz, 2008). There has been little research on the impact of new cycling infrastructure on residential location choice; however, it is unlikely to lead to urban sprawl in the same way that, say, urban freeways do, given the limited speed of bicycles. There is, however, a clear link between bicycle use and destination choice (Hyodo, Suzuki, & Takahashi, 2000), and a separate analysis shows the opening of the George Street Cycleway did have some effect on destination choice (Greaves et al., 2015), so future analyses could model destination and mode choice simultaneously.

Another consideration is that the mode chosen for the first trip of a tour influences the mode chosen for subsequent trips. For example, if bicycle is not used for the first trip, then the traveller may not be able to use a bicycle for subsequent trips.[53] To address this issue, tours could be modelled instead of trips. An alternative approach would be to use activity-based modelling, which also takes into account individuals' scheduling constraints (see Bowman & Ben-Akiva, 2000).

The selection and categorisation of variables for inclusion in the mode choice models was guided by the literature, and the available data. To allow the effect of new bicycle infrastructure to be modelled in a mode choice context, the bicycle distance variable was divided into cycleway distance (low stress) and non-cycleway distance (high stress). In reality, the distinction is not so binary – some quiet laneways and residential streets may offer a low-stress riding environment, yet be categorised in the same way as a high-stress arterial road. Future analyses could use crowdsourcing to gather data about perceived stress levels for all links in the network, as is being done in Portland (United States) with the Ride Report app (Streeter, 2016).

Some potentially significant dependent variables were not included in the models, because the values for these could not be obtained or reliably imputed (e.g., public transport fare, public transport crowding, fuel cost and parking cost). However, the pseudo-R^2 values of the final models are relatively high, indicating that mode choice can mostly be explained by the independent variables that were included. To allow for inclusion of such variables in future analyses, a separate stated preference study could be undertaken, and the resulting data estimated jointly with the revealed preference data.

7.4.3 Travel demand forecasts and economic appraisal

The travel demand forecasts assumed residents would be fully aware of the new cycleway. However, questionnaire responses showed that some respondents were

[53] Except, for example, where bicycle share schemes are available.

not aware of it six months after it opened. Forecasts could be improved by incorporating awareness, as described by Chorus and Timmermans (2009).

It was assumed that average rainfall over the next 30 years would be the same as in the previous 10 years; this cannot be guaranteed in an age of rapid climate change. Other climate variables (e.g., heat, cold, humidity) were ignored. Data were collected during the spring, which is generally a pleasant time to cycle in Sydney, weatherwise. Summers are hot and humid, while winters have dark evenings.

The Complete Network scenario was forecast to result in a significant increase in bicycle traffic. Given the proposed cycleway infrastructure is all single lane (mostly bi-directional), some links and intersections would be expected to reach capacity, resulting in congestion.[54] This congestion was not accounted for, though perhaps such a scenario may result in road authorities reprioritising road space and traffic signals to alleviate it.

The economic appraisal assumed only adults aged 18 to 55 and living within intervention area would benefit from the new cycleway. There are already reports of more children cycling to school, where cycleways have been built (Sydney Cycleways, 2017). Benefits to recreational users were not included, i.e., people just going for a bike ride. Benefits to multimodal transport users were not included, e.g., people travelling to/from a train station by bicycle. Very few such trips were reported in the travel diary, though bicycle could be expected to play an increasingly important role in public transport access/egress as the network develops, and with the recent introduction of dockless bicycle share schemes (Needham, 2017).

Decongestion benefits were not included in the economic appraisal, because latent demand for driving in the study area is high, and any mode shift from driving to

[54] There are already anecdotal reports of bicycle queues not being cleared at some city centre intersections.

cycling would be expected to result in some of this latent demand becoming actual demand, e.g., remaining drivers driving more at peak times. For completeness, the value of this additional car travel could have been included in the appraisal. However, the value of this benefit would be expected to be negligible relative to the bicycle user and public health benefits.

Health benefits for people switching from public transport to cycling may have been overestimated, because accessing/egressing public transport often involves incidental physical activity. In future appraisals, an average value of the health benefit for public transport access/egress could be estimated, and multiplied by the forecast number of reassigned public transport trips, with the product deducted from the benefits stream.

Because there were no financial cost variables in the mode choice models, changes in consumer surplus were estimated in units of hours of driving travel time savings – which has an established monetary value in NSW (albeit one that has been debated) – and then converted into a dollar value. Ideally, a financial cost variable (e.g., public transport fare or road toll) would be included in the model specification.

Like many economic appraisals of transport projects, equity impacts were ignored. It is possible that benefits accrued largely to people who already enjoyed good levels of accessibility and transport options. The appraisal methodology implicitly favours projects that increase bicycle ridership (bicycle kilometres travelled) over those that increase network coverage. But it could be argued building bicycle infrastructure for areas with high levels of transport disadvantage may be a more worthwhile investment, even if it doesn't generate the same levels of ridership or economic benefits (Andersen, 2015; Walker, 2011).[55]

[55] That said, the George Street Cycleway does pass through a large public housing estate.

7.4.4 Intercept survey

A major limitation of the intercept survey is that it did not include people who did not change mode to bicycle after the cycleway opened, nor people who used alternative routes and did not change route to use the new cycleway. A better understanding of the factors predicting route change could be achieved by intercepting riders on alternative routes.

It is acknowledged that it is not possible to know from the intercept survey data how much, if any, influence the opening of the cycleway had on each respondent's decision to change mode or route. There may have been other factors that influenced their decision, e.g., increased crowding on public transport.

Further, it is acknowledged that the GIS-modelled shortest paths via the intercept locations are unlikely to be the same as the actual routes the respondents took. Similarly, the GIS-modelled absolute shortest paths are unlikely to match the routes the respondents would have taken had the cycleway not existed. Therefore, the estimated diversion distances should be treated as approximations.

It is impossible to know how much influence the presence of the cycleway had on each respondent's decision to divert from the shortest path route. For undirected travel (i.e., purely recreational/exercise trips), it is unlikely that respondents would have been aiming to minimise their travel time/distance.

Respondents were asked how long they had been riding regularly as a way to gauge cycling experience. However, there is likely to have been some variation in the way ‘regularly’ was interpreted.

Finally, it was assumed that cycleway users were able to recollect accurately how they travelled before it opened (nine months previously).

7.4.5 Potential researcher bias

All researchers involved in the project, including the author, have an interest in transport and health. Although every effort was made to ensure this did not bias the research in any way, it may have influenced various aspects of the data collection and analysis, including:

1. the choice/wording of survey questions and response categories – and other aspects of survey design – in ways that could have affected responses, and possibly behaviour;
2. choice of analysis methods;
3. decisions and assumptions made during choice data generation and choice model specification; and
4. decisions about which costs and benefits were included in the economic appraisal, and how they were valued.

7.5 Future research

In addition to the recommendations noted in Section 7.4, other research could be undertaken to build on the methods and ideas presented in this thesis.

As others have found, it is difficult to detect changes in population travel behaviour resulting from a single link in an incomplete cycling network. Similar studies in future could assess multiple links, or complete networks. Given long planning, design and construction timeframes, and high residential mobility (in Australian cities at least), collecting panel data may be challenging. Repeat cross sectional data (e.g., household travel survey) could be used instead.

There is the question of how to communicate the user benefits of slow travel (as estimated using discrete choice analysis) to decision makers and other policy stakeholders. 'Travel time savings' are something most people can relate to, but terms like 'consumer surplus', 'inclusive value' and 'logsum' have little meaning for the layperson. An increase in consumer surplus (calculated using the inclusive value approach) can be interpreted as an improvement in accessibility and transport choice (Dong et al., 2006). Future research could test how the use of different terms to describe user benefits of cycling projects affects their likelihood of supporting them.

Future research on temporal bicycle preference transferability could focus on eliminating influences, other than actual changes in preferences that may cause parameter values to change, e.g., survey fatigue. Repeated stated preference surveys would give more control over the survey task.

7.6 Implications for practice and policy

It is clear from this and prior research that individuals derive utility from cycling, and the level of utility increases when low-stress facilities, such as cycleways, are provided. Transport for NSW's cycling project appraisal guidelines should be amended to value these increases in utility appropriately. This thesis has demonstrated how such user benefits can be estimated and valued using a discrete choice modelling approach, and has estimated some parameters that could be adopted for future projects in inner-city Sydney – though it should be noted these parameters were not found to be temporally stable. Care should be taken using these parameters in other areas; alternatively, new parameters could be estimated from existing data sources, e.g., Census for commuting travel,[56] or household travel survey for all travel. The estimated user benefits can easily be incorporated into existing appraisal (social cost benefit analysis) frameworks.

Of course, it is also possible to reduce the disutility of time spent travelling by other modes. Automated vehicles will enable individuals to work or enjoy screen time whilst travelling. This is likely to result in a lower valuation of travel time savings for car travel, meaning potentially longer journeys, and less willingness to pay for tolls.

There were notable differences in parameter estimates between the choice models estimated for commuting and non-commuting. Those involved in modelling bicycle travel demand, and appraising bicycle infrastructure, should model commuting and non-commuting travel separately, as is usual practice for modelling driving and public transport.

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[56] Linked Census records would be required for discrete choice analysis.

The finding (from both the travel diary and intercept survey analysis) that non-commuters divert farther from the shortest path to use a cycleway than do commuters has implications for network design. Bicycle routes intended for commuting should be as direct as possible, or there is a risk they will be under-utilised. Bicycle routes intended for other purposes can be less direct and still attract riders.

Finally, the finding that cycling parameter values can change over time suggests caution should be used when making forecasts and economic valuations based on parameters estimated at a single point in time.

7.7 Concluding remarks

Investment in low-stress bicycle routes and networks can benefit individual travellers, even if their journeys end up being slower. The benefits may include increased comfort and perceived safety, improved accessibility and improved transport options. This research has demonstrated that, by analysing how travellers trade off the various attributes of the alternative transport modes available to them, these benefits can be forecast and monetised: slow travel does have value for those partaking in it, and there is no justification for omitting this value in economic appraisals of new cycling projects.

However, this research has also highlighted some issues with forecasting bicycle demand and economic benefits in the short term (up to 18 months post-intervention), let alone over a 30-year project lifetime typically used in social cost benefit analysis. Preferences around travel and residential/work location choice can change. A government hostile towards cycling can assume power. Technology can be hugely disruptive: apps like Google Maps have made bicycle route planning and navigation easier, helping less confident riders avoid high-stress routes. Mobile technology has facilitated 'gig economy' bicycle delivery services, e.g., Deliveroo and Uber Eats, as well as dockless bicycle share systems. On the other hand, automated vehicles may in future compete with bicycle, while technology and artificial intelligence could transform labour markets and education delivery in ways that dramatically reduce demand for commuting travel.

Of course, concern about the reliability of transport models and forecasts is not limited to cycling projects – few road and rail projects deliver the anticipated demand and benefits.

Furthermore, there is an apparent conflict between the objective of maximising individual utility (an implicit objective of discrete choice analysis), and the objectives of (a) maximising system performance and efficiency for the greater public good, and (b) making cities sustainable. For a new urban motorway, the forecast economic benefits are typically dominated by the forecast value of personal travel time savings. However, instead of reducing their travel time, many individuals simply use the opportunity to move farther from work, where land is cheaper. The value to them of being able to do so is at least equal to the value of the travel time savings they could otherwise have enjoyed (Van Wee & Rietveld, 2008). Though these individuals are now considered better off, the cumulative result of many such projects – urban sprawl, toxic air, road trauma, community severance, a hostile walking/cycling environment, etc. – may be considered unacceptable by a majority of residents. There is no mechanism, in Australia at least, to set a ceiling for any of these impacts.

To make cities more liveable, sustainable and accessible for all, perhaps a different approach is needed to transport and land use planning. Stanley et al. (2017, p. 16) suggest: "start with a clear vision of the kind of city that is desired… then use transport and other measures to help deliver that result", as opposed to the current practice of responding "to problems such as traffic congestion with narrowly conceived transport infrastructure approaches". In other words, 'backcast' instead of forecast. Within such a paradigm, there would still be a role for social cost benefit analysis, e.g., in choosing between alternative strategies, or prioritising links within a network (staging).

Pragmatically speaking, however, it is likely that social cost benefit analysis will remain the principle decision support tool used to justify transport strategies and investments. This thesis has shown how SCBA could be improved to address some of its inherent bias against active transport, and better take into account the positive utility of travel.

Time spent travelling should not be considered purely a cost to be minimised, rather something that can be enriched. Much like researching and writing a thesis, a journey is not always just about the destination.

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APPENDIX A: ONLINE TRAVEL DIARY

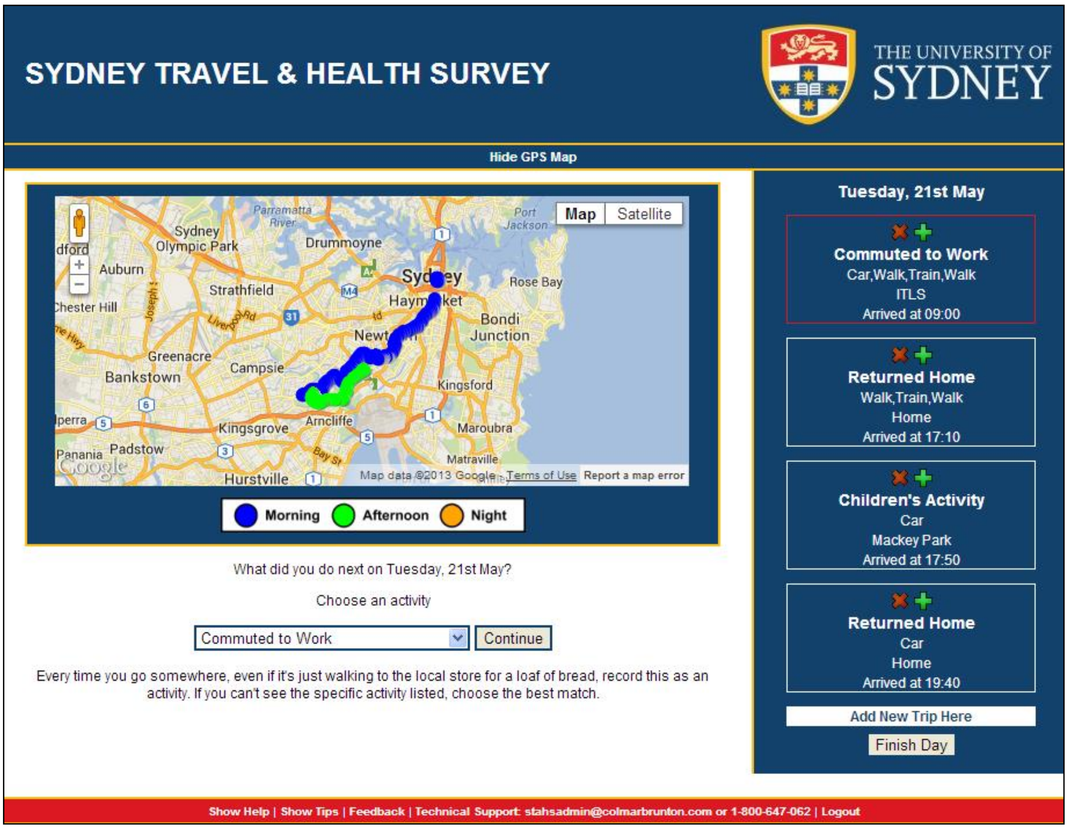

Figure A.1: Online travel diary – activity selection (Form 2)

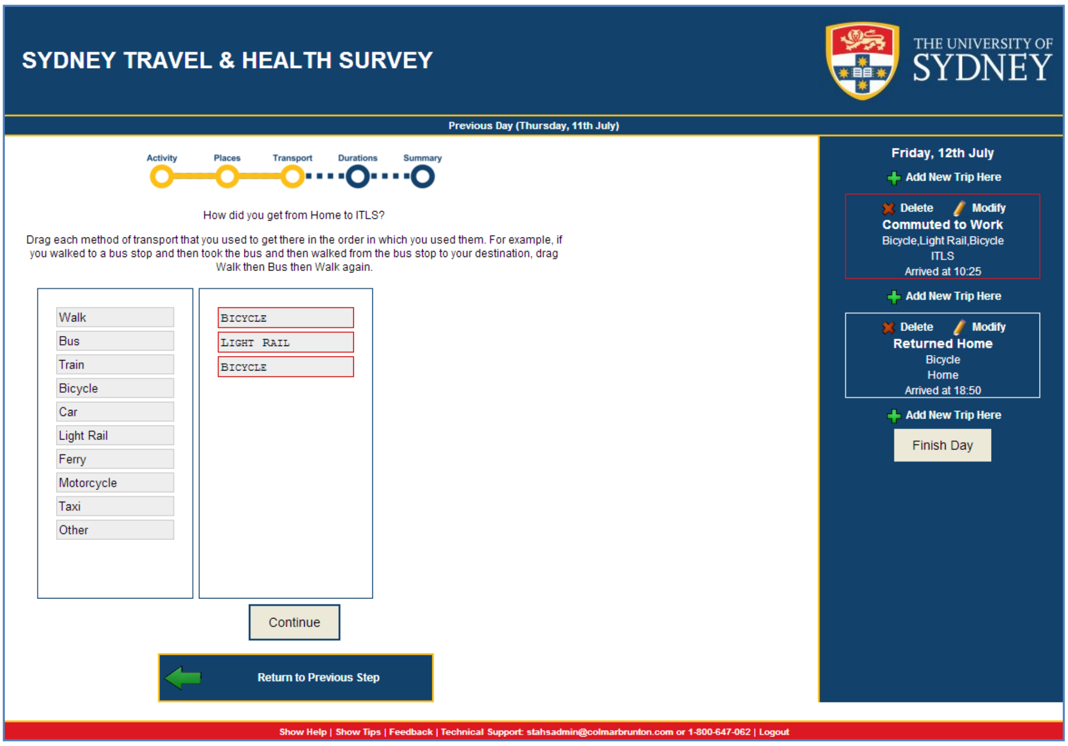

Figure A.2: Online travel diary – mode selection (Form 4)

APPENDIX B: INTERCEPT SURVEY

Table B.1: Intercept survey questions and response categories

Survey question	Pre-coded response categories used by interviewers	Category coding for analysis
Where have you cycled from?	Street/place and suburb	Longitude and latitude (WGS 84 coordinate system)
Where are you cycling to?	Street/place and suburb	Longitude and latitude (WGS 84 coordinate system)
What is the purpose of your cycle trip today?	Commute to work Commute to study	Commuting to work or study
	Exercise Work related Visit friends/family Drop off/pick up kids Shopping/personal business Kids' activity Other Dining Recreation Travel to exercise	Other
What mode of travel would you have used for this trip before the cycleway was built?	Bicycle	Respondent did not change travel mode to bicycle after the cycleway opened (existing rider)
	Walk Bus Train Car Taxi Motorcycle	Respondent changed travel mode to bicycle after the cycleway opened
	N/A (would not have made trip) N/A (just moved to area)	N/A
How long have you been riding regularly?[a]	A few weeks 1 - 6 months Since cycleway opened 1 - 2 years	≤ 2 years
	3 - 5 years 6 - 10 years 10+ years	> 2 years
Have you changed your cycle route since the cycleway was built?	Yes	Respondent changed bicycle route after the cycleway opened
	No	Respondent did not change bicycle route after the cycleway opened
	Sometimes N/A (just moved to area) N/A (new to bicycle riding) N/A (other reason)	N/A
Attire	Cycling-specific Causal Business	Cycling-specific Causal Business
Observed gender	Male Female	Male Female
Estimated age (years)	18 - 29	< 30
	30 - 60 > 60	≥ 30

[a] If a respondent gave a duration between seven months and one year, the interviewer would ask if they started before or after the cycleway opened (which was nine months previously). This prompt allowed the interviewer to establish with greater confidence whether the respondent started before or after the cycleway opened (during pilot testing, respondents found it difficult to recall precisely when they started). In response to this prompt, no respondent said 'before'. If they had, it would have been coded as '1 - 2 years' by the interviewer.