Incentivising Car-shedding Behaviour in the Greater Dublin Area

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DECLARATION

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and it is entirely my own work.

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SUMMARY

This doctoral research examines the behavioural response of commuters within the Greater Dublin Area (GDA), Ireland, to a range of policy incentives devised to encourage travellers to make greater usage of sustainable travel modes for work and education trips. Several policy measures were evaluated using discrete choice and four stage modelling techniques, to identify a means of stimulating a shift from single occupancy vehicle (SOV) use to alternative modes such as walking, cycling, public transport and more sustainable use of the private car, namely carpooling and car-sharing. Such policy tools were utilised to increase potential levels of 'car-shedding' behaviour in the GDA by increasing the likelihood of sustainable mode choice, through making alternative modes more time and cost efficient, safer and ultimately more convenient to use when commuting than private cars. The research presented in this thesis coins the term of car-shedding, which is defined as the incidence of a reduction in private car trips, by means of encouraging the reassessment of the need to utilise a private car for certain trip purposes (Carroll, et al., 2017). In this way, the potential of reducing utility of private vehicles through 'shedding' of single occupancy vehicle trips in exchange for more sustainable means of transport is stimulated exclusively through the incentivisation of alternative modes rather than disincentivising private car use.

A stated preference survey (SP) was employed as the instrument for gathering mode choices and socio-demographic data of a sample of commuters in the GDA, based on a number of hypothetically designed choice scenarios incorporating policy incentives. In this experiment respondents were asked to make a trade-off between the trip characteristics of three modes, one of which being a private car or status quo option (i.e. bus, rail and car). The SP results from this survey were then fed into a multinomial logit (MNL) model to generate likelihood estimates of certain modes being chosen given the introduction of particular policy measures. In addition to this, a range of behavioural indicators were elicited from analysing the output of market elasticities and simulation models from discrete choice modelling. Notable results generated from this analysis determined that policy incentives offering tangible time and cost savings in particular, led to the greatest shift towards sustainable modes across the attributes modelled. The findings showed that reductions in the modal share of SOVs of up to 8% in a 'Do Maximum' scenario could be achieved if policies are put in place to reduce the time and cost attributes of commuting to work by alternative modes. Furthermore, in relation to sustainable car use, a 1% change in the convenience, time and cost attributes yielded a direct elasticity or increase in the probability of carpooling and car-sharing being chosen, of up to 0.34%, suggesting that the carpool and car-share modes may be relatively elastic to such trip characteristic changes.

Extensive four stage modelling work was subsequently conducted using National Transport Authority's (NTA) Regional Modelling System (RMS) to represent the policy changes explored in the SP experiment in order to produce real life estimates of trip making behaviour. Changes to model parameters in the mode choice and trip assignment stages of the Eastern Regional Model (ERM) (covering the Greater Dublin Area) were made to account for improvements made to infrastructure, frequency, time and cost attributes of various modes included in the model. The changes were made based on 'Do Nothing/ Base', 'Do Something', and 'Do Maximum' scenarios, which were designed based on attribute level values from the SP survey. The outputs generated from these model scenarios determined that pedestrians in the GDA were more sensitive to parameter changes made in ERM than the other modes tested. This was highlighted in the active modes and the optimal car-shedding model results, where walking experienced the largest and, in some cases, the only increase in mode share as a result of the policy implementation. In addition to this, daily CO_2, NO_x and $PM_{2.5}$ emission reductions were estimated from changes recorded in vehicle kilometres travelled of private cars. The associated monetary savings from these reductions were similarly estimated, which determined that up to €5,705 from CO_2 reductions, up to €5,499.94 from NO_x reductions and up to €9,010 from $PM_{2.5}$ reductions, could be saved from daily commute trips.

Overall, the results produced in this thesis research suggest that policy incentives alone, leading to tangible improvements to commuters' time and cost trip characteristics can act as effective mechanisms in encouraging car-shedding behaviour or a sustainable mode shift in the GDA. The empirical results explored in this thesis supports this hypothesis which may present valuable guidance and recommendations for policymakers that are pursuing methods of reducing the environmental consequences of emissions from transport in Ireland as a matter of urgency.

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ABBREVIATIONS

ABA	Activity Based Approach
AICc	Akaike information criterion coefficient
ANCOVA	Analysis of Covariance
ASC	Alternative specific constant
BRT	Bus Rapid Transit
CAF	Common Appraisal Framework
CBD	Central Business District
CE	Choice experiment
CO_2	Carbon Dioxide
COPERT	Computer programme to calculate emissions for road traffic
CSA	Census small area
CSO	Central Statistics Office
CSR	Corporate social responsibility
DART	Dublin Area Rapid Transit
DCCAE	Department of Communications, Climate Action and Environment
DCC	Dublin City Council
DPER	Department of Public Expenditure and Reform
DTTAS	Department of Transport, Tourism of Sport
EIA	Environmental Impact Assessment
EPA	Environmental Protection Agency
ERM	Eastern Regional Model
EV	Electric vehicle
FDM	Full Demand Model
FSM	Four stage model
GDA	Greater Dublin Area
HOV	High occupancy vehicle
IIA	Independence from Irrelevant Alternatives axiom
IID	Independently and identically distributed
IPCC	Intergovernmental on Climate Change
IVT	In-vehicle time
LL	Log likelihood
LGV	Light goods vehicle
LOS	Level of service
MaaS	Mobility as a service
MCA	Multi Criteria Analysis

MDC	Mode and destination choice model
MINDSPACE	Messenger, incentives, norms, defaults, salience, priming, affect, commitments, ego
MLE	Maximum likelihood estimation
MM	Mobility Management
MNL	Multinomial Logit
NDFM	National demand forecasting model
NHTS	National household travel survey
NO_x	Nitrogen Oxides
NTA	National Transport Authority
NTEM	National Trip End Model
OGV	Other goods vehicles
OLS	Ordinary least squares
PBC	Perceived Behavioural Control
PCU	Passenger car units
PDF	Probability density function
PDAT	Planning Data Adjustment Tool
$PM_{2.5}$	Particulate matter
PnR	Park and Ride
POWSCAR	Place of work, school or college – Census of anonymised records
PT	Public transport
PSC	Public spending code
RMS	Regional Modelling System
RMSIT	Regional Model Strategic Integration Tool
RP	Revealed preference
RTPI	Real time public transit passenger information
RUT	Random Utility Theory
SCATS	Sydney Coordinate Adaptive Traffic System
SOV	Single occupancy vehicle
SP	Stated preference
SQI	Service quality index
SWOT	Strengths, weaknesses, opportunities, threats
TDM	Travel Demand Management
TPB	Theory of Planned Behaviour
TRB	Transportation Research Board
WHO	World Health Organisation

CHAPTER 1: INTRODUCTION

1.1 Introduction

Car dependency and the dominance of single occupancy vehicle (SOV) use as a transport mode for commuting and other purposes presents a number of costly economic and environmental consequences for urban areas, such as the associated effects of traffic congestion, air and noise pollution (Washbrook, et al., 2006). The World Health Organisation (WHO) estimates that the total economic cost of respiratory health and mortality associated with air pollution amounts to €1.45 trillion per annum, of which transport accounted for 19.5% (11.3 Megatons of CO_2) in Ireland in 2014 (Environmental Protection Agency (EPA), 2016; WHO Regional Office for Europe, 2015). Of the emissions produced from transport, it is estimated that the private car accounts for 52%, with 24% from freight and 4% from public transport (Department of Public Expenditure and Reform (DPER), 2018). In this way, there is an urgency to act and to find ways of stimulating modal shifts to alternative sustainable modes in order to alleviate these adverse effects (DPER, 2018; NTA, 2016). International agreements set by the United Nations Kyoto Protocol (1998), the Intergovernmental Panel on Climate Change (IPCC) (2007) and the European Commission (2012), to reduce emissions by 50% from 1990 levels by 2020 and by at least 80% by 2050 (European Commission, 2012), act as important incentives to take action in order to avoid legally binding financial penalties. However, it has been accepted that Ireland will most certainly fail to meet its 2020 target, as CO_2 emissions alone are projected to increase by 10% by this time, which is a clear indication that not enough is currently being done to decarbonise the Irish economy (Irish Times, 2018; 2017).

To tackle rising emissions from transport, a national development plan, entitled Project Ireland 2040 was launched in 2018 by the Irish government (DPER, 2018). In this plan, several ambitious strategic investment plans, totalling €21.8 billion, were unveiled to accelerate Ireland's transition to a low carbon and climate resilient nation. Such plans included were: to have 500,000 or more electric vehicles (EV) on Irish roads by 2030 with essential improvements planned in EV charging infrastructure to meet this demand; no new conventionally fuelled vehicles are to be sold in Ireland by 2030; a transitional strategy to a fleet of low emitting hybrid or electric buses; an overhaul of the bus public transport network, introduction of a metro/ underground project, extensions to light rail lines and electrification of heavy rail services, in addition to comprehensive improvements made to the cycling and walking network in metropolitan areas (DPER, 2018).

Project 2040 also includes a range of sustainable travel measures, designed to encourage a mode shift to alternative modes and reduce dependency of private cars. The research included in this thesis will specifically examine this aspect of the plan (DRER, 2018).

Sustainable travel measures seek to modify travel behaviour change in favour of green alternatives such as active modes (walking and cycling), public transport and smarter use of the private car, namely, car-sharing and carpooling. Such measures have been termed as travel demand management (TDM) or mobility management (MM) tools, yet much of the focus of these concepts centres on internalising these costs in the form of road pricing and parking charges (Washbrook, et al., 2006). However, this thesis offers a unique approach to the field of transport policy, entitled 'car shedding', which exclusively centres on incentivisation strategies for sustainable modes. This tactic of policy provision differs from TDM as it specifically does not comprise of disincentives or penalties for car users. Rather it seeks to stimulate voluntary travel behaviour change and encourage sustainable deliberation of mode choice. 'Car-shedding' is defined as the method of encouraging the reassessment of the need to use a private vehicle for certain trip purposes, accordingly reducing utility and the incidence of single-occupancy vehicle (SOV) trips by substituting more sustainable transport options (Carroll, et al., 2017).

The encouragement of car-shedding behaviour in the Greater Dublin Area (GDA) is the ultimate aim of the research presented in this thesis, which examines the behavioural response of introducing various policy measures that incentivise sustainable travel modes. It similarly assesses the socio-demographic composition of those commuting to work/education in the GDA, to ascertain the characteristics of individuals that would consider a modal shift to alternative transport modes. A stated preference (SP) survey was constructed to gather mode choice preferences and socio-demographic data from a sample of commuters in the GDA, based on a number of hypothetical policy scenarios. The results from this survey were then used in a multinomial logit (MNL) model to generate likelihood estimates of certain modes being chosen given the introduction of particular policy measures. In addition to this, a range of behavioural indicators such as market elasticities and simulation models were estimated from the discrete choice modelling.

The results of this SP experiment where then used to infer parameter modifications made to the National Transport Authority's (NTA) Eastern Regional Model[1]. Changes to parameters in the mode choice and trip assignment stages of the Eastern Regional Model (ERM) were made to account for improvements made to infrastructure, frequency, time and cost attributes of various modes included in the model.

[1] Travel demand model that predicts all day (AM to OP periods) for a range of modes in the region of Leinster, which includes the GDA.

The changes were made based on 'Do Something', and 'Do Maximum' scenarios, determined by attribute level values from the SP survey, for the 2012 Base Scenario and forecasted 2035 Scenario, based on the NTA's GDA Strategy (2016). Outputs from these model scenarios produced real life mode share estimates derived from new origin-destination trip demand predictions. Furthermore, associated emission estimates were produced based on changes in private vehicles kilometres travelled, in addition to the monetary savings made from reductions in emissions.

1.2 Research Objectives

The following research objectives were set for the research explored in this thesis:

i) To test the hypothesis that a range of transport policy incentives, in the form of 'policy plans' could encourage commuters, particularly those who commute by car, to shift to other more sustainable, convenient and cost effective modes of transport

ii) To conduct a detailed policy appraisal, in order to identify the most suitable policy measures that could be adopted in the GDA to increase the use of sustainable modes

iii) To empirically test the potential of a reduction in car trips through the use of policy incentives alone by quantifying behavioural responses and determine potential car-shedding behaviour in the GDA given significant changes being made to transport policy; in addition to calculating the consequential modal share of the GDA using a travel demand model (i.e. the ERM)

iv) To estimate the environmental outcome of changes in travel patterns and modal choice, by predicting potential CO_2, NO_x and $PM_{2.5}$ emissions reductions and the monetary savings generated as a result

This research ultimately aims to reduce the modal share of the private car, to sway attitudes in favour of sustainable modes and to destabilise long standing car hegemony and driving habits in the GDA by providing the necessary testing of various policy approaches through choice and four stage modelling and emissions estimation. In this way, this research offers a unique approach to policy appraisal and aims to provide policy recommendations based on strong empirical evidence

1.3 Thesis Layout

The thesis is organised into 7 chapters, the content of which will be outlined in this section:

Chapter 2

The study area for this thesis is outlined in Chapter 2, with an account of the current state of the transport system of the Greater Dublin Area (GDA). A delineation of the concept of car-shedding will then be provided in Chapter 2, followed by the benefits and barriers to encouraging car-shedding behaviour. A delineation of the theoretical foundations of travel behaviour research is similarly examined and a review of existing literature in the field of travel behaviour research is provided, with particular attention devoted to research investigating the use of policy incentives as a stimulus for a reduction in car use. Finally, empirical gaps identified in the literature will be outlined with an indication of how this research will contribute to bridging such gaps.

Chapter 3

The theoretical underpinnings of stated preference surveying and discrete choice modelling will be provided in Chapter 3, in addition to an examination of the research design and experimental process employed in the SP experiment. The application of multinomial logit (MNL) modelling in the context of this experiment will be then be set out, followed by a description of the sampling method used.

Chapter 4

The SP experiment conducted in this thesis will be examined in Chapter 4, with a detailed account provided of the discrete choice modelling results produced and behavioural elicitations generated from the preferences collected in the SP survey. A discussion of the behavioural response and policy implications of implementing the policy scenarios will then be presented.

Chapter 5

The travel demand modelling of the policy scenarios tested in the SP experiment will be investigated in Chapter 5, with a delineation of the National Transport Authority's (NTA) Eastern Regional Model (ERM) provided, followed by the methodology of the parameter changes made to the model. The mode share results produced from the ERM model will then be presented to determine the extent of the modal shift encouraged by the policy measures. The emissions savings estimated from changes in private vehicle kilometres travelled and the associated monetary savings from reductions in CO_2, NO_x, and $PM_{2.5}$ will also be set out in this chapter.

Chapter 6

A policy scenario analysis is provided in Chapter 6, where the results of a Multi Criteria Analysis (MCA) and Strengths, Weaknesses, Opportunities, Threats (SWOT) analysis are presented. An evaluation of the most suitable policy scenario tested in this thesis is conducted based on the first and second order effects of introducing each of the policy plans. An overall policy recommendation of the most appropriate policy plan to implement in the GDA to encourage a reduction in car dependency and car use, especially for commuting purposes, is similarly offered.

Chapter 7

A critical assessment of the methodology employed in this thesis is included in Chapter 7, followed by a discussion of the contribution of this research to the current knowledge, and recommendations for further research in this area.

1.4 Greening Transport Project

The research presented in this thesis was undertaken as part of the EPA funded Greening Transport project, which was created with the primary aim of merging the technical evaluation of the emissions produced from transport in the GDA with the behavioural changes needed to realise these reductions in emissions (Greening Transport, 2015). It was identified that previous endeavours to measure the ‘low hanging fruit’ of methods to reduce emissions from transport failed to fully unify the two disciplines of emissions and behavioural change modelling. The project team consisted of representatives from industry, government and academia, whom together formed the steering group for the Greening Transport Project. The research design and objectives were communicated with the project stakeholders and steering group members prior to commencing in order to acknowledge any concerns or suggestions raised. Supplementary meetings were also held with the steering group throughout the project lifecycle to provide an opportunity to update members on the progress of the research and to present findings generated from the study. It was determined from these meetings that in order for the EPA to have a holistic depiction of the extent of possible emissions reductions, it is paramount that the behavioural changes needed to meet international agreements are not overlooked. Thus, this project aimed to bridge the gap between travel behaviour change, discrete choice modelling literature and emissions modelling to provide an all-inclusive solution to car dependency and rising levels of emissions from transport in Ireland.

1.5 Overall Research Structure

The overarching methodology used to meet the objectives of this research can be summarised in Figure 1.1, where the processes involved of the SP experiment and demand modelling are set out. The SP experiment was the first component of the central research structure, where several policy measures were incorporated into three discrete scenarios: active modes (i.e. walking and cycling), public transport (bus and rail) and sustainable car use (i.e. carpooling and car-sharing). These scenarios were then tested hypothetically by surveying respondent mode choices made between three transport modes, one of which was a private car/ status quo option. The preferences collected from this survey were then modelled in a MNL regression model to elicit the behavioural responses and socio-demographic profiling of those most likely to switch modes given the policy implementation. The policy scenarios evaluated in the SP survey were then used as proxies for changes made to NTA's four stage ERM to generate actual disaggregated mode choice and trip data. The policies tested were represented in the ERM by coded modifications made to model parameters affecting trip time, cost and occupancy level values. These parameter modifications were mode-specific in reference to the three policy scenarios modelled. Based on the changes implemented in the model, new mode choices and vehicle kilometres travelled were subsequently generated for several modes, which were then utilised to estimate potential emission reductions and monetary savings from predicted shedding car trips and mode shifting behaviour.

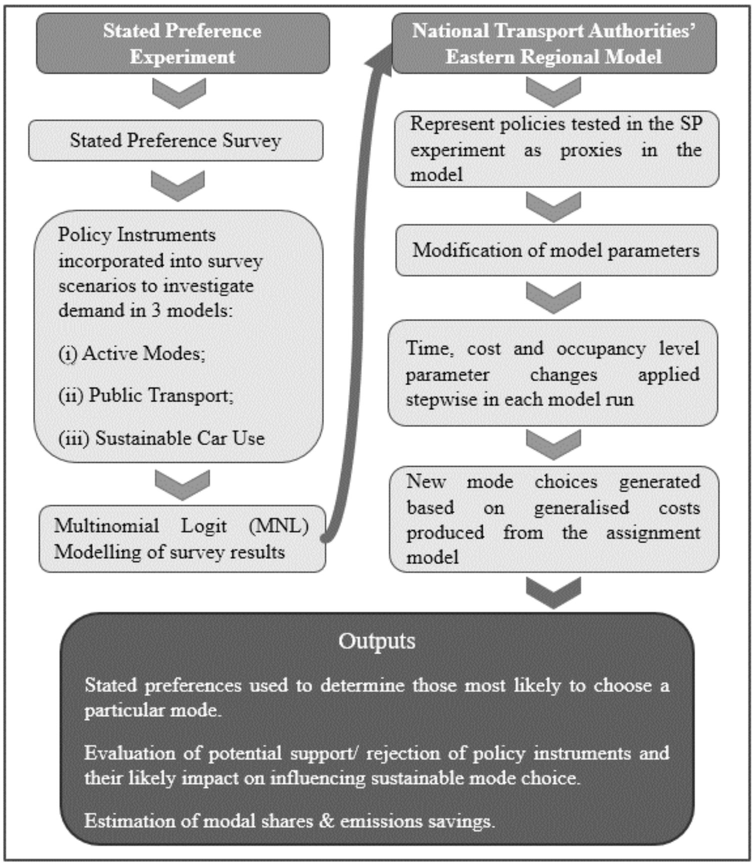

Figure 1.1 Overall Research Structure

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides an in-depth review of current literature in the field of travel behaviour research, with specific attention assigned to how sustainable behaviour change can be encouraged and evaluated with the provision of policy incentives.

Section 2.2 of this chapter outlines why the GDA was selected as the study area in this thesis research, accompanied with a description of the current state of the transport network and sustainable transport provision in the GDA. Section 2.3 delineates the concept of ‘car-shedding’ and outlines the potential benefits and barriers to encouraging car-shedding behaviour, as well as offering context to how it was derived in this thesis, and how the concept conveys the research objectives outlined in Chapter 1. It also discusses the incidence of car-shedding in Ireland and internationally, specifying reasons for a reduction in younger individuals applying for full driving licences. Section 2.4 provides an examination of the key theoretical and conceptual foundations for examining travel behaviour change in this thesis, with particular attention assigned to empirical examples from the Theory of Planned Behaviour and Behavioural Economics. Section 2.5 draws on a range of SP studies and other relevant field experiments that have tested the impact of introducing policy incentives on travel behaviour. The literature reviewed here is specific to the aims and objectives of this research, which inspired the development of the overall research methodology and highlighted gaps in this literature in the context of Ireland. Studies examining the behavioural response of implementing a range of hard and soft policy interventions applied to active modes, public transport and carpooling and car-sharing are reviewed. Finally, Section 2.6 defines gaps in the literature and the availability of research opportunities as a result and outlines how the research produced in this thesis is novel addition to the existing literature in this area.

2.2 Study Area Definition and transportation context of the Greater Dublin Area

The study area examined in the research conducted in this thesis is the GDA, containing the counties of Dublin, Meath, Kildare and Wicklow. The boundaries of the GDA are illustrated in the map in Figure 2.1. Based on the results from 2016 Census of Ireland, the total population of the GDA was 1,907,332 (CSO, 2017), which represented 40.05% of the total population of Ireland in 2016 (4,761,865). The GDA was designated as the most suitable area for this research in Ireland, as a result of there being a greater assortment of alternate and sustainable transport modes available in this region relative to the rest of Ireland. For instance, there are more options available and infrastructure in place to realistically offer viable alternatives to the private car, such as active mode infrastructure, a number of public transport (PT) modes such as the DART[2], the Luas[3], a number of bus operators, and the availability of bike-sharing, car-sharing and carpooling services. While the GDA was determined as the optimal study area in Ireland for this research, it was also considered that this study could conceivably be replicated elsewhere in Ireland or indeed outside of Ireland. This is however subject to the sufficient availability of alternative transport modes to the private car, ideally in urban areas.

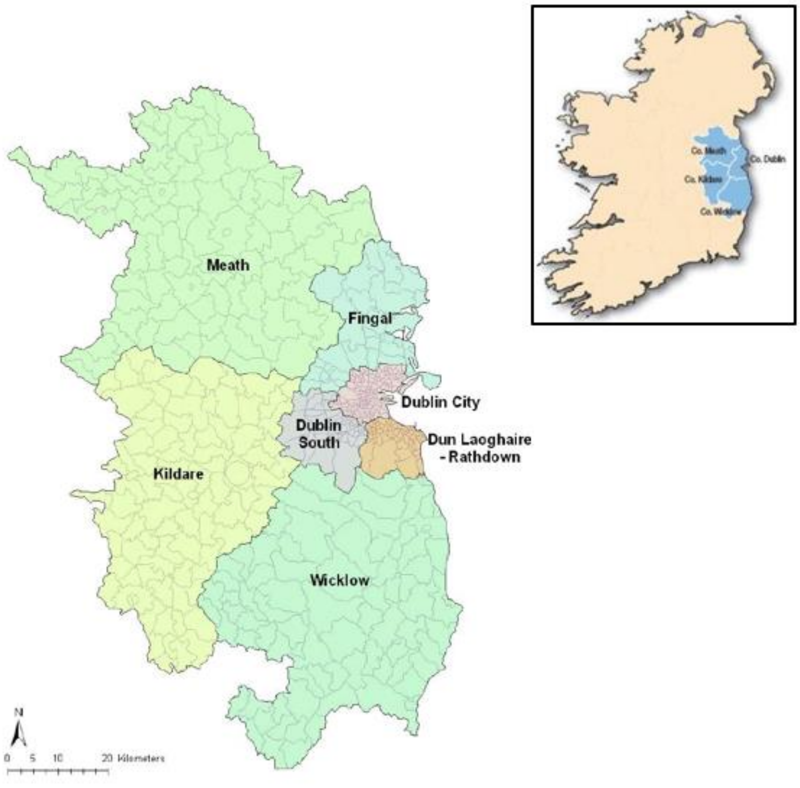

Figure 2.1 Map of the GDA (McDonnell and Caulfield, 2011)

[2] Dublin Area Rapid Transit heavy rail service
[3] Dublin's light rail/ tram service

Sustainable travel within the GDA has experienced a resurgence in recent years (Transport for Ireland, 2017; NTA, 2016; Caulfield, 2014), in line with increasing numbers of people commuting to work, which rose from 1.13 million in 2011 to 1.17 million in 2016, indicating an increase of 3.8%, which is estimated to accelerate further in line with Ireland's growing economic performance (CSO, 2017). The 2016 Census results similarly revealed an increase in PT usage of 15%, with an added 9,264 commuters opting to travel by bus and rail modes to work and education in the GDA (CSO, 2017; Carroll, et al., 2017). Furthermore, between 2006 and 2016 the mode share of cycling grew most across all modes, with an increase of 60% in Dublin city, as 12,089 cyclists crossed the canal cordons of the city, representing an increase of 7,250 in 2016. While a 13% decrease in private cars (6,756 fewer cars) was also found (DCC, 2016). However, during this period, an overall increase in private car usage in the other GDA counties was sustained, as those commuting by car to work in the GDA increased from 406,725 in 2006 to 441,147 in 2016, which represented 37% of the mode share (CSO, 2017). As a result of this, traffic congestion has grown significantly, with average traffic speeds falling by 5.5% between 2014 and 2015 in Dublin and by 18% in the GDA in 2016 in the AM peak (NTA, 2018).

In order to maintain the growth in sustainable mode usage and to reduce the mode share of private cars in the GDA, several large infrastructure projects have been either announced or completed, that aim to extend the coverage of and improve existing PT services and the cycle and pedestrian networks. This work is included in the NTA's 2035 Transport Strategy for the GDA (2016), the National Development Plan 2027, and Project Ireland 2040 (DPER, 2018) which propose a number of transport schemes centred on the GDA such as:

- Light rail: at the forefront of these plans is a high frequency metro link that will connect Dublin city centre to Dublin airport and will service a number of areas in the suburbs of Dublin experiencing poor PT accessibility; and the Luas Cross City project (Luas, 2017), which was completed in December 2017 and connected the two light rail tram lines in Dublin and extended the green line to the north side of Dublin. In addition to this, other light rail extensions of the Luas are also planned in areas not currently serviced by light rail.
-Heavy rail: a number of DART and commuter rail extensions are planned in addition to upgrading more heavy rail lines from diesel to electric energy.
- Bus: the Bus Connects programme aims to revamp the bus transport network by redesigning a number of bus corridors in order to make bus journeys more time and cost efficient and ultimately a more reliable and frequent service (Bus Connects, 2017). Furthermore, a number of Bus Rapid Transit (BRT) corridors will be introduced to deliver improvements to road infrastructure and quality of service through fast boarding/ alighting times and the provision of modern, appropriately designed vehicles.

In addition to the modes defined, there are two car-sharing providers in operation in the GDA: GoCar and Toyota's Yuko car club. GoCar, which launched in 2008, is Ireland's market leader in car-sharing and is in partnership with German car-sharing operator Cambio Mobility services. GoCar provides a fleet of conventionally fuelled cars and vans and fully electric vehicles, and is also in operation in other cities in Ireland such as Cork, Galway and Waterford. Yuko (Japanese for 'Let's Go') launched in 2016 and provides an exclusive fleet of shared plug-in hybrids. Electric vehicles are not treated as a separate alternative in this study, as they may still constitute SOV use of private cars, however, electric vehicles are still considered as part of this study, albeit as part of the fleet of car-sharing services (i.e. GoCar and Yuko).

Furthermore, the Dublinbikes bike-sharing scheme commenced operations in Dublin city in 2009. Since then, it has become one of the most successful schemes of its kind in the world (The Guardian, 2017), with 22 million journeys made since its launch, a long-term subscription base of over 67,600 people and an average journey duration of 14 minutes. In total, there are currently 116 stations in Dublin city and 1,600 bikes (Dublinbikes, 2018). A carpooling/ ridesharing website also exists (Carsharing.ie, 2018) (i.e. sharing car journeys with individuals with matching origins and destinations, not to be confused with the GoCar/ Yuko style service), which was developed by the NTA's Smarter Travel Workplaces initiative (Smarter Travel Workplaces, 2018). This website provides an official place for an online community of individuals or workplaces to engage in carpooling, to facilitate connections with people with matching travel destinations. It is anticipated that the range of sustainable transport options cited above will enhance the likelihood of encouraging car-shedding behaviour in the GDA by incentivising a shift away from private vehicle use, particularly for commuting purposes. A distinction between the market segments of car-sharing and carpooling must be outlined in order to clarify their differences and to avoid any confusion. Carpooling in this study is defined as a formal or informal arrangement whereby individuals share a vehicle on a trip with similar or matching origins and/ or destinations (FHWA, 2016). Car-sharing on the other hand is a membership-based scheme whereby individuals that join the scheme can have access to a car, generally parked in a public area, and may rent a vehicle on an hourly basis. Thus, while car-sharing and carpooling both offer an alternative to owning a vehicle, they target alternate customer bases.

2.3 Car shedding

The policy of car-shedding is defined as a motivational strategy that encourages individuals to 'shed' their car for certain trip purposes, by providing viable alternatives to owning a car such as carpooling, car-sharing, PT and/ or active modes. This tactic considers the motivation of a reduction in SOVs trips, by making alternative modes more competitive in terms of convenience, time and cost efficiency. The utility of private vehicles is, therefore, estimated to reduce as a result of individuals choosing alternative modes of transport and substituting car trips for more sustainable means of transport (Carroll, et al., 2017). For instance, by providing access to a vehicle for certain journey purposes such as grocery shopping, visiting relatives, moving home etc. (i.e. car-sharing), an individual or household may not necessarily need to own multiple vehicles or may wish to avoid the costs of car ownership (i.e. insurance, repairs, parking) by opting for shared use schemes, active modes or PT for commuting purposes.

In this way it is conceivable that with continued disutility of a private car for particular journey purposes that over time individuals may then seek to shed a second or third vehicle, by considering the cost, convenience or environmental factors of alternative modes such as active modes, PT, car-sharing and carpooling (Millard-Ball, et al., 2005). The concept of 'car-shedding' introduced in this research offers an umbrella term in the narrative of transport policy, that is utilised to define ways of reducing car dependency and usage by exclusively employing additional incentives or 'carrot' measures to encourage sustainable voluntary behaviour change in the form of modal shifts. Car-shedding will henceforth be mentioned throughout this thesis, thus, all references to this term will be in respect to the definition provided above.

2.3.1 Benefits and Barriers to Car-shedding

There are a number of economic, social and environmental benefits associated with encouraging individuals or households to shed vehicles and to travel more sustainably. However, in order to achieve these benefits there are several institutional, political and socio-cultural obstacles that must first be overcome. These benefits and barriers to enabling car-shedding behaviour are set out in Table 2.1:

Table 2.1 Benefit and barriers to car-shedding behaviour

Benefits	Barriers
Principally, a reduction in car dependency and a shift in the overreliance of the private car use, particularly for short trips and commuting purposes that can be substituted with active modes PT, car-sharing or carpooling.	Institutional and policy barrier: A lack of vision, leadership and political accountability by central government authorities, agencies and local authorities to take responsibility for the development and adoption of policy incentives to reduce car use. Political inertia is also a major obstacle (Banister, 2004).
Greater priority given to pedestrians, cyclist and PT modes, achieved through signalling changes at junctions.	Insufficient priority assigned to the development of reliable and high frequency PT services and the significance of a safe pedestrian and cycling networks (Browne, et al., 2010).
Infrastructural improvements to fully segregate active modes from PT modes, and PT from other motorised traffic in order to avoid shared use lanes which lead to dangerous conflicts and delays. With additional road space assigned to these modes, important time savings and improvements in reliability, frequency and safety of all modes can be realised (Bus Connects, 2018).	Financial barrier: shortage and/or limitation of financial resources to create, enforce and monitor interventions or policy tools, especially for large infrastructural projects.
A reduction in traffic congestion leading to a range of economic benefits such as: improvements in the time efficiency and reliability of the PT and road networks, and a reduction in traffic delays, collisions and fuel costs.	Socio-cultural barrier: insufficient belief and trust in travel demand management and mobility management approaches due to the relative novelty of them in certain cities. Failure to gain public acceptability (Banister, 2005), leading to the approach seeming unconvincing to government officials and local authority councillors.
Space usually allocated for car parking could be reassigned for bicycle and carpooling/ car-sharing parking or for residential, retail or recreational developments. This would encourage more efficient use of valuable urban land, particularly in dense urban areas e.g. Dublin city.	Physical barriers: geographical space restrictions in urban areas, insufficient room to divide road space equally amongst modes (Browne, et al., 2010; Banister, 2005).
A reduction in vehicle kilometres travelled by private vehicles leading to an abatement in emissions such as CO_2, NO_x and $PM_{2.5}$. Mitigation of respiratory and other associated illnesses linked to air and noise pollution. Monetary savings gained from reducing emissions (see Common Appraisal Framework (CAF), DTTAS, 2016).	Commercial or industry barrier: lack of regulatory and financial incentives for potential market entrants (e.g. car-sharing companies) (Browne, et al., 2010).

2.3.2 Incidence of car-shedding in Ireland and internationally

The car-shedding phenomenon is becoming a growing trend in Ireland and in countries around the world (Klein and Smart, 2017; Kurtz, et al., 2016; Delbosc and Currie, 2013; Kuhnimhof, et al., 2012; Millard-Ball and Schipper, 2011), whereby increasing numbers of young individuals (between the ages of 17 and 29) are waiting until later in life to apply for driving licences. In view of this, these individuals have been found to defer ownership of a vehicle to later in life. In the context of Ireland, this pattern is illustrated in Table 2.2, where Census of Ireland results of the number of full licence holders in age categories between 17 and 29 are listed from 2008 to 2016.

These findings showed that during this period there was a 32.42% decrease in the number of people within the 17-20 age cohort holding a full driving licence, and a 24.29% decrease in individuals within the ages of 17 and 29 with a full licence (Central Statistics Office (CSO), 2017). This trend occurred when there was an overall increase of 11.18% in full driving licence holders, for all age categories during the same period. Thus, these results suggest that younger people in Ireland are becoming less interested in possessing a driver's licence at an early age. This is similarly the case for the numbers of learner's permit or provisional licence holders, with the Irish Times (2017) reporting that the number of people with a learner's permit in the 17-20 age cohort fell by over a third (36.05%) between 2006 and 2016. This trend is also mirrored in figures recorded in the UK, where it was found that from 1990 to 2017, there was a 21% decrease in young people between the ages of 18 to 25 holding a licence (Irish Times, 2017).

Table 2.2 Number of full driving licences by age (CSO Transport Omnibus, 2017)

Years	**Age Categories**			
	17-20	**21-24**	**25-29**	**Total: 17-29**
2008	52,044	131,769	252,347	436,160
2009	46,258	132,124	249,341	427,723
2010	41,718	126,959	241,544	410,221
2011	39,488	121,162	234,366	395,016
2012	35,737	114,115	224,872	374,724
2013	31,634	106,965	213,428	352,027
2014	32,143	104,433	206,451	343,027
2015	34,553	101,966	201,123	337,642
2016	35,173	100,074	194,951	330,198
% diff. 2008-2016	-32.42%	-24.05%	-22.74%	-24.29%

A number of causes have been cited internationally as explanations for why obtaining a driver's licence is no longer the 'rite of passage' that it once was. The motives include factors such as: the growing cost of driving lessons and car ownership costs (e.g. high insurance premiums (Irish Times, 2017; The Guardian, 2014a, 2014b)), the popularity of the 'shared economy' phenomenon for short-term rentals with no longstanding financial commitment (Davidson and Infranca, 2016), and the arrival of the idea of Mobility as a Service (MaaS) provided by companies like e.g. Maas Global (2018).

Other secondary reasons have also been highlighted such as: environmental consciousness i.e. concerns of how private car usage may have negative environmental consequences (Carroll, 2017), growing trends of people opting to postpone marriage and children to later in life (Washington Post, 2016), in addition the rising cost of rental accommodation (Irish Times, 2017; USPIRG Education Fund, 2012). The growing selection of smart and alternative transport options available in urban areas such as car-sharing, bike-sharing, carpooling apps and on-demand taxi services like Uber and Mytaxi have also made not owning a car less of a concern (University of Michigan, 2017; Business Insider, 2017).

Young individuals have been labelled as the 'early adopters' of novel transport modes and intelligent mobility schemes that provide the benefits of shared ownership and help to highlight the disadvantages associated with private car ownership (Millard-Ball, 2005). Early adopters have helped to transform the manner in which transport is perceived, leading to the success of shared mobility, which in turn has enhanced transport accessibility and encouraged a shedding of the number of private vehicles owned by members of such schemes (Shaheen and Chan, 2015).

Car-shedding behaviour is similarly evident in multiple car ownership figures in Ireland between 2006 and 2016, shown in Table 2.3. These results showed that there was a 12.07% reduction in households owning four or more cars nationally and a 41.63% fall in households owning three cars in the GDA. These results suggest that multiple car households are reducing the number of cars owned by shedding additional vehicles, particularly in the GDA. McGoldrick and Caulfield (2015), and Caulfield (2012) explored reasons for these changes in car ownership and examined factors that impact upon multiple car ownership in the GDA. McGoldrick and Caulfield (2015) found that changes in vehicle ownership and mode choice for commuting purposes was determined by the age of individuals and residential density, while the results from an MNL model conducted by Caulfield (2012) showed that level of occupation, the availability of PT modes and similarly residential density have an impact on levels of multiple car ownership.

Table 2.3 Number of cars per household (CSO Transport Omnibus, 2017)

National	**2006**	**2011**	**2016**	**% diff. 2006-2016**
One car	564,249	668,766	696,684	+23.47%
Two cars	481,732	556,036	567,414	+17.79%
Three cars	92,951	101,264	95,238	+2.46%
Four or more cars	34,587	33,620	30,413	-12.07%
No car	288,777	256,852	257,567	-10.81%
GDA	**2006**	**2011**	**2016**	**% diff. 2006-2016**
One car	222,691	263,275	272,687	+22.45%
Two cars	181,314	203,059	205,332	+13.25%
Three cars	57,841	35,038	33,760	-41.63%
Four or more cars	10,395	10,440	10,249	-1.40%
No car	131,214	120,046	119,180	-9.17%

However, it must also be noted in Table 2.3 that, during the period of 2006 to 2016, there was an increase of up to 23.47% in households owning one car nationally and 22.45% in the GDA, and an increase of 17.79% and 13.25% in households owning two vehicles nationally and in the GDA, respectively. These figures suggest that households that were previously non-car owning households, then bought a vehicle during this period. The rationale for this may be due to a number of reasons, chiefly, the negative impacts of the worse recession experienced in the history of Ireland (McGoldrick, and Caulfield, 2015; Caulfield, 2012), in addition to a housing crisis which is resulting in many young professional being forced to live at home with their parents, due to the shortage and expense of housing in Ireland. Thus, this may attribute to the rise in the number of households owing one and two cars during the period of 2006 and 2016.

While the author agrees that the use of apps and other Intelligent Transport Systems (ITS) are useful in encouraging a shift in travel behaviour, digital interventions were slightly outside of the confines of this literature review. However, the arrival of mobility as a service (MaaS) and the use of car-sharing, carpooling service would also constitute digital interventions as they involve the use of an apps to use the service.

2.4 Theoretical and Conceptual grounds for examining travel behaviour change

In order to develop effective strategies of reducing SOV trips an understanding of some of the main theoretical foundations of travel behaviour research is necessary, specifically the psychological determinants of car use reduction and the fundamental concepts underpinning behaviour change. Overall, there are three main inter-related motivational realms that determine the extent to which travel behaviour change can occur based on the nature of the subjective and objective environment, these are: the personal or individual realm that comprises beliefs, perceptions, knowledge and attitudes; secondly, the social realm, whereby communication and interaction with family and friends, the media, influences the development of social norms (behavioural references or patterns common in society); and the environmental realm that deals largely with the geographic characteristics of an area (e.g. the locality of schools, sites of employment, retail and recreational facilities), as well as accessibility of PT services and other amenities (Carroll, et al., 2016; EUFIC, 2014). Consideration of each of these factors are key in designing interventions that aim to stimulate a shift in behaviour by reviewing their cause-effect relationship on behaviour change. However, failure to consider all three realms can often result in a reduction in the probability of true change being achieved (EUFIC, 2014). Therefore, by exploring the nature of daily-travel patterns and the potential for car-shedding behaviour in the GDA through a reduction in SOV trips, a reflection of these realms was necessary to gain a full understanding of the individual thought-process that goes into mode-choice. Changes in behaviour are commonly achieved through a mix of interventions (i.e. hard economic-based instruments such as taxes and fees; and soft measures, namely information provision and individualised marketing), applied over a long period of time (EUFIC, 2014; Bamberg, 2011).

Bamberg, et al. (2011) devised a conceptual framework to demarcate how the objective environment and socio-demographic factors (i.e. the motivational realms) influence car driver's decision making, and how hard and soft policy tools can be utilised to modify the objective environment in favour of sustainable mode choice. This framework which considers the effect of the personal, social and environmental realms is illustrated in Figure 2.2:

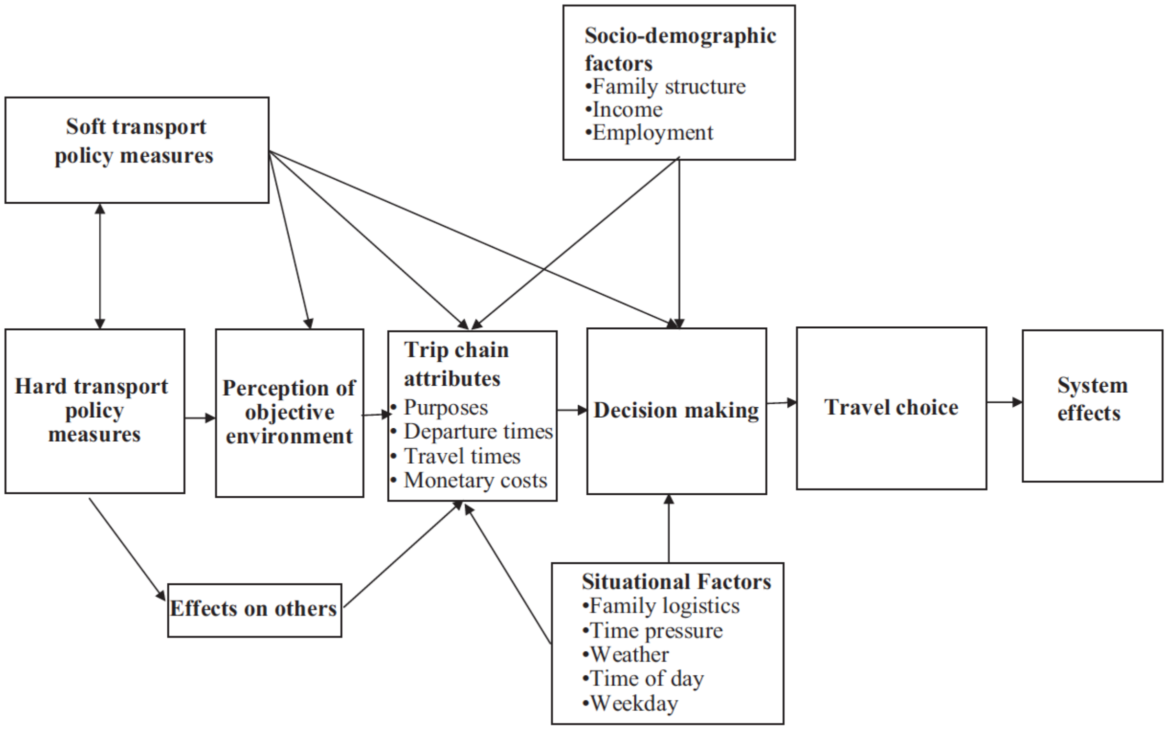

Figure 2.2 Bamberg, et al. (2011) conceptual framework for encouraging sustainable mode choice

They explicate that the perception of features of the objective environment such as the availability of modes and the geographic characteristics of an area are the first determinants and the foundations of travel decisions, which are then defined by trip attributes such as journey time, cost and purpose (Bamberg, et al., 2011). Once these elements are fully considered, other socio-demographic (e.g. employment and income) and situational (weather, time period and day, etc.) factors may be reflected upon before a final mode choice is made. Thus, in order to modify behaviour change, a differentiation is made between hard and soft policy measures in terms of their effect on influencing travel decisions. Bamberg et al. (2011) highlight that hard measures alter the objective environment through, for example, changes made to time and cost parameters of certain modes as a result of infrastructural improvements being made. Soft interventions, on the other hand, directly modify perceptions of the objective environment, which in turn, alter individual attitudes and empower individuals to shift modes. Hence, it is emphasised in this study that the use of both hard and soft measures is an effective conceptual approach to achieving travel behaviour change.

Brög, et al (2009; 2002) propose a slight counterargument, indicating that attitude change is best achieved by means of a soft policy strategy alone, whereby individuals are able to access or receive information that enable them to make informed decisions with sufficient knowledge of the options that are available. In this way, individuals can be empowered to voluntarily choose modes, 'rather than telling them what they should do' (Brög, et al., 2009). They stress that the use of hard measures, in the form of financial disincentives (e.g. fees and charges) for car use, limit personal freedom and can often force decisions upon people. In view of this, the car shedding approach employs both hard economic incentives and soft policy (information provision) in conjunction with each other in order to offer a holistic solution to car dependency and hegemony. For this reason, the research conducted in this thesis explores incentivisation of alternative sustainable modes alone as the approach to encourage car-shedding for particular trip purposes in the GDA. While disincentives such as fees and charges applied to car users are also found be effective tools in reducing car use (see literature presented in Section 2.5), this research focuses solely on the behavioural impact of offering a range of incentives in encouraging SOV use. This decision was made for a number of reasons, namely: there are few alternatives to the private car in outer urban and rural areas of the GDA, hence, by introducing discentives to use a private car in such areas would be unjust until adequate and sustainable alternative modes are made available, secondly, the introduction of stick measures such as a congestion charge for example would present a political and logistical challenge to implement. As a result, it was decided that this study would focus on making analysing the behavioural impact of enhancing or making carrot measures bigger, in order to attract more commuters to sustainable modes of transport.

2.4.1 The Theory of Planned Behaviour

A fundamental feature in the examination of behaviour change is the formation of habits and intentions as they can be determined by the way in which attitudes or perceptions are established. Habits and intentions are interlinked, in that one affects the other in a sort of reciprocal relationship, as an intention is the precursor of actual behaviour (Bamberg, 2011). This is particularly the case where an individual may develop an attitude towards an entity based on the reception of certain stimuli generated by information passed on by other sources (e.g. family, friends and the media) (Bamberg, 2011; Brög, et al., 2009). In this way, the social realm acts as a messenger which relays information to an individual that may determine the composition of factors in the personal realm through the formation of attitudes and beliefs. Such factors can determine how individuals form positive or negative attitudes towards, for example, a particular mode of transport, based on the views of peers, which can often result in a major obstacle in attracting people to alternative modes and altering travel decisions. Hence, more work and resources may be needed to alter perceptions, especially in the case that they become ritual habits, e.g. commuting by car to work (Brög, et al., 2009; Petty and Cacioppo, 1986).

One of the leading theories underpinning research in behaviour change is the social psychology notion of the Theory of Planned Behaviour (TPB), coined in the 1970s by Ajzen and Fishbein (1977) (Bamberg, 2011). The TPB sets itself apart from microeconomic concepts of discrete choice, such as utility maximisation, as it considers the formation of intentions which are influenced by behavioural, normative and control beliefs (Bamberg, 2011).

Whereas discrete choice assumes that decisions are based on rational reasoning (Ben-Akiva, et al., 1999), as an intention is defined as a commitment to engage in an action driven by a desire to act, which is subjective and cannot be accurately explicated by rational economic theory (Fuijii, and Gärling, 2003; Sen, 1977). Planned behaviour is in particular reference to the social realm of behavioural impetus, that is driven by the analogous mind-sets of peers or individuals interacted with in society and the juxtaposition of behavioural control (i.e. the relative ease at which an action can be completed) (Fujiia and Gärling, 2003). In the context of transport, an attitude towards a particular mode is similarly shaped by personal experience or the perceived difficulty to use a mode, which is identified as perceived behavioural control (PBC) (Bamberg, 2011). Bamberg, et al. (2010) emphasise the significance of social norms in the determining the way in which personal norms are established. They state that social norms 'inform people about what behavioural standards their social reference group view as appropriate in a particular context. When people internalise these social expectations, social norms become the content of their personal norms' (Bamberg, et al., 2010).

Schultz, et al. (2007) investigate the effect of social norms and normative messaging (personalised social norm marketing) on behaviour change. A field experiment was conducted to examine the influence of normative messaging on the promotion of pro-environmental household energy consumption in California, USA. Descriptive norm messaging is a strategic method of social norm marketing used to reduce adverse behaviour of individuals by altering misperceptions of the prevalence of behaviour (Schultz, et al., 2007; Cialdini, et al., 1991). In this study, households in the study area were provided with details of their energy consumption (kilowatt-hours per day), compared with the average consumption of other households in the neighbourhood. In reference to the average household consumption, each household were then identified as being either above or below the average, which acted as the descriptive normative tool in the experiment. Households above the average were then provided with information on how to reduce their consumption with a range of conservation practices such as substituting electric fans for air conditioning systems. Following provision of normative messaging, households in both categories (above and below the average) were examined for changes in behaviour in terms of energy consumption levels, to test the effect of the intervention. In this way, households with good energy performance were used as 'anchors' or 'reference points' to enhance relativity and test the strength of social norms in encouraging sustainable behaviour change. Schultz, et al. (2007) showed that the provision of a descriptive norm led to a significant reduction of 1.22kWh per day in energy consumption from the average. This suggested that households above the baseline consumption decreased their energy consumption to benefit from energy savings gained by other households. On the contrary, households categorised as being below the average were found to increase their consumption to meet the average, which demonstrates the negative impact of social norms and the incidence of the 'boomerang effect[4]' (Schultz, et al., 2007). This study identifies how social norms can act as powerful incentives that are difficult to modify once they have been adopted into habitual behaviour, yet with the support of social 'reference points' and 'anchors', behavioural change can be achieved. Car-shedding interventions similarly seek to create sustainable travel norms as a strategy to destabilise current unsustainable car dependent norms.

Kormos, et al. (2015) conducted a similar experiment to Schultz, et al. (2007), in which they applied the concept of social norms in the field of transport. In this study, the impact of the provision of descriptive social norms were examined in encouraging sustainable transport behaviour, specifically in stimulating a reduction in private car use. A longitudinal field experiment was employed to investigate the extent to which university students, staff and faculty members would be willing to reduce self-reported car use in response to receiving descriptive social norm information (Kormos, et al., 2015). Individuals in the sample were asked to report their commuting travel behaviour (i.e. number of car and PT trips) for a period of three weeks, which was then used in comparison with average levels of car use. During the study the university also conducted a campaign to reduce car use for commuting purposes by 25% across the university as a goal setting measure. Participants were first given a pack which included an information package with a personalised travel plan enclosed, a selection of material in relation to transport modes in the area, in addition to varying degrees of descriptive social norm information, that informed participants of the mode share of commuters in the university in previous years. Data collected from the pre and post-experiment self-reported travel behaviour, socio-demographic characteristics of the participants and responses to a follow-up questionnaire, were then used to perform three analysis of covariance (ANCOVA) models to assess the effect of the descriptive social norm on commuting mode choice. The findings produced from the ANCOVA models showed a linear increase in sustainable commuting behaviour in direct response to the increase in levels of descriptive social norm provision. This suggested that participants with above average car use levels in the experiment reduced their car use by switching to other modes, in response to receiving descriptive social norm information. The study identified that while past travel practice was the main determinant of future travel behaviour; the results revealed that the provision of social norm information also encouraged sustainable travel behaviour change with no boomerang effect, which was in contrast to studies such as Schultz, et al. (2007) and Perkins, et al. (2005)

[4] Social psychological concept used to describe the inadvertent or opposite reaction of a receiver of persuasive communication (Levy and Maaravi, 2017).

2.4.2 Behavioural Economics

The microeconomic assumption underlying the maximisation of utility (i.e. the benefit or use an individual derives from a good or service) has traditionally been employed to explain rational decisions made by 'rational' beings (i.e. *homo economicus* or the economic man). Humans are, in this way, assumed to assess the potential costs and benefits of making a choice (Thaler and Sunstein, 2008). However, research conducted by Thaler and Sunstein (2008), Ariely (2008) and Kahneman (2011) refute this claim and suggest otherwise, as they are of the belief that rational choice theory does not account for instances in which humans act irrationally and impulsively in certain situations where there are market inefficiencies (Thaler and Sunstein, 2008). They suggest that behaviour can be explained by a range of contextual factors such as norms, defaults, messengers, priming, affect, salience, commitment and ego. This field of research is known as behavioural economics, which is being increasingly adopted in the social sciences and in areas of public policy to predict the outcome of the future behaviour of humans (Metcalfe, and Dolan, 2012).

The foundations of behavioural economics can be traced back to research conducted by Simon (1955) and Kahneman and Tversky (1979), in which observational studies highlighted the impact of incentives on behavioural response. Metcalfe and Dolan (2012) state that this seminal work can be summarised into several effects such as: how humans express loss aversion e.g. the higher sensitivity of commuters to longer wait times rather than improvements to trip times; the influence of social reference points or anchors on predicting modal choice; mental accounting of car ownership costs versus PT fares; and hyperbolic discounting (Laibson, 1997), in other words, the augmented valuing of current costs against inconsistent valuing of future costs such as climate change mitigation.

With these effects considered, there have been various initiatives and schemes developed to guide European and international projects that aim to explore the effect of policy on changes in attitudes and behaviour. For example, the TAPESTRY (Travel Awareness, Publicity and Education supporting a Sustainable Transport Strategy in Europe), was financed by the European Commission to concentrate research efforts on the promotion of sustainable travel in Europe. Moreover, the UK Cabinet Office (2010) developed the MINDSPACE (Messenger, Incentives, Norms, Defaults, Salience, Priming, Affect, Commitments and Ego) initiative, which was designed to set out the guiding principles for research seeking to use public policy as an instrument to encourage behaviour change. MINDSPACE is a mnemonic of several contextual factors, which play important roles in stimulating changes in behaviour that can be used when devising policy (Metcalfe and Dolan, 2012). Conceptual frameworks like MINDSPACE are invaluable resources in the creation of soft policy and market-based interventions as they set the grounds for policies to ultimately interrupt unsustainable habits or intentions. The conceptual structure of MINDSPACE is set out in Table 2.4.

Table 2.4 MINDSPACE mnemonic (Metcalfe and Dolan, 2012; UK Cabinet Office, 2010)

Messenger	The effect of family, friends and the media as messengers or disseminators of information that can influence the formation of personal norms, habits and intentions.
Incentives	Hard economic/ market-based instruments or soft individualised descriptive norm measures that are used as carrots or sticks in the enticement or discouragement of particular behaviours.
Norms	Personal, social and cultural norms, adaptation of behaviour to adhere to a way of thinking.
Defaults	Pre-selected opt-out decisions such as pension schemes or retirement plans, organ donation, automated email marketing.
Salience	Behaviour induced by novelty or what seems to be easily comprehendible or relevant, e.g. the salient cost or experience on a certain mode can influence a future decision to take that mode or not.
Priming	Acts influenced by exposure to certain stimuli or anchors that can form sub-conscious cues
Affect	Emotional feelings towards an entity can obscure the rationality of decision making, e.g. product marketing campaigns that elicit emotional responses
Commitments	Consistency of certain actions or responsibilities that form strong habits and reciprocal behaviour
Ego	Behaviour that boasts positive self-image and the creation of a feeling of self-worth or importance

Thaler and Sunstein (2008) outline that behavioural economics provides an effective counterargument to utility maximisation, as the reality in which individuals behave is studied, rather than assumptions of how individuals rationally should act (Thaler and Sunstein, 2008). In the context of transport, mode choices are generally treated as rationed decisions; however, as discussed in Section 2.4.1, such decision-making behaviour can be easily influenced by certain interventions aimed at shifting personal attitudes, norms and perceived behavioural control (Waygood and Avineri, 2011). Work conducted by Thaler and Sunstein (2008), and Ariely (2008) centres on how key information is presented and accessed by the target group and how the dissemination of information can play an important role in influencing the probability of behavioural change taking place. Techniques like this come under the umbrella of ‘choice architecture’, that seek to ‘nudge’ individuals into making certain decisions such as sustainable mode choice. Metcalfe and Dolan (2012) outline that ‘nudges can help individuals overcome biases they may have and can be used to highlight certain choices for them, increasing the effect of behavioural change’. This approach is defined by Thaler and Sunstein (2008) as ‘libertarian paternalism’, which considers modification of choice architecture while also supporting voluntary decision making as an effective yet non-punitive and less intrusive method of achieving desired behaviour change. There has been limited use of behavioural economics in the area of transportation policy, however, Avineri (2012) states that nudges work most effectively in situations where unintentional/ automatic behaviours take place in a controlled context, a prime example of which is habitual car use and car dependency for commuting purposes. Avineri (2012) suggests that behavioural economics can be used to improve or accelerate the effect of policy incentives used to encourage sustainable behaviour change rather than as a substitute for the interventions themselves.

2.5 The role of policy incentives in delivering sustainable modal choice behaviour

Travel demand management (TDM) and mobility management (MM) measures are popular approaches to policy intervention, that use both incentives and disincentives as tools to stimulate sustainable behaviour change or mode choice. Structural policies such as laws and regulations, economic market-based instruments or changes to the physical environment are examples of the type of interventions included in these approaches (Eriksson, et al., 2010). Travel Plans, for instance, typically incorporate a range of policy mechanisms designed as a means of introducing mobility management to a specific site such as a workplace or shopping centre etc. An example of this in Ireland is set out in the NTA's travel plan guide (2012), which comes under the NTA's Smarter Travel Workplaces Initiative. These plans are generally 'targeted at a specific site by an agent with a strong relationship with the local transport users to deliver transport and wider goals to the organisation and society as a whole' (Enoch, 2012). 'Travel Plan Plus' in the County of Bages in Catalonia, is another example of where TDM measures such as company mobility audits, PT fare subsidies and the creation of a joint car and vanpooling programme were implemented, the impact of which resulted in a 3% reduction in SOV use. Other notable European travel plan examples cited by Enoch (2012) are in Cambridge, England and Gyor, Hungary, which were found to have resulted in 6% and 3% falls SOV use respectively.

The following sub-sections include a review of a selection of studies that examine the use of mode-specific policy incentives in reducing SOV use. Section 2.5.1 explores literature specific to encouraging active travel (i.e. walking and cycling), Section 2.5.2 considers PT policy literature, and Section 2.5.3 examines policies used to incentivise carpooling and car-sharing. The literature reviewed is particularly relevant to and similarly motivated the research conducted in this thesis. For instance, the policy incentives tested in the literature offered empirical evidence of the success or failure of various measures that was then used as the basis for selecting interventions employed in the SP experiment and demand modelling conducted in this thesis. It was similarly valuable in identifying the gaps in the literature and research opportunities that will be discussed in Section 2.6.

2.5.1 Policy incentives to encourage walking and cycling

Walking

Guo and Loo (2013) examine the feasibility of modelling pedestrian route choice behaviour in New York City and Hong Kong using revealed route choice models. In this study pedestrians were interviewed in each city to gather information on walking patterns and to identify routes taken in the selected neighbourhoods. This information was then used to propose alternative walking routes. Revealed data were utilised in multinomial probit models to assess characteristics of the built environment from a pedestrian perspective and its effect on route choice. In a survey, pedestrians were asked to rate on a Likert scale of 1-7, several features associated with the pedestrian environment such as: route length, traffic volumes, the number of street crossings and associated waiting times at such crossings, the perceived level of safety of certain routes, in addition to the presence of noise pollution. The modelling of route choices in New York showed that sidewalk width and open space increased the likelihood of such routes being chosen, which could be improved as a means of increasing the mode share of walking. Traffic volume was negatively correlated with route choice, in other words, routes with high levels of traffic, predictably, reduced the probability of individual choosing such routes. In the Hong Kong model, the number of street crossings and the presence of retail frontage/ facade was found to be valued by pedestrians and increased the likelihood of routes with high levels of these features being chosen by individuals. In addition to this, direct and cross elasticities generated in the model also found that the existence of retail frontage had a statistically significant impact on route choice. Route length, footpath width and the presence of open space followed and were similarly shown to increase the utility of such routes. Overall, these results highlight the importance of the pedestrian environment in determining pedestrian route choices, and in this way, should be considered alongside trip time, distance and safety in transport assessments.

Hine (1996) conducted a number of in-depth interviews to explore pedestrian perceptions of and behavioural response to traffic flow conditions in Edinburgh, Scotland. The flow of traffic is referred to as a traffic barrier in this study, which can, at high levels and low speeds, present a physical obstacle to pedestrians and cause pedestrian congestion on footpaths, delays and dangerous crossing behaviour at unsuitable crossing points. In-depth interviews were utilised to elicit alternative qualitative information such as sensitivities to risk and safety associated with route characteristics and traffic flow barriers, that would otherwise not be possible to elicit from a closed-ended questionnaire. In this way, the perception and behavioural response to traffic flow could be better interpreted. Of the 21 individuals interviewed, age and health were major points of concern for pedestrians. Elderly respondents stated that they felt threatened and unsafe at some crossings in the city, especially where drivers proceeded without slowing down or stopping at pelican crossings and at crossings with short traffic light signalling times. These perceptions were compounded by previous bad experiences. As a result of the perceived intimidation of high traffic volumes on certain routes, elderly respondents stated that they would often schedule their daily activities to avoid such periods of high traffic levels. In relation to route choice, perceived traffic flow levels and route directness were of most concern to younger respondents who were under time pressures. Routes with lower traffic levels were preferred as they were less stressful paths to take (Hine, 1996). Parked cars similarly presented a major obstacle to pedestrians as they obstructed movement on footpaths and at bus stops. In summary, information generated from the in-depth interviews offered evidence of the way in which pedestrians make route choice decisions based on traffic barriers in the pedestrian environment. This study offers an insight into the behavioural responses of pedestrians to varying levels traffic activity and physical obstacles, which should be considered in policy provision and route planning.

Guo (2009) conducted a study of egress paths choices of subway commuters in Boston from subway stations to workplaces. In this study, the pedestrian environment was considered as the determinant factor in the utility of working. Path choice is the examination of individual route decision making in a choice set of multiple options with matching origin and destination pairs. Sub-path choice models are used to analyse access or egress portions of trips from or to a specific mode. Thus, for example, the pedestrian environment is indicative of the sub-path choices made by individuals commuting by subway to their place of work. This study assessed the trade-off behaviour of commuters in downtown Boston based on design variables of the pedestrian environment. The attributes considered were: the density or flow along paths, footpath width, pedestrian flow at junctions, the availability of open space and the topography of the route. Using these characteristics, the causal relationship between the pedestrian environment and the utility of walking was investigated in a binary logit model. The findings of this model showed that higher footpath densities and wider footpaths would result in an increase in the likelihood of pedestrians opting for the route. This preparedness to walk given the availability of the footpath characteristics led to people opting to walk longer distances, which ‘increases the length, frequency, and mode share of walking and enlarges the catchment area of a transit system’ (Guo, 2009). Higher densities at junctions were also shown to increase probability of such paths being chosen, which was termed in this study as an ‘encouraging’ effect on walking. Thus, this research confirmed that the pedestrian environment does affect the utility of walking, to the extent that a 21-33% increase in walking could be achieved in the study area examined, which was outlined as sufficient to warrant policy intervention.

Muraleetharan, et al. (2005), examined the pedestrian environment to determine varying pedestrian behaviour and level-of-service at crossings and junctions in Sapporo, Japan. In this study, factors such as available space at crossing facilities, the turning axis of motorised vehicles, signalling times and pedestrian-bicycle interactions are analysed for their effect on pedestrian level-of-service (LOS) at junctions in a multi-variable regression model. The importance of pedestrian LOS at crossings is emphasised due to the risks that exist when motorised traffic, cyclists and pedestrians converge and interact with each other at strategic links in the network. As a result of this, the complexity and difficulty in ensuring efficient flow of all modes and that each mode is equally considered, is highlighted. This study collected geometric and operational aspects of a number of crossings and junctions by means of a field survey in the area of Hokkaido University, Sapporo. A questionnaire was then conducted to determine stated or perceived levels of difficulty of crossing a particular junction. This was measured on a scale of difficult to cross to comfortable to cross, the score of which was subsequently defined as the dependent variable in a regression analysis. The results of the regression model found that the turning vehicle factor effected the pedestrian LOS most. This meant that as the number of turning vehicles increased, the perceived level of pedestrian safety decreased (Muraleetharan, et al., 2005). In addition to this, the results showed that signalling delays and the interaction of pedestrian and motorised vehicles, and pedestrians and bicycles were statistically significant factors at junctions. A number of suggestions for improving the junctions were proposed by the respondents surveyed, in which they favoured high visibility crossing enhancements and segregated paths for bicycles in order to increase the perceived level of safety at the crossings. This pedestrian LOS model expresses the safety concerns of pedestrians in large urban areas and offers an effective approach of determining the performance of crossing facilities from the perspective of pedestrians, which is a valuable input in the planning process.

Cycling

The increase in the popularity of cycling in many European and American cities, particularly in the past decade, has been represented by a surge in cycling research being produced in academia, with an average increase in academic publications from 197 annually in the period of 1991- 1995 to 610 per year in 2011-2016 (European Cyclists' Federation, 2017; Pucher and Buehler, 2017). A brief review of some studies conducted during this period is presented in this section.

Abraham, et al. (2002) assessed the attractiveness of a cycling in Calgary, Canada in response to proposed improvements being made to travel times on different categories of cycling facilities (i.e. shared and segregated cycle lanes), in addition to the availability of cycle-friendly facilities at the destination (e.g. secure parking and showers/ locker rooms). A household SP survey was designed to collect preferences of cycling facilities, and the responses were then analysed in a logit model that ultimately measured the relative attractiveness of cycling based on the attributes listed in the study. This research method highlighted the usefulness of the behavioural elicitations produced from a SP survey in guiding larger demand modelling of cycling facilities when combined with revealed or observed data sources, as a means of informing cycling policy through empirical recommendations. The results from this study found that while cyclists prefer routes that offer short trip times, cyclists would also be prepared to travel longer distances on routes providing proper cycling infrastructure and destination amenities. In other words, cyclists would be willing to make a trade-off between shorter trip times and the incidence of improved cycling infrastructure. The results also showed that the cyclists surveyed demonstrated a high preference for off-street cycle lanes and routes in residential areas with low traffic levels, which enhanced the perceived safety of routes.

Stinson and Bhat (2003) similarly explored the topic of cycle route choice with the use of a SP survey, as a method of examining the potential of increasing the mode share of active modes to reduce car usage. The SP survey was used as an instrument to collect and model commuting preferences in Austin, Texas, USA. In this study, it is outlined that cycling mode choice decisions are determined by two categories, namely: link and route-level factors. Link-level factors consist of the availability of cycling infrastructure, the presence or volume of road traffic adjacent to cycle routes and the physical condition of the infrastructure, whereas route-level factors consider the continuity of cycle lanes and the average trip time on such routes based on the presence of traffic management measures and the number of junctions etc. Improvements to link (infrastructure and surface type, route hilliness, the availability of parking) and route-level (travel time, lane continuity, number of red lights and crossroads) factors were then used as the policy measures that impact on the trip characteristics in the SP survey. The link-level results from this study found that cyclists preferred residential routes with low traffic volumes, partly separated from motorised traffic and as expected, smooth riding surfaces were preferred over rough and coarse surfaces. The route-level findings demonstrated that there was a high preference for continuous cycle routes with few traffic controls (i.e. traffic lights, stop signs) and routes without large intersections or junctions. Finally, Stinson and Bhat (2003) determined that travel time was the trip attribute of most interest to cycling commuters with segregated cycling infrastructure following.

Caulfield, et al. (2012) conducted a SP study that examined the infrastructure preferences of cyclists in Dublin, Ireland. A number of infrastructure and route attributes or characteristics such as the type of infrastructure, the number of junctions on the route, the volume of cyclist traffic and adjacent traffic speed were tested in this survey to determine the impact of such factors on the utility of cycling. The trade-off behaviour between attributes and attribute levels included in the study were utilised to elicit infrastructure and route preferences, that were modelled in a MNL model. This model produced a number of behavioural indicators that can be used as valuable recommendations to aid policy provision. The results of this analysis found that short travel times (i.e. 10 mins), with a statistically significant coefficient at 95%, was the preferred attribute tested, based on the positive sign and the size of the coefficient. This meant that lower trip times would result in higher increases in the utility of cycling in the model. Furthermore, routes with a 30km/h speed limit imposed, in addition to off road and greenway cycle facilities, statistically significant at 90%, were also found to increase the likelihood of individuals choosing cycling as a mode in Dublin. Conversely, routes with no cycle lanes and shared bus-cycle lanes were predictably found to decrease the likelihood of cycling being chosen.

Li, et al (2017) examine cyclist route choice behaviour utilising data generated from a smartphone application in Toronto, Canada, which was evaluated in a MNL model of commuting trips preferences. Observed cycling decisions were collected from a purposely designed smartphone application developed to monitor cycling data through a built-in GPS used in conjunction with cartographic data provided by Toronto’s Open Data portal (Li, et al., 2017). Based on data collected in the smartphone app, route choice sets were created by comparing a number of alternative cycling routes with the observed routes from the GPS data. Key cycle route characteristics were then applied to the chosen route to form the utility function of the MNL model. Some of the main factors considered were: route distance, energy consumption, number of PT stops, traffic volumes and the levels of cycling infrastructure/ facilities on the route. This model was then replicated for alternative routes with matching origins and destinations in order to compare the revealed sample model with other possible routes that could be chosen by respondents. This comparison was ultimately used to determine preferences for cycling infrastructure and route choices as a means of generating recommendations for infrastructure planning. The results of this analysis found that shorter distance routes with less traffic volumes and segregated or off-road cycling infrastructure were preferred, consequently increasing the likelihood of routes with these features being chosen.

2.5.2 Policy incentives to encourage public transport use

A SP experiment conducted in New Zealand by O’Fallon et al. (2004), investigated the potential behavioural response of introducing a selection of policy measures that aim to shift private car driver’s decisions to commute by car to work or education. In this study, individuals were interviewed in-person in three different cities (Auckland, Wellington and Christchurch), that were subsequently modelled separately and compared against each other in three MNL models. The SP experiment included 11 policy tools, of which 5 were disincentives or ‘sticks’ for continued car use (i.e. increases in parking charges (private and on-street), an increase in the incidence of metered parking, the introduction of a cordon charge before 10am, and a vehicle registration surcharge based on the number of kilometres driven). The remaining 6 policies were incentives for PT use (i.e. improved frequency and coverage of services, lower PT fares, reduced trip times and increasing the number of off-peak services), and cycle use (i.e. increasing cycle lane continuity). Based on the introduction of these policies tested on three varying levels, the respondents were prompted to choose one mode from 7 (continue driving, passenger in a car, carpool, walk and use PT, park and use PT, cycle or other including the option of telecommuting). The preferences from this exercise were then used in MNL models to estimate the likelihood of the mode alternatives being chosen given the presence of the policy measures. The results from this analysis determined that the walk and use PT option was the most popular alternative chosen across the three cities, which suggested that the policy incentives applied to PT were most effective in encouraging a sustainable mode shift. Of these measures, increasing PT frequency at peak times was seen as the most attractive pull factor to PT, followed by improved trip times by taking PT modes. The increase in the provision of cycle lanes however, did not have a positive effect on influencing a shift from private cars to cycling, which was comparable to results produced by Mackett (2001), who found that only a 2% shift to cycling from private cars could be achieved based on improvements made to cycling infrastructure (O'Fallon, et al., 2004).

Ahern and Tapley (2008) performed an SP experiment to gather rail and bus passenger perceptions and mode preferences in Ireland, to ascertain what improvements could be made to attract more potential PT passengers to such services. In this study, questionnaires were distributed to passengers on-board bus and rail services travelling Dublin to Sligo, and Dublin to Galway. The first section of the survey gathered the respondent's revealed mode choices that were then compared with the stated preferences elicited from the second section in which respondents were tasked with making hypothetical mode choices based on varying degrees of improved trip characteristics such as: trip cost, frequency, length, service reliability and the availability of toilets. The results from the SP component of the survey were analysed by means of a MNL model that was used to generate behavioural indicators of the effect of improving certain trip attributes. The findings revealed that time and cost were the trip characteristics of highest statistical significance, based on the coefficient size preferences, which were both with negative signs, meaning that as expected, cheaper and quicker journeys increased the probability of such modes being chosen. Service reliability did not have as much of a bearing on mode choice than time and cost did, however it was found that respondents valued services that were punctual.

Caulfield and O'Mahony (2009) investigated the impact of the availability of real time public transit passenger information (RTPI) in Dublin, Ireland through the use of a SP survey. This experiment asked individuals to choose between three alternative forms of RTPI: text message or SMS service, a physical passenger information display or a call center service. The preferences generated from the SP scenarios were then used to determine which of the variables associated with these RTPI alternatives, i.e. wait time, cost and the quality of information distributed from the services, would increase the probability of the service being chosen. Essentially the study assessed the trade-off behaviour of respondents in the sample to the attributes included in the choice scenarios. The preferences for both bus and rail users were then analysed in a nested choice model to produce the behavioural response indicators from the experiment. The results from this research determined that the quality and type of information was the coefficient of highest statistical significance in the model for each of the RTPI types, which were all statistically significant at 99%. This suggested that bus and rail users were more likely to pay for the service in order to enjoy the benefits of accessing real time information, especially those experiencing longer wait times. However, bus users were shown to benefit most from the provision of physical RTPI displays, rather than a call center or SMS service, which presents a valuable recommendation in prioritising need for such a service or in cost benefit analyses. This research highlights the importance of providing additional incentives such as RTPI in increasing the utility of PT modes and in addressing the LOS of PT services, as an approach to encourage a modal shift to PT.

Eriksson, et al. (2010) conducted a study which investigated the potential reduction in car use in response to TDM measures in a 'carrot' and 'stick' approach in Sweden. This research tested the behavioural response of introducing pull factors to make PT modes more time and cost effective, namely, by reducing fares and increasing the frequency of services, in addition to a disincentive of increasing fuel-based taxes. The degree to which car drivers modified their car use given these TDM actions was first examined from responses collected from an attitudinal pre-questionnaire that determined the perceptions of the policies and potential intentions or motivations to reduce car use. Social or personal norms (see Section 2.3), i.e. the psychological feeling of individual responsibility to reduce car use in order to limit negative environment impacts, were explored in this pre-questionnaire. The measures were then surveyed in greater detail in a follow-up SP questionnaire that was used to estimate the behavioural reaction to the carrot and stick measures, that were analysed in univariate ANCOVA and hierarchical regression models. The results from the ANCOVA models found that the combined measure of raised fuel taxes with reduced PT fares and increased frequency of services revealed the highest main effect, suggesting that it was most effective in reducing car use in the sample, as opposed to offering these measures on their own. The regression findings showed more in-depth details of the socio-demographic profile of respondents who were willing to reduce their car use in response to the policies examined. The results from this model found that the number of cars owned was the greatest determinant of behavioural response to the PT incentives, in other words, respondents who owned fewer cars were more likely to use PT given cheaper fares and a more frequent service. Personal norms were similarly shown to be statistically significant (at 95%) factors and increased the likelihood of respondents reducing their car use from the introduction of the combined tax and PT measure. Overall, this study identified that levels of car ownership and social psychological factors such as personal norms have a statistically significant effect on the extent to which individuals may respond to push and pull measures to limit car usage and increase the numbers of people travelling sustainably.

Enoch and Potter (2003) examined the use of local government incentives in the UK, to encourage employee up-take of sustainable 'travel plans', that seek to make it more convenient for individuals to commute by alternative modes of transport to their workplace, rather than in SOVs. Case studies where travel plan incentives were found to be successful in reducing car usage were similarly drawn upon in this study. A number of benefit mechanisms available to employers in order to attract their employees to get involved in employee travel plans were suggested such as: information and exhortation, regulation, subsidies and fiscal measures. Information and exhortation addresses the misconception that travel plans are costly to introduce and result in no real benefits to the company. Rather, it emphasises the contrary, as travel plans and mobility management can: result in cost savings from reducing the need to securely monitor and maintain car parks, improve employee productivity and the public image of businesses/ organisations, as well as addressing issues of corporate social responsibility (CSR) by tackling emissions targets (Enoch, 2012). Regulation considers that local authorities in the UK include travel plans in their planning policy and ensure that sites of employment, retail and recreation provide evidence of a developed travel plan for the site. Public subsidies were similarly cited as an effective means of financial assistance to develop travel plans, with lessons drawn from examples in Italy, Canada and the USA. In these case studies, subsidies are designed in the form of discounts for PT or travel passes to entice employees to commute by PT modes. It is suggested that public subsidies such as tax exemptions could also provide a financial benefit to companies in exchange for promoting and clearly adopting travel plans. It is advised that the fiscal system could be modified accordingly to allow for and support the introduction of such tax exemptions or other public subsidies and to ensure that benefits to employers exist. However, at the time of writing such tax reforms were withdrawn in the UK (Enoch and Potter, 2003).

Ultimately, this study highlights the lack of action being taken in the UK to support employers and to incentivise them to offer travel plans to their employees in order to realise the full potential of travel plans in reducing car use for commuting purposes. The informational approach was stated as not being effective enough on its own, without the support of economic instruments to entice employers, and until such funding is allocated for such instruments, the authors emphasise that the intended results of travel plans will not be realised.

Fujii and Kitamura (2003) also offer evidence of implementing the TDM approach through a soft policy investigation, whereby PT concessions in the form of free bus passes were given to a sample of car drivers for one month. This tactic was adopted to test the effectiveness of offering a clear and direct incentive to commuters, in order to unsettle the car-use habit and substitute it with a bus-use habit (Carroll, et al., 2017; Garling and Axhausen, 2003). The results of this study found that car drivers attitudes were immediately enhanced as they viewed bus travel in more positive light. This was represented in an increase in the frequency of bus use in the months following the period when the free bus pass was offered (Fuijii and Kitmura, 2003).

2.5.3 Policy incentives to encourage carpooling and car-sharing

The availability of car-sharing and carpooling services have also grown considerably in the past decade, which has resulted in a shift in the way in which the private car is considered and has introduced a new transportation landscape (Martin, et al., 2010). This section reviews studies that have examined the behavioural response of offering incentives to making more sustainable use of the car in the form of car-sharing and carpooling.

Baldassare, et al. (1998) studied the behavioural implications of introducing two diverse strategies, one of which offered a selection of incentives to solo car drivers and the other suggested a range of disincentives for SOV use in California, USA. They evaluated the effectiveness of these approaches by collecting choice preferences in a SP survey conducted by telephone. The incentives tested in this experiment (i.e. employer paid cash bonuses for carpooling or PT use for commute purposes, and the expansion of the coverage of carpools and PT services to ensure their availability for commuters) were suggested as measures of encouraging a shift away from solo driving. The respondents were asked if these measures were available, how likely they would attract them to carpooling or PT modes.
Based on the disincentives suggested (i.e. workplace parking fees, smog/ emission kilometric charges and a rush hour congestion fee on highly congested roads), the respondents were then asked to rate the likelihood of these measures stopping them from driving alone or the likelihood of them considering other modes for commuting, on a scale of 'not likely at all' to 'very likely'. The results of these SP questions were modelled in logit regression models to analyse the predictors of solo driving and to determine which of the measures tested were most effective in stimulating a shift away from SOV use. The findings from these models revealed that solo drivers were twice as likely to switch away from SOV use for commuting purposes in response to an incentive than disincentives such as a fee or charge, and one in three were very likely to consider an alternative mode given the availability of incentives (Baldassare, et al., 1998). Specifically, young solo drivers with lower levels of education, who lived in close proximity to their work, were most likely to reduce their solo driving habits in response to a workplace parking fee and congestion fee. Of these drivers, males showed higher probability to act in accordance with the introduction of parking and emission charges, whereas, females were more likely to reduce their solo car use in response to a congestion charge. The incentives regression model showed that young, female respondents, living close to their workplace, who were aware of the environmental consequences of car use were more likely to switch to carpooling or PT given the availability of a cash bonus and improved PT coverage.

Chan and Shaheen (2012) conducted an in-depth longitudinal review of the state of carpooling/ ridesharing in North America from post-World War II to modern day and highlighted the transformations that the service has undergone during this period. In this study they outline the range of incentives or tangible benefits that carpoolers have been offered in the USA, such as: time and cost savings acquired from the availability of high-occupancy vehicle (HOV) lanes and by sharing travel costs amongst other car occupants, reduced commute stress for longer distances and the convenience associated with designated parking for carpools at the workplace (Chan and Shaheen, 2012). The authors stress that these incentives are paramount in encouraging people to create carpools, and employer incentives such as: tax deductions, reduced on-site congestion and an investment in the welfare of employees, are vital to ensuring that there is sufficient support available to staff for carpooling. However, they highlight that some individuals may be indifferent to the prospect of sharing their journeys with other people due to psychological aspects like the lack of desire to share personal space and the avoidance of delays associated with pick-ups and drop-offs. Therefore, there are some mental obstacles that must be overcome. Chan and Shaheen (2012) also stressed that ultimately, carrot policies must express to individuals that carpooling will lead to improvements in trip attributes or as a minimum be competitive to the SOV option through tangible incentives, in order to achieve a genuine mode shift (Carroll, et al., 2017).

Catalano et al. (2008) investigated the demand for car-sharing and carpooling in Palermo, Italy given the context of a future of scenario, in which various policy measures were put in place. In this study a SP survey was used as the instrument to collect observations and preferences to measures such as: a car kilometric charge and parking charges for SOVs, improvements made to in vehicle times of car-sharers and carpoolers from lower parking and access times, in addition to a reduction made to PT fares. The preferences from this experiment were then analysed in a MNL model, as a means of estimating the model share of the demand for carpooling, carsharing, SOVs and PT. An emphasis was placed on car-sharing and carpooling as modes to reduce the mode share of SOVs, which could also result in higher numbers of individuals using bus and rail as a consequence of negating the need to own a vehicle. The results from this study found that the number of available cars to the household was the highest determinant of whether alternative modes would be adopted or not. In other words, households with fewer cars available were more likely to mode shift than households with multiple cars. Travel cost was shown to be the trip attribute of highest statistical significance, which the coefficient was also negative indicating that modes with lower trip costs would attract more people to shift away from driving alone. This was followed by the time associated with parking, which is in favour of carpooling and car-sharing services whom generally have designated free parking available to them. The overall mode share findings showed that the mode share for car-sharing grew by up to 10%, with carpooling and PT staying relatively the same, in response to the policy incentives reducing in-vehicle times (IVT), wait times and rising parking fees for SOVs.

Conversely, Washbrook, et al. (2006) conducted a similar SP study in Vancouver, Canada, which examined the behavioural effects of introducing road pricing and parking charges in a choice set of driving alone, carpooling or an express bus service. However, in this study it was found that employing road pricing and parking charges would have the effect of stimulating more reductions in the demand for SOV trips than other measures delivering time and cost savings to other modes such as carpooling. In other words, Washbrook, et al. (2006) found that disincentives performed better than incentives in reducing car use in the context of Vancouver.

Enoch and Taylor (2006) review a number of policy mechanisms that are used worldwide to encourage the adoption of car-sharing or ‘car clubs’, as they are referred to in the UK. They begin by discussing the benefits associated with car-sharing which include, a reduction in car dependency and congestion, consequently leading to fewer emissions produced and parking space pressures, in addition to the cost incentives of avoiding high insurance premiums and repair costs of private vehicles. The authors then pinpoint a range of popular incentive measures that have been successful in attracting members in countries like Germany, Italy, Canada and the USA, namely: information provision for policymakers to generate support for the creation of a car-sharing strategy; the integration of car-sharing companies with other public transport services to stimulate collaboration in the transport sector; the provision of free on-street parking in strategic areas of the city centre (e.g. in the central business district (CBD)); fiscal mechanisms such as public subsidies to kick-start car-sharing schemes and tax exemptions for car-sharing providers. This study concludes that local authority support in particular is a key stimulus in starting and ensuring the success of a car-sharing service. It is suggested that best practice and lessons learnt from car-sharing in cities like Bremen, Germany; San Francisco, USA; Toronto, Canada, and multiple cities in the Netherlands, should be considered in order to accelerate growth in car-sharing and thus, reduce dependency on the private car for short trips.

Table 2.5 outlines the findings of several other studies that are relevant to the research examined in this thesis.

Table 2.5 Review of the literature regarding policy interventions for behaviour change

Author(s)	Year	Title	Main findings
Bamberg and Schmidt	2001	Theory-driven, subgroup-specific evaluation of an intervention to reduce private car-use.	An increase of 15% in student PT usage was found following the introduction of a semester-ticket intervention, which resulted in a decrease in car use of 13.6% during the same period.
Brazil and Caulfield	2010	Examining the factors that impact upon mode choice for frequent short trips.	Pleasant weather was found to increase the likelihood of individuals walking or cycling, while poor weather led to an increase in SP respondents opting for the driving alternatives. However, trip time, distance and the load for the trip were all shown to be of greater consideration than weather in the decision of whether to walk or cycle or not. In addition to this, amount of CO_2 emitted during a short trip was found not to be a concern for drivers.
Farrell, et al.	2010	Estimating the potential success of sustainable transport measures for a small town.	Soft policy measures leading to reductions in travel times, and changes to departure times and travel distances that are implemented in isolation were found to not be as effective as a combination of measures. Changes in vehicle kilometres travelled attained from the introduction of sustainable policy measures were shown to result in substantial CO_2 emission savings, of up to 34.64 tonnes annually based in a 10% shift to cycling and 29.97t from a 10% shift to ridesharing.
Loukopolulos, et al.	2004	Car-user responses to travel demand management measures: goal setting and choice of adaptation alternatives.	The focus group participants showed a higher likelihood to mode switch for commuting purposes than for any other purpose. While there was a reduction in car use overall, a negation regression coefficient suggested that there was fall in efficient car use, i.e. as car trips decreased, the efficiency of car-use also decreased.
Mackett	2001	Policies to attract drivers out of their cars for short trips.	The action that would do most to attract drivers away from their cars is to improve bus services; 21% of short car driver trips could be attracted to bus. The main actions that are required are improvements to the route pattern (10%) and improvements to frequency (6%), another 1% would like them to operate all night. Most popular attributes for mode shifting to alternatives: improvements to bus routes and frequency, cost of travel reduced, bus information improved, improvements to cycling facilities
Malodia and Singla	2016	A study of carpooling behaviour using a stated preference web survey in selected cities of India.	It was suggested that SOV drivers would be more likely to consider carpooling if it was depicted as part of a social norm by employers, in other words, if carpooling is perceived as being a popular mode of transport for commuting it would encourage others to take carpooling more seriously and devote more attention to it. Time was found as being the main cause for concern for potential carpoolers, as added wait and walk times are associated with the modes for pick-up purposes. This was followed by cost, which was found to be one of the main pull factors for carpooling as the travel cost can be shared amongst the other occupants.
Meloni, et al.	2013	Propensity for voluntary travel behaviour changes: an experimental analysis.	Most of the car drivers are in fact not aware of their alternatives and most of the times they are not able to quantify possible benefits deriving from behaviour changes. This study also highlighted that there are individual habits, such as pro-environmental efforts, that characterise a higher probability to change also travel mode behaviour.
Millard-Ball, et al.	2005	Car-Sharing: Where and How It Succeeds.	A major obstacle in establishing a successful car-sharing service is a lack of understanding of how and where it succeeds and the absence of financial incentives such as free usage credits for joining and pricing structures that are easy to comprehend.

Meyer	1999	Demand management as an element of transportation policy: using carrots and sticks influence travel behaviour.	This paper suggests that there are strategies that can be used to begin the process of gaining public support for more controversial actions. These strategies attempt to link the general public sense of fairness to public policies aimed at negatively affecting someone's ability or cost to travel by single occupant vehicle. The basic ingredient to successful future adoption of area-wide TDM actions is to link it to broader goals that the public can support.
Ogilvie, et al.	2008	Interventions to promote walking: systematic review.	Policy measures such as individualised or personalised marketing and information provision was found to increase walking amongst respondents by on average 30-60 minutes a week in the short-term.
Pooley, et al.	2011	Household decision-making for everyday travel: a case study of walking and cycling in Lancaster (UK).	Attempts to increase rates of walking and cycling in urban areas are unlikely to succeed unless the convenience of the car is countered by restrictions on car use and the complexities of everyday travel are addressed.
Pooley, et al.	2013	Policies for promoting walking and cycling in England: a view from the street.	Respondents listed safety concerns, familial responsibilities and the social perceptibility of cycling amongst their peers and family as reasons for not considering alternatives modes.
Rock, et al.	2016	The economic boom, bust and transport inequality in suburban Dublin, Ireland.	The study survey revealed that 70.5% of car-owning households viewed owning a car as a necessity to get about where they lived. Although there are a high percentage of people with these views, there are still 42% of multi-car households that stated they would be willing to consider reducing to one car if local services and public transport were improved.
Sottile, et al.	2015	Measuring soft measures within a stated preference survey: the effect of pollution and traffic stress on mode choice.	Utility of Park and Ride (PnR) increases with the level of awareness, aspects associated with stress have a greater influence on travel choice than environmental aspects. Reduced stress and pollution was found as an effective determinant in encouraging individuals to consider PnR.
Taylor and Ampt	2003	Travelling smarter down under: policies for voluntary travel behaviour change in Australia.	Whilst voluntary behaviour change programs are not yet for the whole community, the trials around Australia have shown firstly that a sizeable minority of households and individuals can be attracted to the programs, and secondly that the participants can achieve ongoing, substantial reductions in their usage of private motor vehicles.
Ubbels and Verhoef	2005	Behavioural responses to road pricing. Empirical results from a survey among Dutch car owners	A reduction in the mode share of SOVs of between 6% and 15% for all trip purposes could be achieved from introducing road pricing in the form of kilometric charges.
Weibin, et al.	2017	Urban commuters' valuation of travel time reliability based on stated preference survey: A case study of Beijing.	Level of income and time restrictions have a strong influence on mode choice for commuting purposes. Those earning high incomes were found be more likely to choose modes with less travel time and higher reliability. Time reliability was of more concern to the majority of commuters than travel time.

2.6 Gap in literature and Conclusions

The review of literature presented in this chapter has highlighted a number of opportunities for research and gaps in the literature that require further attention. The following aspects have been identified as the main gaps in literature that examine the effect of policy measures on reducing car use:

1. The review of literature pertaining to incentivisation of sustainable travel modes in Ireland, identified that this area of research is currently under researched, particularly in relation to active modes, car-sharing and carpooling. Very few studies produced in Ireland have examined ways of reducing car usage and ownership by addressing pedestrian and cycling priority and infrastructure, and by offering tangible time and cost benefits to carpool or car-sharing members. The 'sharing economy' is a relatively new phenomenon in the urban landscape (Davidson and Infranca, 2016); thus, this could explain the shortage of research in carpooling and car-sharing. In this way, the approach explored in this thesis is dissimilar to other research in this field internationally, as it emphases the effect of policy incentives exclusively, on the utility of active modes, PT, carpooling and car-sharing, as opposed to incorporating disincentives or a blend of both push and pull measures

2. The policy term of 'car-shedding' introduced in this thesis presents an umbrella term in the narrative of transport policy research. While concepts such as TDM and mobility management are similar in their implications for reducing car use, car-shedding differs in that it focuses explicitly on reducing the number of SOV trips for commuting purposes, by making alternative modes increasingly competitive to the car in terms of time and cost efficiency, comfort, convenience and safety. In this way, the term of car-shedding makes a key contribution to the field of transport policy analysis, which can be used in policy appraisal and analysis to examine the use of incentives as an effective approach in promoting sustainable modes of transport

3. It was found that the practice of using of behavioural outputs produced from SP surveys, such as regression coefficients and direct and cross elasticities, etc., in informing changes to transportation demand modelling tools was not a common exercise in Ireland and internationally. Thus, this research aims to emphasise the effectiveness of utilising SP data in demand modelling as a means of predicting travel behaviour in future years based on the introduction of certain policy instruments

4. Few studies in Ireland merge the technical analysis of emissions reductions achieved from incentivising sustainable mobility with the behavioural changes required to achieve such emissions (Greening Transport, 2015). While research has been conducted in this area in Ireland, such as Alam, et al. (2018), Farrell, et al. (2010), Caulfield (2009), Legge and Scott (2009), more work is needed to fully understand the direct behavioural effects of changes in modal shares, on environmental outcomes such as emissions savings. In addition to this, the monetary savings associated with emissions reductions in gases such as $CO_{2,}$ NO_x and $PM_{2.5}$ have been rarely explored in the literature pertaining to this topic

With these aspects in mind, the research produced in this thesis was conducted to address these gaps in the literature and to offer an empirically sound method of policy appraisal for car-shedding interventions in the GDA.

In consideration of the research opportunities and gaps identified in the review of the current literature, Chapter 3 sets out the methodology and research design underpinning the SP experiment conducted in this thesis.

CHAPTER 3: STATED PREFERENCE RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

The following chapter outlines the theoretical underpinnings of SP surveying and discrete choice modelling employed in the SP experiment. The experimental design implemented in the SP study will be examined in-depth in Section 3.2, which includes utilisation of the mathematical framework of discrete choice statistical modelling. In Section 3.3 the theoretical background of multinomial logit (MNL) modelling will be set out in addition to a discussion on interpreting the output from the model in Section 3.4, before exploring the application of this approach in the context of this study in Section 3.5. Finally, the design and sampling methodology applied in this study will be described.

3.2 Stated Preference Survey Design and Structure

SP surveying, in contrast to Revealed Preference (RP), assesses the behavioural response of a sample to a range of hypothetical scenarios that elicit a trade off in choice making between alternatives. RP on the other hand, considers actual or observed market occurrences to existing market forces. For instance, Census and National Household Travel Survey (NHTS) data are examples of RP data, collected based on reported past activities of a sample. SP approaches are extensively utilised in travel behaviour research to identify choice making behaviour in contexts that are designed by an analyst. Assessing potential modal choice behaviour in response to the introduction of a new transport mode or policy scheme, are examples of how SP methods are often utilised in the field of transport (Hensher, 1993). Kroes, et al. (1988) define that, SP methods include a host of statistical techniques that estimate utility functions, i.e. the benefit or usefulness that an individual gains from using a service or transport option, based upon individual preferences collected in an SP experiment. As a result, SP experimentation has become a common process of assessing behaviour in the context of transportation and popularity for this method is also mounting in fields such as marketing, geography, regional science and tourism (Hensher, 1993). However, SP data is often most beneficial if collected in conjunction with RP data and *vice versa*, as observed and hypothetical data complement each other and in such a way, improve the validity and accuracy of the results produced from the research. Relative to RP data, the process of collecting SP data is more economical and cost effective, as RP data collection can be time consuming and expensive, requiring more financial resources (Sanko, 2001). Another issue with RP data is the high degree of collinearity between attributes in an experiment, which leads to issues when estimating the disparity in such attributes. SP methods, however, provide the ability and flexibility to design hypothetical scenarios that mitigate this risk of multicollinearity (Accent, 2010; Kroes, et al., 1988).

SP experimentation was deemed as an appropriate and established method of evaluating the potential impacts of implementing hypothetical policy measures on mode choice behaviour from examining similar studies (O'Fallon, et al., 2004; Baldassare, et al., 1998; Louviere, et al., 2000; Beaton, et al., 1998). However, few studies, of the nature of the SP experiment conducted in thesis, have been conducted in Ireland, thus, it was estimated that this study would contribute to our understanding of how sustainable travel behaviour could be incentivised by applying a particular 'carrot' policy approach.

In the study presented in this thesis, respondents were asked to rank in order their preferences from a choice set of three alternatives or modes, with their first preference being considered in the choice modelling. Each one of these choice tasks were framed as a choice scenario with differing levels of attribute intensity associated with the alternative in question. The success of a SP survey design is determined by the ease at which individuals can make trade-offs between coherent and realistic alternatives, in addition to the capacity of individuals to comprehend the scenarios and the context in which they are set in (Boxall, et al., 2009). Attributes are essentially the variants in the experiment, in which case they differ depending on the choice alternatives in each model. Policy incentives were the instruments that modified the respondent's trip characteristics or trip attributes.

Figure 3.1 outlines the three defined models used in the experiment, one examining public transport (bus and rail), the second concerning active modes (walking and cycling), and the third considering sustainable usage of the private car, namely: carpooling and car-sharing. Each of the three models were analysed independently to examine the influence of a number alternative-specific attributes or policy tools on modal choice behaviour. The models were represented in separate choice sub-sections within the SP survey in order to effectively isolate the choice scenarios. As shown in Figure 3.1, a private car (drive alone) option is present in each model, which was considered as a constant or 'no choice' / 'status quo' option that had no policy attributes applied to it. Essentially this constant is used to compare changes in the other modes against each other in other to stimulate trade-offs in choice making. This decision was made for a number of reasons: firstly, there was reluctance to dis-incentivise car owners by, for example, raising the costs of owning a car as these costs generally grow year-on-year, which would perhaps bother or anger potential respondents. Secondly, it is held in the literature that including a base alternative or 'current choice' option, brands decisions more realistic and leads to better predictions of market penetrations, as well as better mimicking consumer choices and increasing experimental efficiency (Brazell, et al., 2006; Haaijer, et al., 2001; Louviere and Woodworth, 1983). This leads to better model parameter estimates and in this way more accurately predicts modal choice changes in the population (Brazell, et al., 2006). Dhar (1997) states that forcing a respondent to choose amongst a limited number of options might lead to biased parameters when modelling such survey results. Thus, in the context of this study, an assumption was made that the respondents would determine the utility for each mode choice and only chose the car option if none of the other modes were appealing enough to them based on improvements being made to frequency, time, cost, infrastructure, and convenience factors, or in other words, if the other alternatives offered insufficient utility to the respondent (Vermeulen, et al., 2008).

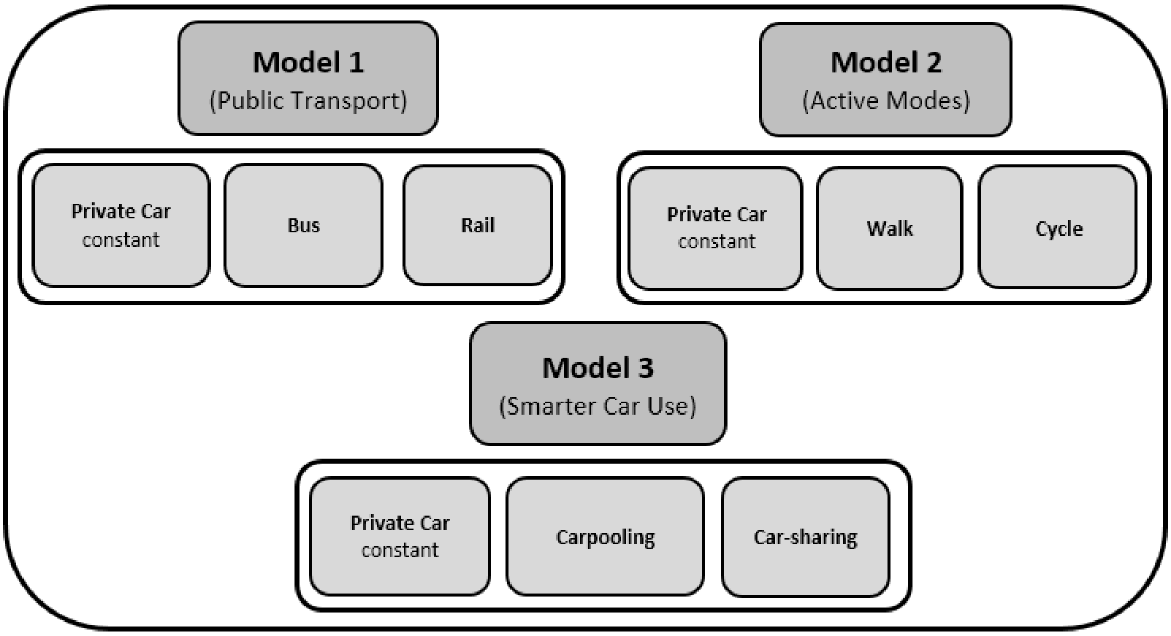

Figure 3.1 Stated Preference experiment structure

3.3 Discrete Choice Modelling

Discrete choice modelling is an econometric method of predicting the behaviour of an individual based on choice behaviour theory (Ben-Akiva and Lerman, 1985). In a choice experiment (CE) the collection of options or alternatives that an individual survey respondent is asked to choose from is termed a choice set. The choice set is central to the structure of the experiment, and as such, it must follow the discrete choice framework, that holds the following three characteristics (Train, 2003):

- The alternatives must be *mutually exclusive* from the decision maker's perspective. Meaning that the decision-maker can only choose one of the alternatives in the choice set. For example, if bus, rail and car are the three alternatives in Model 1, the respondents may only choose one mode per scenario.
- The choice set must be *exhaustive*, in that all possible alternatives are included. The car option is included in each of three models in the event that the decision-maker does not wish to choose one of the alternative modes incentivised by the policy plans. In this way, the car option acts as a status quo option.
- The number of alternatives must be finite. Meaning that the 'researcher can count the alternatives and eventually be finished counting' (Train, 2003).

In reference to the first of the three characteristics, Long and Freese (2006) quote McFadden (1973) in stating that Multinomial and Conditional logit models should only be used in cases where the alternatives ‘can plausibly be assumed to be distinct and weighted independently in the eyes of the decision maker’, as such the alternatives should be distinct from one another.

The foundation of discrete choice modelling is derived from the traditional economic theory of consumer behaviour (Louviere, et al., 2000) and is examined under the Random Utility Theory (RUT). RUT revolves around the concept of ‘utility’ or the benefit that an individual assumes from a certain good or service (e.g. a mode of transport). Humans are assumed to be rational beings and like this they seek to maximise the utility they derive from a good or service, which is defined as the theory of utility maximisation. Train (2003) identifies the difference between regular regression models and discrete choice models by stating that ‘regressions examine choices of ‘how much’ and discrete choice models examine choices of ‘which’. Equation 3.1 illustrates that an individual will only choose alternative *i* if the utility of this alternative is greater than the utility derived from all other alternatives in the same choice set.

Equation 3.1

$$U_{in} > U_{ij} \forall j \neq i$$

There are two distinct components of utility, the deterministic or ‘representative’ component V_i , and a stochastic error term ε_i , which refers to the unobserved influences that are independently and identically distributed (IDD) across the population (Hensher, et al., 2005). In the context of this study the deterministic element is represented by the attributes (policy incentives) being applied to each of the alternatives, and the error term is calculated with the use of an alternative-specific constant (ASC), that takes account of all the things which either can’t be quantified in the model or generally, or are unknown factors which influence behaviour/decision-making. As the utility of an individual cannot always be observed by the researcher, the attributes associated with each of the alternatives are thus examined, in addition to the various characteristics of the decision maker (Train, 2003). These alternative specific and socio-demographics attributes together are what is labelled as ‘representative utility’. The utility expression for random utility models can be written as:

Equation 3.2

$$U_{\boldsymbol{i}} = V_i + \varepsilon_i$$

The deterministic component (V_i) is calculated based on an equation of attributes assigned to each alternative in the choice set, the attribute coefficients and an ASC, which can be defined as a linear expression, whereby each attribute is weighted by a parameter to represent the attribute's utility input (Hensher, et al., 2005):

Equation 3.3

$$V_i = \beta_{0i} + \beta_{1i} f(X_{1i}) + \beta_{2i} f(X_{2i}) + \beta_{3i} f(X_{3i}) + \ldots + \beta_{Ki} f(X_{Ki})$$

where:

β_{1i} is the weight (or parameter) associated with attribute X_i and alternative i

β_{0i} is the ASC, which represents the role of all unobserved sources of utility

k is the number of estimated parameters considered in the equation

For example, the beta parameter representing the Bus alternative is estimated with the associated attributes, which are frequency, time and cost. The utility equations for each of the models are discussed in more detail in Chapter 4, Section 4.3.

As the random error component in Equation 3.2 cannot be modelled, the probability of an individual choosing an alternative i from a choice set is the probability that this utility is greater than the utility of any other alternative in the choice set, which is represented as:

Equation 3.4

$$P_i = Prob\left(U_i > U_j\right) \forall j \neq i$$

3.3.1 The Multinomial logit (MNL) model

MNL models are the most commonly used discrete choice model, frequently labelled 'the workhorse'. The reason it remains the most popular choice modelling framework is due to a number of reasons, namely: the ease of estimation, which provides the capability of conducting likelihood tests of potential market shares in response to the introduction of changing policy scenarios or infrastructure, and the quick production of model indicators such as: goodness of fit, the sign of parameters, log-likelihood, and chi-squared values, etc. (Louviere, et al., 2000).

The MNL is a logistic regression model used with a nominal (unordered) dependent variable, when more than two alternatives exist. It is utilised to explain the relationship between the dependent variable and one or more continuous independent variables. The MNL form requires that the unobserved effects on choice are independently and identically distributed (IID), according to the extreme value type I (EV1)/ Gumbell distribution (Hensher, et al., 2005; Ben-Akiva and Lerman, 1985). In other words, the variances of each alternative are unique and the unobserved influences on choice are not linked across pairs of alternatives (Hensher, et al., 2005). Therefore, the probability of an individual choosing an alternative (e.g. bus or rail) in a choice set in an MNL model can be written as:

Equation 3.5

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}}$$

where:

P_i is the probability that an individual will choose alternative i

V_i is the deterministic component of the utility expression in Equation 3.2

j is the number of alternatives in the choice set

IIA Property Axiom

The Independence from Irrelevant Alternatives (IIA) axiom holds that the ratio of the probability of one alternative being chosen is not influenced by the existence of other alternatives (Louviere, et al., 2000; Ben-Akiva and Lerman, 1985). For instance, by adding a car alternative to a choice set of bus and rail, the probability of bus being selected would not be affected by this introduction.

The axiom is one of the main limitations or criticisms of the MNL approach in choice modelling, which is centred on this primary probability axiom. It is reported in the literature that the IIA axiom weakens the choice model as the attributes or options used in an experiment cannot be independent of each other. Yet, on the other hand, it can also strengthen the model as it provides a 'computationally convenient method of estimation without the need for re-estimation' when alternatives are removed or introduced to an experiment (Hensher, et al., 2005; Train, 2003; Louviere, et al., 2000).

3.3.2 Maximum Likelihood Estimation of Discrete Choice Models

An important difference exists between regular linear regression and logistic regression; in linear regression models parameters are estimated using the method of ordinary least squares (OLS) where the dependent variable is held as continuous. While in logistic regression probability of the outcome is categorical i.e. the alternative is either selected (1) or not (0), and the method of maximum likelihood estimation (MLE) is employed, which produces estimates for parameters in a population set that occur most frequently based on the sample observed.

The theory behind MLE is provided by means of an example, that considers a random sample of *n* observations of a random variable $Z\ (z_1, \ldots, z_n)$ taken from a population set with an unknown parameter θ (i.e. variance) (Louviere, et al., 2000). If these *n* values are independent, the joint conditional probability density function (PDF) can be represented as:

Equation 3.6

$$f(z_1, z_2 \ldots, z_n/\theta) = f(z_1/\theta) \ldots, f(z_n/\theta)$$

In Equation 3.6, it is considered that the *Zs* are able to vary and the θ is fixed. If, however, this assumption was reversed, i.e. if the random variable *Z* were fixed and the θ parameter were able to vary, then Equation 3.6 would transform into a likelihood function rather than a PDF.

If the population depicted in Equation 3.6 were to have additional θ variable(s) in consideration, this equation could then be extended, with the *Zs* following a normal probability distribution thus featuring a mean (μ) and a variance (σ^2). The likelihood function of Equation 3.6 may then be maximised to a θ vector if this population characteristic were defined as 2-dimensional vector of μ and σ^2 (Louviere, et al., 2000).

In MNL models, a random sample of *Q* individuals is considered, with a choice observation for each individual *q* being collected from values in a choice set X_{jkq}. Therefore, if individual *q* selects alternative *i* in an experiment, the associated PDF can be represented as $f(Data_q | \beta)$, where $Data_q$ relates to data collected for individual *q* and β is the vector of utility parameters in the representative element of utility (V_{jq}). If the data collected is found to be independent, the $f(Data_q | \beta)$ can be replaced with the probability expression of the alternative chosen by the individual *q* (Louviere, et al., 2000). Such an expression may then written as follows:

Equation 3.7

$$L = \prod_{q=1}^{n1} P_{lq} \prod_{q=n1+1}^{n1+n2} P_{2q}, \ldots, \prod_{q=Q-n_j+1}^{Q} P_{Jq}$$

Which can be revised introducing a dummy variable *fjq* = 1 if *j* is chosen, and 0 if not chosen:

Equation 3.8

$$L = \prod_{q=1}^{Q} \prod_{q=j=11+1}^{J} P_{jq}^{f_{jq}}$$

Given Equations 3.7 and 3.8, the log likelihood may then be defined and written as:

Equation 3.9

$$L^{*} = \sum_{q=1}^{Q} \sum_{j=1}^{J} f_{iq} \, lnP_{jq}$$

Thus, log likelihood (LL) can accordingly be maximised with respect to the β parameters used in the utility equations in the experiment, set out in Chapter 4, Section 4.3. LL is one of many statistical indicators of model fit and quality produced from NLOGIT discrete choice modelling software (Econometric Software In., 2017) in this study, that will be discussed in the next section.

3.4 Interpretation of MNL Outputs

When the models have been estimated using the preferences and attributes levels from the survey experiment, there are a number of indicators that measure the performance of discrete choice models, that vary depending on what modelling software is utilised. The responses collected from the SP survey in this study were modelled from the equations in Section 3.3 using NLOGIT specialised discrete choice modelling software, which provides programs for estimation, simulation and analysis of multinomial choice data. It is the only statistical program available that supports mixing stated and revealed choice data sets (Econometric Software Inc., 2017). NLOGIT produces various significant outputs that require interpretation, these are: the log likelihood function, pseudo-Rho^2, the Akaike Information Criterion Coefficient (AICc), the sign of the coefficient, the statistical significance or p-value, in addition to other supplementary behavioural tests such as elasticities and 'what if' simulations (Ryley et al., 2014; Hensher et al., 2005).

Likelihood ratio test

As discussed in Section 3.3.2, LL is a key indicator produced from MLE of individual choices in discrete choice models. In a typical MNL model, two LL values are produced, of which one is generated for the observed base outcome from the data collected and the other is based on the predicted values or outcome. To determine whether the overall model is statistically significant, the difference between the LL function of the observed outcome (constants only/ base model) is compared with the LL of the predicted outcome, which is known as a *Likelihood ratio test,* illustrated in Equation 3.10. This indicator tests the relative statistical performance of the observed model output to the estimated output. The Likelihood ratio test can be calculated using the following equation:

Equation 3.10

$$-2(LL_{base\ model} - LL_{estimated\ model})$$

The -2LL value produced from the test is compared to a chi-square value at an interval of confidence of usually 0.05, with the degrees of freedom determined based on the difference between the parameters in the base and estimated models (Hensher, et al., 2005). If -2LL result exceeds the chi-square value at the level of confidence, the null hypothesis can then be rejected, meaning that alternative hypothesis, that the estimated model is a better fit to the data and performs better than the base model, can be accepted.

Pseudo Rho-squared

The Rho^2 statistic provides a measurement of the quality of the estimated model. Yet, the Rho^2 in logistic regression in choice models should not be treated the same as R^2 in linear regression as the MNL model is non-linear, thus it is not analogous. For this reason, the Rho-squared statistic in logit modelling is termed *pseudo Rho-squared*, which is calculated using the following equation (Hensher, et al., 2005):

Equation 3.11

$$Rho^2 = 1 - \frac{LL_{Estimated\ model}}{LL_{Base\ model}}$$

This formula demonstrates that the Rho-statistic is the statistical relationship between the log-likelihood of the estimated model and the base model, of which the result can vary between 0 and 1. The higher the pseudo-Rho^2 value is, the better the result, therefore a value of close to one indicates that the model estimated fits well to the sample dataset. However, even if a low Rho^2 value is produced, it should be interpreted with caution for it is not equivalent to R^2 produced from ordinary least squares (OLS) in linear regression (Hensher, et al., 2005; Louviere, et al., 2000). Thus, in the event that a low pseudo-R^2 is generated, statistically significant regression coefficients generated in the model still account for the mean variation in the response for one unit of change in the predictor *ceteris paribus* (Minitab, 2013).

Akaike Information Criterion Coefficient (AICc)

The Akaike Information Criterion Coefficient (AICc) is another goodness-of-fit measure of the relative quality of the model for the dataset used in the analysis. Much like the likelihood ratio test, it is used as a means of comparison of estimation between models of the same datasets (e.g. comparing the base model with the estimated model). The better the model fits to the data, the lower AICc for that model will be. However, the AICc is limited as providing a test of the overall quality of the model is separate to hypothesis testing (Hensher, et al., 2005; Louviere, et al., 2000). Equation 3.12 outlines the formula for calculating the AICc indicator:

Equation 3.12

$$AIC = -2LL + 2k$$

where:

LL is the likelihood value

k is the number of estimated parameters (Burnham, and Anderson, 2002)

The Sign of the Coefficient

When analysing the main output of an MNL model, the first element that will come to the attention of the analyst will be the sign of the parameter estimate, which should usually appear logical in the context of the experiment. In this study, a number of policy incentives that act as the main attributes in the model are estimated to increase the probability of choosing the sustainable modes incentivised in the SP scenarios. In other words, the main attribute coefficient signs for these sustainable modes (i.e. walk, cycle, bus, rail, carpool and car-share) should appear positive if people respond positively to the attributes, as the respondent's choice making behaviour is modified in favour of alternative modes. In this way, as these trips become cheaper, quicker and more convenient the respondents should, in theory, be more likely to choose those modes of transport, signifying an increase in the utility of the mode. In view of this, the signs of the coefficient should make intuitive sense. However, the size preference of the coefficient should similarly be consulted, especially when comparing variable coefficients from the same model.

Statistical Significance

The statistical significance or p-value (probability value) of the parameter estimates and of the model as a whole (i.e. the prob [chi squared > value]) are other important statistical indicators to consider in the MNL output. The p-value of a parameter accounts for the probability of the model results being replicated in the market or within the population. The analyst compares the p-value of the model and the parameter estimates with a level of acceptance, known as alpha, *a*. The standard levels of acceptance are most commonly, alpha values of 10%, 5% and 1%, which are represented in the analysis as significant at 90%, 95% and 99%, respectively (Louviere, et al., 2000). Usually, the level of acceptance is taken as 0.05, which means that if the p-value falls below level of alpha, the null hypothesis may be rejected (Hensher, et al., 2005).

The Wald Statistic (z-statistic)

The *z*-statistic, which is analogous to the *t*-statistic in linear regression, is also used to determine the fit of individual predictors to the model. Akin to the *t*-statistic, the *z*-statistic indicates if the beta coefficients in the model are significantly different from zero (Field, 2013). The given significance levels at the alpha values mentioned (10%, 5% and 1%), correspond to the *z*-stat values of ±1.50, ±1.96, and ±2.56 respectively. The z-statistic is calculated by dividing the regression coefficient by the standard error:

Equation 3.13

$$z = \frac{b}{SE_b}$$

where:

b is the regression coefficient

SE_b is the standard error for coefficient in question

Elasticities

Increases and decreases in the economic cost of using different travel modes have been found to influence travel behaviour (Jacobsson, et al., 2009; Heath & Gifford, 2002; Bamberg & Schmidt, 2001), and estimates of transport elasticities provide information of the extent to which travel demand is sensitive to changes in trip cost, time and trip characteristics such as frequency and convenience (Litman, 2017). Transport elasticities (direct and cross) in SP studies are expressed as the ratio of proportional behavioural change relative to changes in fares or services (Eriksson, et al., 2010). Direct and cross elasticities are key behavioural outputs, as they provide a greater insight into the varying effects of changes to specific attributes in the model, and they explicate these impacts in the form of choice probabilities. Direct elasticities measure the percentage change in the choice probability of an alternative in a choice set as a result of a percentage change in an attribute associated with that same alternative (Hensher, et al., 2015). Direct-point elasticity in a MNL model is calculated using the following equation:

Equation 3.14

$$E_{X_{ikq}}^{P_{iq}} = \frac{\partial P_i}{\partial X_{ik}} \cdot \frac{X_{ikq}}{P_{iq}} = \frac{\partial V_{iq}}{\partial X_{ikq}} \, X_{ikq}(1 - P_{iq})$$

Equation 3.14 expresses the elasticity of the likelihood of alternative *i* being chosen for respondent *q* given a percentage change in the attribute (*k*) of the alternative *i* (i.e. X_{ikq}) in the choice set (Hensher, et al., 2015). For example, if there was a 1% increase in the time attribute of the bus alternative, representing a 1% decrease in trip time for bus, what would be the consequence of this in terms of choice probability and the utility of this mode.

Cross elasticities, on the other hand, measure the probability of choosing an alternative given a percentage change in a different or competing alternative, which is expressed as:

Equation 3.15

$$E_{X_{jkq}}^{P_{iq}} = -\beta_{jk} X_{jkq} P_{jq}$$

An example of a cross elasticity in this study is, if there was a 1% increase in the time attribute of the bus alternative, what effect would this have on the choice probabilities of the rail or car alternatives.

3.5 Applying the Discrete Choice modelling approach

In Figure 3.2 the key phases in conducting a SP study are outlined (Johnson, et al., 2013). Hitherto, the research objectives, the alternatives in each of the three models in the experiment, in addition to the modelling requirements for the study have been set out. The policy attributes have been alluded to, however a more in-depth examination of the attributes and attribute levels, and how they fit into the core experimental design of the experiment, will be explored in this section.

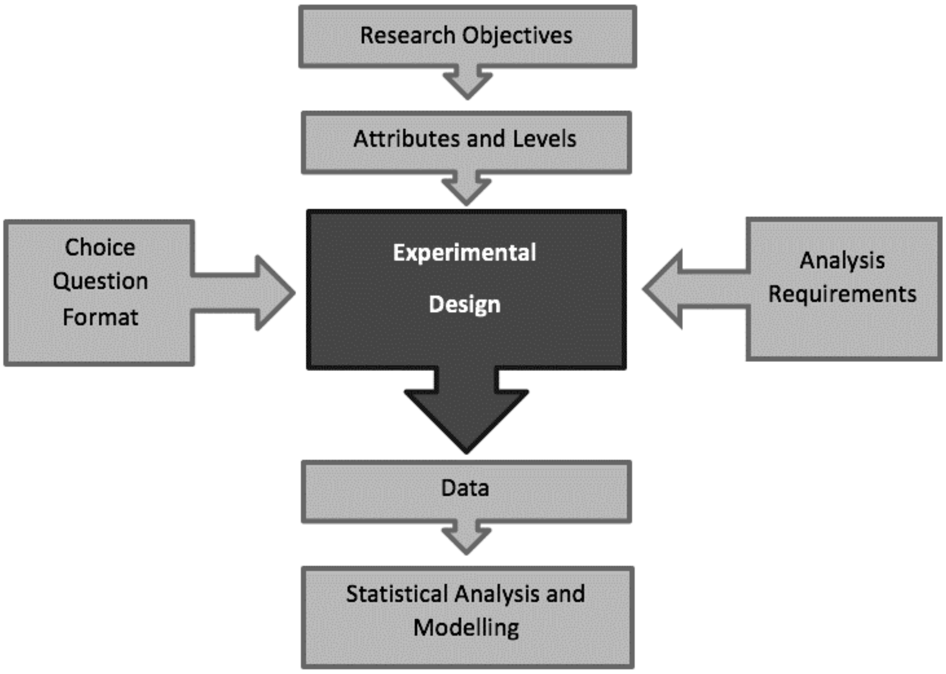

Figure 3.2 Key stages for developing a discrete-choice experiment (Johnson, et al., 2013)

3.5.1 Defining the attributes and attribute levels

In order to create an effective SP choice scenario, it is necessary to provide the respondents with a scenario in which they are prompted to make a trade-off between a number of alternatives. The attributes or trip characteristics associated with the alternatives define the attractiveness of each option, thus highlighting their importance in a SP survey. The alternative-specific attributes for active and public transport modes, carpooling and car-sharing in the three models were carefully considered, in reference to the literature (Malodia and Singla, 2016; Short and Caulfield, 2004; Eboli and Mazzzulla, 2008). As the attributes in this experiment were determined by how they are influenced by the mode specific policy incentives tested, it was necessary to first consider what elements or characteristics of each mode included in the SP survey could be improved in order to increase the utility of them.

In designing the SP experiment, the following assumptions were made and steps were taken in developing the experimental design:

- As illustrated in Figure 3.1, each of the mode categories incentivised in this study were modelled in isolation in different models. This was done in order to investigate the choice making behaviour of the sample in the context where the SOV option was a status quo alternative set alongside improved sustainable modes.
- By designing three models, it was possible to analyse to a greater extent how individuals respond to the incentives for each mode, and to determine which mode-specific trip attribute was of most interest to the respondents.

- The behavioural findings were generated from observing the trade-off patterns in respondent decision making between the trip characteristics presented. Owing to this, a factorial research design, discussed in Section 3.5.2, required that each of these models be analysed separately, meaning that one choice would be made for each choice scenario. Thus, as a result of the experimental design of this study, all of the modes were unable to be modelled together in one model.
- All attributes in the models were presented at three attribute levels to account for low, medium and high levels of the impact of the policy incentives. The three levels were also used to determine at what attribute level a respondent would consider an alternative mode attractive enough to warrant a shift to that mode. This was to create an environment for the respondent to make trade-offs between the modes in the scenario based on the mode-specific characteristics.
- The trip characteristics/ attributes utilised in the SP survey were selected and sense checked for the realism and suitability of their use in this study in reference to comparable studies reviewed in the literature.

Time and Cost

Time and cost were consistently used as attributes in SP experiments in the literature mentioned in Chapter 2, Sections 2.3 and 2.4 (e.g. O'Fallon, et al., 2004; Mackett, 2001; Bamberg and Schmidt, 2001) as they are common identifying factors and trip characteristics in studies concerning commuting trips. For example, the role of real-time public transport information at stop locations was explored in an SP experiment by Caulfield and O'Mahony (2009), who determined that less frequent bus users could benefit most from this technology. Malodia and Singla (2016) stated, in their study of carpooling behaviour using a SP survey, that cost and in-vehicle times (IVT) increased the likelihood of carpool being chosen. This statement is also closely comparable to public transport modes such as bus and rail, while time is similarly a necessary consideration in the decision to walk or cycle. O'Fallon, et al. (2004), similarly investigated the effect of improved trip times on commuting practices, through a policy of offering incentives, in a SP study conducted in New Zealand. In this study, all attributes were set on three levels, with the time attribute levels defined at: 10%, 25% and 35% improvements in trip times, and trip cost attribute levels defined at: no change, 25% and 50% decreases in cost, as a result of implementing a range of policy incentives. In reference to these studies, time and cost were used as attributes in the PT and smarter car use models, while time was incorporated into the active modes model. Furthermore, as a result of a 'sense check' conducted in reference to the literature cited above, which determined the appropriateness of using certain attribute level values, it was decided to define the time and cost attributes in this thesis on three evenly differentiated ordinal levels, namely: 15%, 25% and 35% reductions in trip time and cost.

Public Transport Model (Bus, Rail)

Frequency

Bus and rail are commonly considered by commuters in terms of the cost associated with the service, in addition to trip time and the reliability of it, which is linked to the frequency or the level of service. These factors have been widely examined in SP literature, Weibin et al. (2017) for example, conducted a SP experiment to determine urban commuter's valuation of travel time reliability. They found that both income level and time constraints had significant effects on PT utility for commuters, and individuals in higher income levels usually preferred a mode with less travel time and higher reliability (Weibin, et al., 2017). Thus, consideration was placed on travel reliability and its associated factors such as the frequency of service and headways on routes. Frequency has similarly been used consistently as an attribute in SP literature in examining modal choice. For instance, the Transportation Research Board's (TRB) 'Handbook for Measuring Customer Satisfaction and Service Quality' (1999) lists as a guideline that, frequency should be included in questionnaires concerning transport quality of service. Research conducted by Eboli and Mazzulla (2008) similarly incorporated frequency as a main attribute in a SP study examining PT and found that service frequency was a statistically significant attribute for measuring service quality in PT in Italy, by means of an MNL model. Their analysis found that increasing bus frequency to every 15 minutes (from only one every hour) *ceteris paribus,* resulted in an increase of 2.6 on the service quality index (SQI) (Eboli, Mazzulla, 2008; Hensher, et al., 2003). Bourgeat (2015) also found that bus frequency had an impact on the likelihood of bus being chosen by commuters and it was the favored method of reducing the uncertainty of bus arrival times. Moreover, he stated that raising awareness of bus frequency is essential in generating demand among non-users (Bourgeat, 2015). Finally, O'Fallon, et al. (2004) examined improved frequency of PT services as an attribute and policy incentive in their SP study, which they defined at three levels: no change, 50% more often and twice as often.

As a result of this review, frequency was identified as the third attribute used in the PT model of the SP experiment in this thesis, which was defined as: 25%, 50% and twice as often. The attributes and attribute levels tested in the PT model are displayed in Table 3.1.

Table 3.1 Public Transport Model - alternatives, attributes and attribute levels

Public Transport Model			
Mode	**Attribute**	**Policy Incentives**	**Attribute Level**
Bus	Frequency	Scheduling improvements to improve reliability, punctuality and increase in frequency/ reduced headways of bus services. Increase the continuity of bus lanes to ensure segregation from other traffic.	25% more often
			50% more often
			Twice as often
	Time		15% reduction in trip time
			25% reduction in trip time
			35% reduction in trip time
	Cost	Reduction in cost of bus fares, simplification of the fare structure, cashless payments.	15% reduction in trip cost
			25% reduction in trip cost
			35% reduction in trip cost
Private Car (drive alone)	Cost	No incentive	Gradual increase in the ownership costs of a car
Rail	Frequency	Scheduling improvements to improve reliability, punctuality and increase in frequency/ reduced headways of rail services.	25% more often
			50% more often
			Twice as often
	Time		15% reduction in trip time
			25% reduction in trip time
			35% reduction in trip time
	Cost	Reduction in cost of rail fares, simplification of the fare structure, cashless payments.	15% reduction in trip cost
			25% reduction in trip cost
			35% reduction in trip cost

Model 2 - Active Modes (Walk and Cycle)

Infrastructure and Adjacent Traffic Speed

For active modes, Short and Caulfield (2014); and Pooley, et al. (2013) examined the challenge of ensuring safety along cycling routes, and identified speed and available infrastructure as necessary attributes and the main perceived risk factors associated with cycling. This was specifically in relation to increasing the segregation between cyclists and other traffic, consequently leading to short trip times and the enhancement of the image of cycling as a safe and sustainable form of transport. Evidence from Caulfield, et al. (2012) supported this, as it was concluded that segregated infrastructure was the preferred form of cycling infrastructure from the results of an SP experiment, which was followed by cycle routes through residential streets and parks, where lower speed limits and traffic levels were the norm. In this thesis, the infrastructure attribute, akin to all the attributes, was presented on an ordinal scale of three pre-defined levels in accordance with the experimental design, to represent three levels of infrastructure provision, i.e. poor, fair and excellent). Poor levels of infrastructure in this experiment relates to incidences of little or no availability of cycling facilities and inadequate space assigned to pedestrians; the fair level signifies some availability of infrastructure but the facilities are not available throughout the active modes network; and the excellent level relates to fully segregated and well maintained facilities for active mode users such as segregated cycle lanes and wide unclutter footpaths. To reflect this ordinal scale, the levels of infrastructure chosen were: 20%, 40% and 60%, to account for low, medium and high levels of infrastructure, which were defined in reference to a sense check conducted by reviewing a number of similar SP studies such as: Guo and Loo, (2013); Tilahun, et al. (2007); Brown, et al., 2007; Abraham et al. (2004), Stinson and Bhat (2003); Bovy and Bradley (1985), and Hopkinson and Wardman (1996), whom determined that surface quality, facility type, and adjacent traffic levels, assessed on various attributes levels, were the main considerations of potential active modes commuters. The purpose of these levels was to consider how individuals value pedestrian and cycling infrastructure, i.e. the facilities available on certain routes in the network.

Lowering urban speeds was also found to be associated with reducing serious injury rates and this was correlated with accident severity, which generally increases with speed (Short and Caulfield, 2014, Nilsson, 2004). It was similarly determined in this literature that only 5% of collisions are severe in 30km/h zones, thus, justifying ‘adjacent traffic speed’ is a main policy variable to be considered with cycling and walking. It was decided to present the adjacent traffic speed attribute at the levels of: 50%, 75% and 100% of a trip with a 30km/h speed limit, for two reasons: 1) given the 0-5 kms distance that most commuters were found to walk and cycle within for commuting purposes from home to work or education (Caulfield, 2014; NTA, 2013b); and 2) considering that there is already a 30km/h speed limit in many residential and urban areas in the inner and outer metropolitan area of the GDA (Dublin City Council, 2017). As a result of this review, infrastructure, time and adjacent traffic speed were selected as the mode-specific attributes to be modelled in the Active Modes Model, which is shown in Table 3.2.

Table 3.2 Active Modes Model - alternatives, attributes and attribute levels

<table>
<tr><th colspan="4">Active Modes Model</th></tr>
<tr><th>Mode</th><th>Attribute</th><th>Policy Incentives</th><th>Attribute Level</th></tr>
<tr><td>Private Car (drive alone)</td><td>Cost</td><td>No incentive</td><td>Gradual increase in the ownership costs of a car</td></tr>
<tr><td rowspan="9">Walk</td><td rowspan="3">Infrastructure</td><td rowspan="3">Widening of and evenly surfacing footpaths, reduction of street clutter and improved street lighting.</td><td>20% of trip with even surfaced, widened paths, separated from traffic</td></tr>
<tr><td>40% of trip with even surfaced, widened paths, separated from traffic</td></tr>
<tr><td>60% of trip with even surfaced, widened paths, separated from traffic</td></tr>
<tr><td rowspan="3">Time</td><td rowspan="3">Reduce pedestrian waiting times at junctions by increasing signalling times given.</td><td>2 minutes off trip time</td></tr>
<tr><td>4 minutes off trip time</td></tr>
<tr><td>6 minutes off trip time</td></tr>
<tr><td rowspan="3">Adjacent Traffic Speed</td><td rowspan="3">Reduction in speed limit to 30km/h</td><td>50% of trip with 30km/h speed limit</td></tr>
<tr><td>75% of trip with 30km/h speed limit</td></tr>
<tr><td>100% of trip with 30km/h speed limit</td></tr>
<tr><td rowspan="9">Cycle</td><td rowspan="3">Infrastructure</td><td rowspan="3">Increase cycle lane continuity and incidence of fully segregated cycle lanes</td><td>20% of trip fully segregated from traffic</td></tr>
<tr><td>40% of trip fully segregated from traffic</td></tr>
<tr><td>60% of trip fully segregated from traffic</td></tr>
<tr><td rowspan="3">Time</td><td rowspan="3">Cyclist priority and early starts at major junctions</td><td>2 minutes off trip time</td></tr>
<tr><td>4 minutes off trip time</td></tr>
<tr><td>6 minutes off trip time</td></tr>
<tr><td rowspan="3">Adjacent Traffic Speed</td><td rowspan="3">Reduction of speed limit to 30km/h</td><td>50% of trip with 30km/h speed limit</td></tr>
<tr><td>75% of trip with 30km/h speed limit</td></tr>
<tr><td>100% of trip with 30km/h speed limit</td></tr>
</table>

Model 3 – Carpooling and car-sharing

Convenience

It was identified in the literature that convenience, time and cost were the main attributes affecting mode choice behaviour of carpooling and car-sharing (Malodia and Singla, 2016; Horowitz and Sheth, 1976). Time and cost have a direct impact on the perceived convenience of these modes, as convenience is closely linked to the time attributes through varying access and wait times (Malodia and Singla, 2016). For example, as access and wait times increase as a result of pick up delays determined by the number of carpool members in the car, the inconvenience associated with the trip also increases. Horowitz and Sheth (1976) referred to convenience when stating that carpooling and SOVs, as modes of travel for commuting to work, are evaluated on individual evaluative beliefs with respect to cost, time saving and convenience etc. Malodia and Singla (2016) then took inspiration from Horowitz and Sheth (1976), in a SP study that incorporated a 'time-convenience' factor that was found to discourage carpooling in the experiment as this factor decreased. From this review, convenience was identified as being a significant attribute used in studies of carpooling and car-sharing, and as a result of this, it was added as an attribute in the Smarter Car Use Model. As convenience is represented in terms of access and wait times, this attribute was presented on three attribute levels: 10%, 30% and 50% reductions in access/ wait times, which were based on a sense check of similar studies conducted by with O'Fallon, et al., 2004; Mackett, 2001; and Bamberg and Schmidt, 2001. Table 3.3 illustrates the structure of attribute and attribute level allocation to the alternatives in the Smarter Car Use Model.

Table 3.3 Smarter Car Use Model - alternatives, attributes and attribute levels

<table>
<tr><th colspan="4">Smarter Car Use Model</th></tr>
<tr><th>Mode</th><th>Attribute</th><th>Policy Incentives</th><th>Attribute Level</th></tr>
<tr><td rowspan="9">Carpooling</td><td rowspan="3">Convenience</td><td rowspan="3">Help to find a carpool partner. HOV lanes, guaranteed ride home (i.e. free taxi home if let down by carpool members).</td><td>10% reduction in access/ wait time</td></tr>
<tr><td>30% reduction in access/ wait time</td></tr>
<tr><td>50% reduction in access/ wait time</td></tr>
<tr><td rowspan="3">Time</td><td rowspan="6">Free on-street, private parking and exemption from road tolls for carpoolers.
Financial incentives/ rewards for car-sharing provided by employers.</td><td>15% reduction in trip time</td></tr>
<tr><td>25% reduction in trip time</td></tr>
<tr><td>35% reduction in trip time</td></tr>
<tr><td rowspan="3">Cost</td><td>15% reduction in trip cost</td></tr>
<tr><td>25% reduction in trip cost</td></tr>
<tr><td>35% reduction in trip cost</td></tr>
<tr><td rowspan="9">Car-sharing (Go Car/ Toyota Yuko)</td><td rowspan="3">Convenience</td><td rowspan="3">Help to find/ sign up to a car-share scheme, guaranteed ride home is there are no car-share vehicles available in the area.</td><td>10% reduction in access/ wait time</td></tr>
<tr><td>30% reduction in access/ wait time</td></tr>
<tr><td>50% reduction in access/ wait time</td></tr>
<tr><td rowspan="3">Time</td><td rowspan="6">Free on-street and private parking for car-sharers, exemption from road tolls for carpoolers.
Financial incentives/ rewards for car-sharing provided by employers.</td><td>15% reduction in trip time</td></tr>
<tr><td>25% reduction in trip time</td></tr>
<tr><td>35% reduction in trip time</td></tr>
<tr><td rowspan="3">Cost</td><td>15% reduction in trip cost</td></tr>
<tr><td>25% reduction in trip cost</td></tr>
<tr><td>35% reduction in trip cost</td></tr>
<tr><td>Private Car (drive alone)</td><td>Cost</td><td>No incentive</td><td>Gradual increase in the ownership costs of a car</td></tr>
</table>

3.5.2 Experimental design

SP surveys require crucial planning at the design stage, which can control the validity and quality of the modelling results produced later in the experimental process (Hensher, et al., 2005). For instance, the selection of alternatives and attributes determine the choice making behaviour of the respondent or the ability of the decision-maker to make trade-offs between the alternatives. An example of this is the carpool alternative that considers the trip characteristics: convenience, time and cost. As previously stated in Section 3.2, there were three attributes assigned to each of the 3 models (active modes, public transport, smart car use), resulting in there being a total of 9 attributes considered in the experiment overall, which is defined as the fixed choice set design. For each of these attributes there were 3 attributes levels, that determine the extent to which the attribute varies or the intensity of the policy measure and its impact on the trip characteristics. To determine the total output of the model (i.e. every possible combination of attribute levels), a full factorial design was first run, which produced 19,683 possible choice observations. This is based on the full enumeration of possible choice sets equal to $L^{MA} = 3^9$ for labelled choice experiments (as opposed to unlabelled experiments, where the attributes are named 'Attribute A', 'Attribute B', etc.), where L is number of attribute levels; M is the number of attributes; and A is the number of alternatives (Hensher, et al., 2005).

A full factorial design can be calculated using the following equation:

Equation 3.16

$$S^{ff} = \prod_{j=1}^{J} \prod_{k=1}^{K} l_{jk}$$

where:

S^{ff} is the total number of choice situations

J are the alternatives

K are the attributes

l are the levels within the attributes

The full factorial result of 19,683 individual choice observations were naturally excessive for the experiment to handle and impractical due to the number of attributes and attribute levels. Thus, the most commonly used solution to reduce the size of the experiment is an orthogonal main effects fractional factorial design, which represents a select portion of the treatment combinations generated from the full factorial design. In this way, only the main effects of the study are estimated, resulting in a more efficient and practical experimental strategy. Fractional factorial designs are supported by the rationale that only some interactions are significant or of empirical interest to the researcher. In truth, a main effects design accounts for the majority of variance in observed choice data, at 80% or more (Louviere, et al., 2000). Thus, by implementing a main effects design, the majority of variance can be accounted for (Hensher, et al., 2005). To generate the fractional factorial, IBM's SPSS software (IBM, 2018) was used to produce the most appropriate combination of attribute levels to be used in the experimental design. In total, 27 individual choice combinations were generated in the experiment. The orthogonal design ensures that multi-collinearity between attributes is avoided and that the attributes are varied independently from one another (Hensher, et al., 2005), in other words, there is zero correlation between the attributes. As 27 combinations would still be excessive for one respondent to answer and would lead to low response rates from fatiguing effects (Sage, 2018; Porter, 2004; Beaton, et al., 1998), the survey was then 'blocked' or divided equally into 9 versions to allow for 9 SP scenarios to be assigned in each survey version. By blocking the variables, the number of scenarios each respondent was required to answer was reduced. The 9 versions of the survey were then randomly assigned to respondents to minimise the influence of learning and fatigue (Beaton, et al., 1998), using the Qualtrics' survey flow randomiser function (Qualtrics, 2017). This function ensured that each version of the survey was presented an equal number of times to the respondents of the survey, also allowing for each of the choice combinations (i.e. grouping of attributes and attribute levels) to be distributed equally. The mechanic was employed to rearrange and randomise the blocks of SP survey questions that were varied in each of the 9 survey versions. This ensured that each respondent only saw one of the page blocks, thus reducing the risk of duplicated responses.

3.5.3 The survey instrument

The SP survey was conducted online in March 2017, using Survey Monkey, and was distributed randomly to a sample of the population resident in and who similarly work or study in the area of interest for this experiment: the GDA (see Chapter 2, Section 2.2 for a discussion of why the GDA was selected as the study area). Survey Monkey was utilised as the main tool for designing the appearance of the survey itself, for example in selecting of the colour scheme, organisation of the number of pages in the survey and the number of questions per page, which impacted on the flow and coherence of the survey. It was also used in the administration of the survey for tasks such as ensuring that each version of the survey was identical in appearance, monitoring the number of respondents, in addition to exporting the survey results in format that could then be prepared for input in discrete choice modelling software.

As a reference point, a copy of the survey, in addition to the invitation emails sent to potential respondents, are included in Appendix A of this thesis.

The survey was organised into 4 parts, as illustrated in Figure 3.3, entitled:

1: Introductory questions

2: Perceptions of policy measures

3: Stated preference scenarios

4: Demographic characteristics

The introductory section set-out questions that mirror those used in the Census of Ireland, so that the results could be used to measure the representativeness of the sample collected. These questions determined the trip characteristics of the sample such as: the observed mode of choice, journey length, distance, time and costs of the respondent's commute to work or education, followed by eliciting whether the respondent possessed a driving licence. This section represented the revealed preference component of the survey as it collected responses from the sample on current travel practices that are revealed in the market. Part 2 of the survey explored the perception, acceptability and impacts of various policy measures or incentives on the decision to travel more sustainably. Measures such as: in work cycling facilities, carpool/ car-share assistance, provision of timetabling information, financial incentives and the availability of the option to telecommute were suggested as ways in which people could be encouraged or motivated to change their mobility practices. This approach aimed to create an environment that made walking, cycling and public transport appear more accessible and practical than SOVs and in such a way, it was designed to provoke deliberation on modal choice. The ultimate objective was to spur individuals to consider shifting to more sustainable modes voluntarily, rather than simply forcing them to act in response to external pressures or disincentives associated with car use (Taylor and Ampt, 2003). In Part 3 of the survey, the main SP component was featured, consisting of a range of choice scenarios, that were then followed by further attitudinal questions that encouraged the respondents to reflect on how they answered the SP scenarios. The final part of the survey included a number of socio-demographic questions, that were based on Census of Ireland questions. These questions were used to create profiles of the respondents and explanatory variables that were used in the discrete choice modelling of the results. Before exiting the survey, the respondents were presented with an opt-in incentive that was alluded to on the introductory page of the survey (see a copy of this in Appendix A), which offered the respondents the opportunity to be entered into a draw for three chances to win €50.

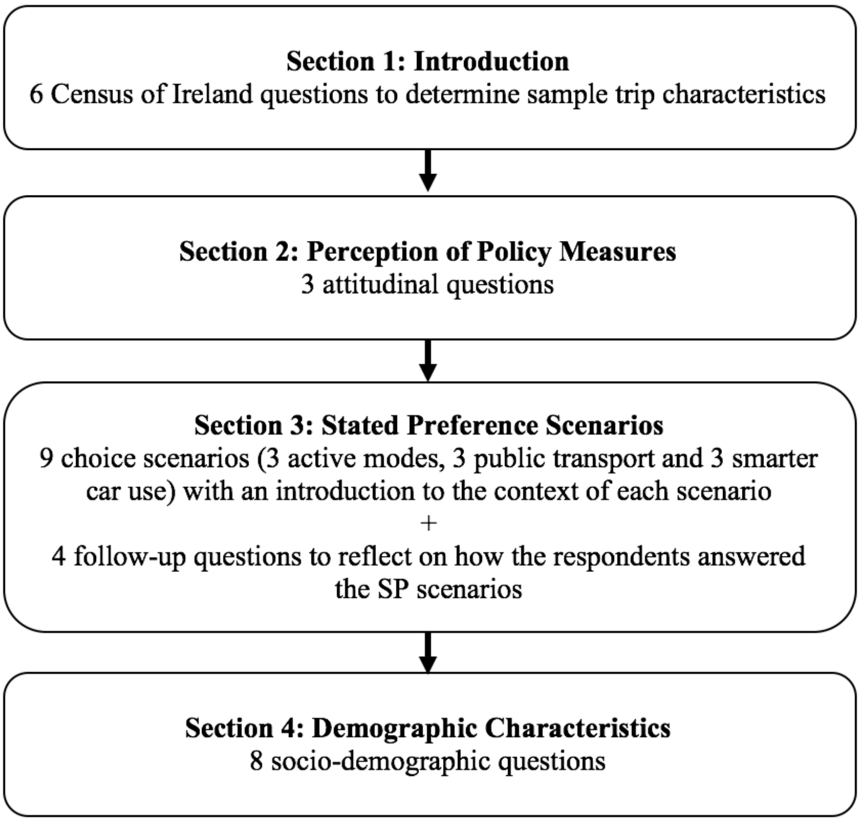

Figure 3.3 Structure of the SP survey

The SP experiment itself, motivated the respondents to decide on which trip characteristic or which combination of attributes were most important to them on their commute. Respondents were then asked to rank their mode choice in order of preference, based on the three modes given, with their first preference being considered for modelling purposes. For instance, as shown in Figure 3.4, if their trip was 25% cheaper and 15% quicker taking the train or Luas to work/ education as a result of various policy tools being implemented, would this encourage them to switch to this mode or would they simply continue with their current mode of choice (i.e. no change). This was one of the main research questions that were explored in this thesis.

Option	Policy	Effect on your trip		
		Frequency	Time	Cost
Bus 	Bus Policy Plan	Twice as often	15% reduction in trip time	15% cheaper trip
		Cost		
Private Car (drive alone) 	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		
		Frequency	Time	Cost
Train/ Luas  	Train Policy Plan	Twice as often	25% reduction in trip time	25% cheaper trip

13. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Bus
- Private Car (drive alone)
- Train/ Luas

Figure 3.4 Example of a SP scenario

In order to 'set the scene' of the stated preference choice scenarios and to ensure that the survey respondents fully understood the nature of the policies being introduced, a graphical scenario vignette was devised for each of the three mode groups (i.e. active modes, PT and smarter car use modes). These infographics (included in Appendix A of this thesis) listed the range of mode-specific policy incentives considered in the survey, which were also accompanied with text emphasising that, hypothetically, the respondent should imagine that he/she has been offered a new job in a new location and that they must decide on what mode to take when commuting to work based on the availability of the policy measures.

3.6 Sampling method and sample results

The sample selected for this study was the population of the GDA, specifically those working and studying within the GDA, as the SP survey in this experiment considered incentivisation of alternative modes for commuting purposes.

To calculate the required sample size based on the population of the GDA, the following equation was used (Dillman, 2000):

Equation 3.17

$$Ns = \frac{(Npp)(pp)(1-pp)}{(Npp-1)(\frac{B}{C})^2 + (pp)(1-pp)}$$

where:

Ns is the sample size required for the desired level of precision

Npp is the size of the population

pp is the proportion of the population expected to choose one of the three response categories. To allow for maximum variation in the sample, a 50/50 split was utilised (i.e. 50% the respondent chooses an option, 50% they don’t choose an option)

B is the acceptable amount of sample error

C is the Z-statistic associated with the response level

Therefore, in the SP experiment, Equation 3.17 was written as:

Equation 3.18

$$Ns = \frac{(1{,}907{,}332)(0.5)(1-0.05)}{(1{,}907{,}332)(\frac{0.05}{1.65})^2 + (0.5)(1-0.5)} = 385$$

Equation 3.18 indicated that 385 respondents were found to be satisfactory for the estimation of the survey results, based on the population of the GDA (1,907,332) recorded in the 2016 Census (CSO, 2017), a 95% confidence level, 5% margin of error and the associated z-statistic of 1.65. The sample was collected online with the aid of Delve Research (2017), an independent survey research company, who operate a panel of respondents nationally in Ireland. The pool of respondents utilised by Delve in this study were firstly engaged from their own database of panellists, which was later extended to include an external panel pool in order to meet the target sample requirements. As mentioned in Section 3.5.3, the panellists were awarded three chances to be entered into a draw for a prize incentive of €50, in exchange for fully completing the survey provided (Delve Research, 2017). Delve Research ensured the receipt of a representative sample with a 50-50 gender split, with respondents only being accepted if they were living and working in the GDA counties. This was achieved by filtering out those residing outside the GDA by means of a pre-survey questionnaire. It must be highlighted that the use of this survey company posed no limitation to the conduct of the survey. In order for the dataset to be finalised, only respondents that fully completed the survey, including final the socio-demographic section, were considered in the discrete choice modelling in this study.

Prior to finalising the design of the survey, a pilot version of the survey was distributed to steering group members and other project stakeholder and friends and family to highlight any outstanding issues with the survey design or the length of the survey itself. This exercise presented a valuable opportunity to improve the survey by acknowledging the pilot respondent's opinion of the survey. Based on results of the pilot survey, it was decided to clarify the instructions of the stated preference component of the survey to ensure that new respondents fully understood the task in hand, in addition to reducing the number of attitudinal questions in the survey, as survey fatigue was noted as an issue in the piloted version.

Table 3.4 provides a breakdown of the number of responses in each survey version as well as the gender split attained. The number of responses achieved for each of the 9 survey versions was satisfactory considering the number of scenarios in each survey. In total 9 survey versions were necessary to allow for 9 of the 27 different SP scenarios to be equally assigned and to avoid respondent fatigue (Sage, 2018; Porter, 2004). Similarly, the gender split of 44.53% males and 55.47% females achieved was received as being satisfactory, on the basis that ensuring an equal gender split required additional prompting to male respondents.

In total 552 responses were recorded, of which 432 were fully completed surveys. This resulted in 1,605 individual choice observations being collected in the study, which was determined by the number of choice sets used in the survey, where there were three, and not the number of respondents (Hensher, et al., 2005). As there were 1605 responses recorded from the 3 choice sets (PT, active modes and smart car use), this meant that there were 535 respondents that attempted or partly answered the SP section of the survey. However, as some respondents did not answer each individual choice scenario, these observations were not counted and the confirmed number of respondents modelled was 432, as shown in Table 3.4. Further analysis of the characteristics of the sample is provided in Chapter 4, Section 4.2.

Table 3.4 Number of survey responses

Survey Version	Total No. of Responses Recorded	No. of fully complete surveys	Gender Split			
			Male		Female	
Version 1	65	49	27	55.10%	22	44.90%
Version 2	61	44	13	29.55%	31	70.45%
Version 3	60	51	18	35.29%	33	64.71%
Version 4	61	45	22	48.89%	23	51.11%
Version 5	60	46	20	43.48%	26	56.52%
Version 6	58	46	22	47.83%	24	52.17%
Version 7	61	52	28	53.85%	24	46.15%
Version 8	63	48	20	41.67%	28	58.33%
Version 9	63	51	23	45.10%	28	54.90%
Total	552	432	193	44.53%	239	55.47%

3.7 Conclusions

This chapter has outlined the theoretical foundations, experimental design, sampling method and mathematical formulae for the research produced as part of the SP experiment conducted in this study. Section 3.2 provided a delineation of SP surveying and how it differs from revealed preference, in addition to why it was a suitable approach to apply to the research question. Section 3.3 offered an in-depth examination of discrete choice modelling and theory behind it. The MNL was then defined as the tool selected to analyse the SP data collected, in order to produce behavioural estimates of mode choice based on the choice scenarios. The application of discrete choice modelling in the context of this research was discussed with specific attention given to the fractional factorial experimental design adopted to create the three models (Public Transport, Active Modes and Smarter Car Use). The structure and design of the survey instrument itself was then examined. In Section 3.6 the sampling method utilised for data collection and the calculation of the required sample size were discussed, followed by an introduction to the sample results attained from the survey.

Chapter 4 provides an in-depth analysis of the sample characteristics collected from the survey, followed by a report on the discrete choice modelling results produced from the preferences recorded in the SP experiment. Furthermore, a discussion of the policy implications of introducing the car-shedding incentives tested in the choice scenarios is provided.
The methodology employed in the four stage modelling of the policy incentives tested in the SP experiment are discussed in-depth in Chapter 5.

CHAPTER 4: STATED PREFERENCE EXPERIMENT AND DISCRETE CHOICE MODELLING

4.1 Introduction

In this chapter, the SP experiments conducted in early 2017 are presented, followed by a discussion of the discrete choice modelling results of the survey responses. The methodologies used for this study, are set out in Chapter 3 (Sections 3.3 and 3.4). The SP experiments were designed to gauge the behavioural output of a sample of commuters in the GDA to a range of car-shedding policy incentives. Section 4.2 of this chapter outlines details of the sample and trip characteristics collected in the SP survey. Section 4.3 provides an examination of the utility equations used in the multinomial logistic modelling of the survey responses followed by a presentation of the outputs of the discrete choice analysis of the SP data. Finally, Section 4.4 sets out the policy implications of offering a range of incentives to commuters in the GDA.

The results from this study were used to estimate the choice making behaviour of the sample, by producing estimates of the likelihood of commuters choosing a particular mode of transport with mode-specific policy incentives applied to them. In other words, potential levels of car-shedding behaviour in the GDA (i.e. a reduction in SOV trips) was estimated following the introduction of the policy incentives, which was predicted by assessing the trade-off behaviour between the policy attributes. The results of this experiment were also presented in Carroll, et al. (2017a, 2017b).

4.2 SP Survey Results

A summary of the socio-demographic characteristics of the sample are presented in Table 4.1. In this table the survey data collected are compared with Census 2016 data in order to link the survey results with state figures for the same region to ensure that the sample was representative of the population of the GDA. From this data, it can be observed that a greater percentage of the sample were aged within the 35-44 and 45-54 years old cohorts (compared to the 2016 Census), with at least a secondary school education, married with no children, an average household income of between €24,999 to 49,999 per annum, living in the inner suburbs of Dublin and working in Dublin city centre. A higher percentage of the sample were in employment, rather than in education, which was expected. The gender split, in addition to the age ranges, number of children/ dependents, level of educational attainment, marital and economic status characteristics, outline in Table 4.1, of the sample were found to be representative of the population of the GDA when compared with the 2016 Census results for the GDA, thus verifying the authenticity of the sample recorded (CSO, 2017).

Table 4.1 Characteristics of the sample

Variable	Survey		Census 2016 (GDA)		Variable	Survey		Census 2016 (GDA)	
Gender	N	%	N	%	**Marital Status**	N	%	N	%
Male	193	44.68	935,849	49.07	Single	179	41.53	1,055,977	55.36
Female	239	55.32	971,483	50.93	Married	215	49.88	693,749	36.37
Total	432	100.00	1,907,332	100.00	Separated	19	4.41	46,127	2.42
					Divorced	15	3.48	41,373	2.17
Age					Widowed	3	0.70	70,106	3.68
18 - 24 years old	38	8.80	168,686	11.68	Total	431	100.00	1,907,332	100.00
25 -34 years old	84	19.44	304,968	21.12					
35 - 44 years old	114	26.39	315,197	21.83	**Children/ dependents**				
45 - 54 years old	109	25.23	242,078	16.76	None	199	46.96	140,349	29.17
55 - 64 years old	67	15.51	186,756	12.93	One	65	15.01	136,252	28.32
65+ years old	20	4.63	226,362	15.68	Two	98	22.63	124,728	25.93
Total	432	100.00	1,444,047	100.00	Three	49	11.32	57,916	12.04
					More than 3	22	5.08	21,817	4.54
Education					Total	433	100.00	481,062	100.00
No formal education/ training	3	0.69	16,711	1.46					
Primary education	8	1.84	113,325	9.93	**Economic Status**				
Secondary education	130	29.89	369,637	32.40	Working for payment or profit	267	61.81	853,116	55.25
Technical or vocational	46	10.57	99,092	8.68	Looking for first regular job	8	1.85	54,951	3.56
Advanced Certificate/ Completed Apprenticeship	26	5.98	63,322	5.55	Unemployed	24	5.56	99,248	6.43
Higher Certificate	49	11.26	59,886	5.25	Student	24	5.56	164,621	10.66
Ordinary Bachelor Degree/ Diploma	66	15.17	99,679	8.73	Looking after home/ family	40	9.26	115,164	7.46
Honours Bachelor Degree	55	12.64	156,350	13.70	Retired	36	8.33	197,761	12.81
Postgraduate Diploma/ Degree	48	11.03	147,700	12.94	Unable to work due to permanent sickness or disability	17	3.94	53,890	3.49
Doctorate (PhD) or Higher	4	0.92	15,550	1.36	Other	16	3.70	5,350	0.34
Total	435	100.00	1,141,252	100.00	Total	432	100.00	1,544,101	100.00
Income*					**Living Location**				
€24,999 or less	110	25.29			Dublin City Centre	55	12.70		
€25,000 - 49,999	129	29.66			Inner Suburbs	141	32.56		
€50,000 - 74,999	74	17.01			Outer Suburbs	101	23.33		
€75,000 - 99,999	27	6.21			Commuter Town	78	18.01		
€100,000 or more	17	3.91			Rural Area	58	13.39		
I'd rather not say	78	17.93			Total	433	100.00		
Total	435	100.00							
					Working location*				
					Dublin City Centre	135	33.75		
					Inner Suburbs	116	29.00		
					Outer Suburbs	67	16.75		
					Commuter Town	53	13.25		
					Rural Area	29	7.25		
* Data not collected in the Census					Total	400	100.00		

The trip characteristics of the sample are detailed in Table 4.2. These results revealed that the majority of respondents drove to work, while the bus and rail (DART and Luas) modes were used for almost a quarter of trips and walking had a mode share of 11%, which all matched closely to the results from the 2016 Census. A total of 4% of the respondents stated that they regularly or only telecommute (i.e. work from home), and 2.4% carpooled to work or education. Table 4.2 displays these modal shares amongst various other trip characteristics of the sample such as the trip times and distances travelled to work and education by the respondents. These attributes are also compared with data from the 2016 Census. It was found that a quarter of the respondents' commute to work or education took 40 minutes or more, closely followed by 11-20 minutes and 21-30 minutes on average. The majority of respondents surveyed travelled over 8 kilometres to work or education. Similarly of interest are the number of cars available to each household, of which close to half of the sample stated was one, followed by 32% stating that two cars were available to their household. Table 4.2 shows that the mode shares attained from the survey were representative of the population of the GDA, as the Census 2016 results produced a similar modal share. While the trip time data collected from the survey showed that the respondents travelled further to work or education, i.e. 40 minutes or more, in comparison with the Census results, which determined that more people's commute to work or education took between 11 and 20 minutes.

Table 4.2 Trip characteristics of the sample

	Survey		Census 2016 (GDA)				Survey		Census 2016 (GDA)	
Mode	N	%	N	%		**Trip time**	N	%	N	%
Not at work/education	67	12.14				10 mins or less	75	14.68	300,944	26.86
On foot	61	11.05	217,912	18.14		11 - 20 mins	112	21.92	355,748	31.76
Bicycle	27	4.89	60,454	5.03		21 - 30 mins	106	20.74		
Bus, minibus, coach	78	14.13	162,818	13.55		31 - 40 mins	88	17.22	255,094	22.77
Train, DART, Luas	51	9.24	73,005	6.08		40+ mins	130	25.44	208,463	18.61
Motorcycle or scooter	7	1.27	5,566	0.46		Total	511	100.00	911,786	100.00
Driving a car	218	39.49	441,147	36.72						
Passenger in a car	13	2.36	176,265	14.67		**Cost of commute***				
Van	6	1.09	35,594	2.96		€0	164	30.43		
Other, incl. taxi or truck	2	0.36	2,746	0.23		€1 - €10 per day	196	36.36		
Work mainly from home (i.e. telecommute)	22	3.99	25,782	2.15		€5 - €10 per day	122	22.63		
Total	552	100.00	1,201,289	100.00		€10 - €15 per day	39	7.24		
						€15+ per day	18	3.34		
Distance Travelled*						Total	539	100.00		
Less than 2kms	92	17.39								
2 – 4kms	85	16.07				**Cars owned per household**				
4 – 6kms	74	13.99				One	246	44.97	272,687	42.53
6 – 8kms	57	10.78				Two	177	32.36	205,332	32.02
8+ kms	221	41.78				Three	26	4.75	33,760	5.26
Total	529	100.00				Four or more	9	1.65	10,249	1.60
						None	89	16.27	119,180	18.59
						Total	547	100.00	641,208	100.00
* Data not collected in the Census										

4.3 Discrete Choice Modelling Results

The first step in modelling the survey results was to construct a base comparison model for each of the three models as part of this experiment. In this study a base model refers to a SP model consisting only of the main policy attributes, attribute levels and alternative-specific constants assigned to each respective alternative/ mode (see Chapter 3, Section 3.5.1). Attention must be devoted to understanding and making empirical sense of the base model output, for it acts as the main form of comparison with other more complex models produced later (Louviere, et al., 2000). The purpose of the base model is to examine the influence of the policy attributes on modal choice, without considering the socio-demographic characteristics of the decision makers. The utility equations for each of the three models are set out in Table 4.3. In all models produced in this study, the car alternative was set as the base outcome or reference category, which served as the main contrast point in the experiment and drove the interpretation of the results. In this way, the car alternative was considered as a status quo option, that was unaffected by the policy attributes. The attributes included in each model, in addition to the utility functions and linear expressions of the representative element of the utility equation used in this choice experiment are displayed in Table 4.3 (see Chapter 3, Section 3.3, for more information).

Table 4.3 Model utility functions and linear expressions

Model	Attributes	Utility functions	Linear Expressions
Public transport (Model 1)	Frequency, Time & Cost (e.g. busfreq, bustime, buscost)	Equation 4.1* $U_{bus} = V_{bus} + \varepsilon_{bus}$ $U_{car} = V_{car} + \varepsilon_{car}$ $U_{train} = V_{train} + \varepsilon_{train}$	Equation 4.4** $V_{bus} = \beta_{0bus} + \beta_{1bus}$ * busfreq + β_{2bus} * bustime + β_{3bus} * buscost $V_{car} = \beta_{0car}$ $V_{train} =$ β_{1train}* trainfreq + β_{2train} * traintime + β_{3train} * traincost
Active modes (Model 2)	Infrastructure, Time & Adjacent Traffic Speed (e.g. walkinfra, walktime, walkadjs)	Equation 4.2* $U_{car} = V_{car} + \varepsilon_{car}$ $U_{walk} = V_{walk} + \varepsilon_{walk}$ $U_{cycle} = V_{cycle} + \varepsilon_{cycle}$	Equation 4.5** $V_{car} = \beta_{0car}$ $V_{walk} = \beta_{0walk} + \beta_{1walk}$ * walkinfra + β_{2walk} * walktime + β_{3walk} * walkadjsp $V_{cycle} =$ β_{1cycle} * cycleinfra + β_{2cycle} * cycletime + β_{3cycle} * cycleadjsp
Smarter car use (Model 3)	Convenience, Time & Cost (e.g. carpconv, carptime, carpcost)	Equation 4.3* $U_{carpool} = V_{carpool} + \varepsilon_{carpool}$ $U_{carshare} = V_{carshare} + \varepsilon_{carshare}$ $U_{car} = V_{car} + \varepsilon_{car}$	Equation 4.6** $V_{carpool} = \beta_{0carpool} + \beta_{1carpool}$ * carpoolconv + $\beta_{2carpool}$* carpooltime + β_{3bus} * carpoolcost $V_{carshare} =$ $\beta_{1carshare}$* carshareconv + $\beta_{2carshare}$* carsharetime + $\beta_{3carshare}$ * carsharecost $V_{car} = \beta_{0car}$
*where: U = Utility or benefit an individual assumes from a certain good or service (i.e. of mode of transport) V = the deterministic or representative component of utility, ε = the stochastic error term **B_{1i} = the weight (or parameter) associated with attribute X_i and alternative *i* B_{0i} = the alternative-specific constant (ASC), which represents the role of all unobserved sources of utility			

The utility equations in Table 4.3 were coded into NLOGIT (Econometric Software Inc., 2016) choice modelling software and MNL regression models were estimated to examine the choice making behaviour of the sample. The factorial research design of the choice scenarios utilised in this experiment required that each of the policy plans be modelled separately, as each mode-specific model incorporated alternative trip characteristics. This meant that the modes included in the survey had to be modelled in three mode-specific MNL models, rather than one single model.

Figure 4.1 details the order of the different stages of analysis conducted using the SP data. The Base Comparison Model (a) is presented firstly, followed by the Extended Model (b) with the addition of socio-demographic variables, then the elasticity models (c), ‘what if’ simulations (d), and finally cross tabulations and comparison of mean analyses (e).

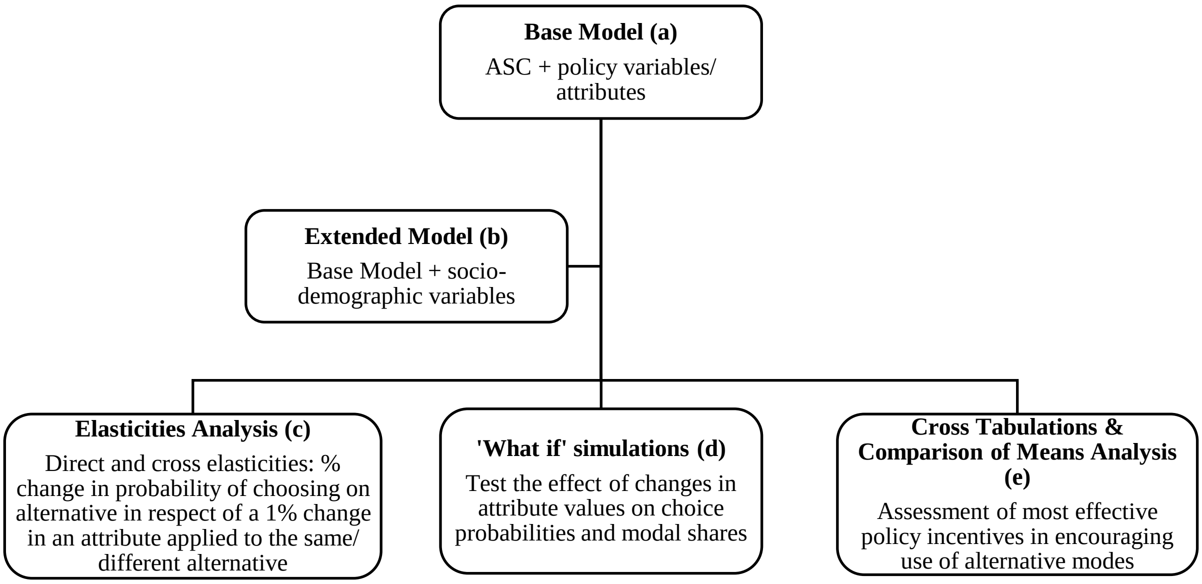

Figure 4.1 Stages of Discrete Choice Modelling and other analyses of survey results

4.3.1 Base Model 1a (Public Transport Model)

The first set of models, presented in this chapter, estimate the potential of incentivised public transport to encourage a sustainable modal shift. The initial set of results, in Table 4.4, show the proportions of respondents that chose each of the alternatives. It is observed that 42.93% of the sample opted for the Bus alternative, the rail option was chosen by over a third of the sample, whereas only 22.49% chose car.

Table 4.4 Model 1 sample proportions

Choice	Observation Count	Survey (%)	Census 2016 Count	Census 2016 (GDA)(%)
Bus	689	42.93	162,818	24.05
Car	361	22.49	441,147	65.16
Rail	555	34.58	73,005	10.78
Total	1,605	100.00	676,970	100.00

The base model results in Table 4.5 show that a number of the coefficients were statistically significant, with the exception the frequency attribute for both the bus and rail alternative, which displayed low and insignificant coefficients. The cost attribute in particular, was statistically significant and the sign of the coefficient was positive, for both the bus and rail alternatives (99% significance for bus and 95% for rail), indicating that if these trips became cheaper (i.e. a 15-35% reduction in fares), the utility for these modes could increase. This demonstrates, as one might expect, that the likelihood of individuals choosing to commute by bus and rail increases if a policy incentive to reduce bus/ rail fares were introduced. Another statistically significant coefficient in the base model for Model 1(a) was *Traintime,* of which the coefficient was also positive, suggesting that policy incentives to reduce rail times could result in a higher utility for this mode. The *Bustime* coefficient was statistically significant and positive at 80% significance, while this may represent a slightly low level of statistical significance, it still intuitively shows that the utility for bus transport increased as the trip time decreased, therefore warranting it's inclusion in this analysis. However, the coefficient for *Bustime* (0.0089) was statistically lower in preference then the *Traintime* (0.0279) coefficient, meaning that the train was preferred over the bus given equal changes to the trip time attribute.

Albeit, the pseudo rho-squared value for this model (0.012) can be considered poor, with values closer to 1 indicating a good model fit, (Hensher, et al., 2005; Louviere, et al., 2000), it is useful in comparing other larger models to the base comparison. However, as a result of this low rho^2 value, some caution is required when interpreting the model results. These rho-squared values represent the complexity in predicting human behaviour, particularly in relation to modal choice in hypothetical scenarios, as similar SP studies in the field of transport, such as: Elsayed, et al. (2018), Hensher, et al. (2015b), McCarthy (2015), Petrik, et al. (2013) and Catalano, et al. (2008), have also produced Rho^2 values lower than one. It must also be reiterated that the Rho^2 used in logistic regression is not analogous to the R^2 statistic in linear regression, as MNL models in discrete choice analysis are non-linear.

Thus, the pseudo rho-squared here is not equal to the same R^2 value in a linear regression model (Hensher, et al., 2005) (see Chapter 3, Section 3.4 for more information). It is utilised as a means of comparison between two MNL models from the same dataset. Yet, the chi-squared p-value was found to be 0.000, which was below the alpha value of 0.05, signifying that the null hypothesis that the policy attributes tested in this model do not incentivise alternative modes and increase the utility of public transport modes, can be rejected.

Table 4.5 Base Model Output for Model 1a

Observations N = 1605			
Variable		Coefficient	Z-stat
Busfreq	Frequency	0.0025	0.94
Bustime	Time	0.0089*	1.33
Buscost	Cost	0.0228****	3.53
Trainfreq	Frequency	0.0015	0.56
Traintime	Time	0.0279****	4.00
Traincost	Cost	0.0155***	2.29
Log Likelihood -1459.354			
Constants only LL -1477.314			
AICc 2934.7			
Pseudo Rho Squared 0.012			
Prob. Chi-squared 0.000			

* Significant at 80% confidence, ** Significant at 90% confidence, *** Significant at 95% confidence, **** Significant at 99% confidence

4.3.2 Extended Model 1b – Public Transport

Model 1 was extended to include the various socio-demographic variables listed and coded in reference to Table 4.6. These variables were added to the base model to improve the predictive power of the model estimation, to provide more context to the choice making behaviour of the sample and to account for the variation in the choices made in the SP scenarios (Ortúzar and Willumsen, 2011; Hensher, et al., 2005; Train, 2003; Louviere, et al., 2000). The performance and the degree to which the model fits with the data collected is explicated through a number of statistically indicators described in Chapter 3, Section 3.4.

Table 4.6 Socio-demographic Variable Coding

Variable	**Coded Coefficient Abbreviation**	**Coding**
Socio-demographic variables		
Gender	GEN (e.g. Busgen – the impact of gender on bus usage)	Male = 1, Female = -1
Age range	AGE (e.g. Trainage – the impact of age on train usage)	18 - 24 years old = 1, 25 -34 years old = 2, 35 - 44 years old = 3, 45 - 54 years old = 4, 55 - 64 years old= 5, 65+ years old = 6
Highest level of education	EDU (e.g. Busedu – the impact of education on bus)	No former education/ training = 1, Primary education = 2, Secondary education = 3, Technical or vocational = 4, Advanced Certificate/ Completed Apprenticeship = 5, Higher Certificate = 6, Ordinary Bachelor Degree/ Diploma = 7, Honours Bachelor Degree = 8, Postgraduate Diploma/ Degree = 9, Doctorate (Ph.D.) or Higher = 10
Average annual household income range	INC (e.g. Traininc – the impact of income on train usage)	€24,999 or less = 1, €25,000 - €49,999 = 2, €50,000 - €74,999 = 3, €75,000 - €99,999 = 4, €100,000 or more = 5, I'd rather not say = 6
Living location	LIVE (e.g. Buslive – the impact of living location on bus usage)	Dublin city centre (i.e. within the canals) = 1, Inner Suburbs (i.e. within canals & M50 motorway) = 2, Outer Suburbs (i.e. outside M50 motorway = 3, Commuter Town = 4, Rural Area = 5
Working location/ Location of education	WORK (e.g. Trainwork – the impact of working location on train usage)	Dublin city centre (i.e. within the canals) = 1, Inner Suburbs (i.e. within canals & M50 motorway) = 2, Outer Suburbs (i.e. outside M50 motorway = 3, Commuter Town = 4, Rural Area = 5
Employment status	EMPL (e.g. Busempl – the impact of employment status on bus usage)	Working for payment or profit = 1, Looking for first regular job = 2, Unemployed = 3, Student = 4, Looking after home/ family = 5, Retired = 6, Unable to work due to permanent sickness or disability = 7, Other = 8
Marital Status	MARI (e.g. Trainmari – the impact of marital status on train usage)	Single = 1, Married = 2, Separated = 3, Divorced = 4, Widowed = 5
Number of children/ dependents	CHIL (e.g. Buschil – the impact of no. of children on bus usage)	None = 1, One = 2, Two = 3, Three = 4, More than 3 = 5
Possession of a driving licence	LIC (e.g. Trainlic – the impact of owing a driving licence on train usage)	Yes = 1, No = 0
Number of cars owned per household	OWN (e.g. Busown – the impact of no. of cars owned on bus usage)	None = 1, One = 2, Two = 3, Three = 4, Four or more = 5

Free parking available at workplace/ college?	PARK (e.g. Trainpark – the impact of the availability of free parking at the workplace on train usage)	Yes = 1, No = 0

The results, presented in Table 4.7, are used as a means of comparison between the base and extended models in the study. For example, the log-likelihood (LL) value for the estimated model was -872.445, which was much lower than the figure produced in the base model (-1459.354), adding evidence to the assumption that the extended model is a better estimate and more statistically accurate model than the base comparison. This is similarly reinforced by the pseudo rho-squared value of 0.102, suggesting that the statistical fit of the model is good (i.e. 'the greater the explanatory power of the policy attributes are to an aggregate, constant-share prediction' (Louviere, et al., 2000)), and the AICc value of 1800.9, which, when compared to the base model figure of 2934.7, is a marked improvement in the statistical quality of the estimation produced. The statistical improvement in model fit and performance reveals how introducing socio-demographic variables can build upon the base utility models, which only estimate the effect of tested attributes on modal choice. A comparison of these statistical indicators is provided in Table 4.7, which demonstrates that with the addition of the individual socio-demographic variables in the model, a greater percentage of the variation in mode choice is represented in the extended model.

Table 4.7 Comparison of model fit and performance indicators for Model 1b

Indicator	Base Model 1	Extended Model 1a
Log-likelihood (LL)	-1459.354	-872.445
AICc	2934.7	1800.9
Pseudo Rho-squared	0.012	0.102
P-value (chi-squared)	0.000	0.000

The extended model output, in Table 4.8 shows that many of the variables were statistically significant. For example, some of the main attributes in the model displayed an increase in statistical significance in the extended model at the 95% and 99% significance, such as the *Bustime* and *Buscost* coefficients, representing the policy incentives reducing bus travel times and fares. For the bus and rail options, those with a higher level of education were more likely to choose these modes than those with lower levels of education, described by the size preference and the positive signs of the coefficients (*Busedu*: 0.1116, *Trainedu*: 0.1743). This is also true for the employment and marital statuses of the individuals, which showed similar results (i.e. positive sign and high size preference of the coefficients). Those who were not in full time employment and those were married were more likely to travel by car than by bus or rail. The *Buschild* coefficient suggests as it is negative that individuals with one or more children are less likely to commute to work or education by bus. Older age groups showed greater odds of taking rail to work or education, delineated by the positive sign, in this way increasing the utility for this mode.

Table 4.8 Extended Model Output Model 1b

Observations N = 1605			
Variable		Coefficient	Z-stat
Busfreq	Frequency	0.0038	1.10
Bustime	Time	0.0147**	1.71
Buscost	Cost	0.0307****	3.70
Busedu	Education	0.1116***	2.51
Busempl	Employment Status	0.1092***	2.07
Busmari	Marital Status	0.5686****	3.48
Buschil	No. of Children	-0.1116**	-1.86
Buslic	Licence	-1.6312****	-5.44
Busown	Car ownership	-0.4931****	-4.00
Trainfreq	Frequency	0.0019	0.54
Traintime	Time	0.0316****	3.52
Traincost	Cost	0.0165**	1.92
Trainage	Age	0.2264***	2.57
Trainedu	Education	0.1743****	3.70
Trainempl	Employment Status	0.1370***	2.52
Trainmari	Marital Status	0.2936**	1.75
Trainlic	Licence	-1.4228****	-4.62
Trainown	Car Ownership	-0.5399****	-4.19
Trainpark	Free parking	-1.0903****	-4.49
Log Likelihood -872.445			
Constants only LL -971.709			
AICc 1800.9			
Pseudo Rho Squared 0.102			
Prob. Chi-squared 0.000			

* Significant at 80% confidence, ** Significant at 90% confidence, *** Significant at 95% confidence,
**** Significant at 99% confidence

Having a driving license and access to at least one car per household negatively influenced the chances of individuals commuting by bus or rail, which was dictated by highly negative coefficients that were statistically significant at 99%. These results were expected given the results from Table 4.9, that examines the percentage of the sample that possessed a driving licence and had access to free parking. It was found that almost three quarters of the sample were in possession of a driving licence and 29% were not, and more than two thirds of the sample had access to free parking, whereas 31% did not. The results from these questions similarly account for the statistically negative effects that the availability of free parking and possession of a driving licence have on the preferences of active modes, carpooling and car-sharing, examined in Models 2b and 3b, explored later.

Table 4.9 Availability of free workplace/ University parking and possession of driver licence results

Availability of free workplace/ University parking	%
Yes	69.31
No	30.69
Possession of a driving licence	%
Yes	71.09
No	28.91

4.3.3 Elasticity and simulation results Model 1c and 1d

Table 4.10 displays the results of direct and cross elasticities estimated in NLOGIT (Econometric Software Inc., 2018) given changes being made to each of the three policy attributes present in Model 1. The direct elasticities (see Chapter 3, Section 3.4 for more information) measure the percentage change in the probability of choosing one alternative in the choice set (either bus, rail or car) in respect of a one percent change in a policy attribute applied to that same alternative in the model (Hensher, et al., 2005). The cross elasticities measure the same percentage change in the likelihood of one alternative being chosen given a one percentage change in an attribute applied to a different alternative (Hensher, et al., 2005). For example, a one percentage increase in the frequency attribute for bus would result in a reduction in the likelihood of rail and car being chosen in the choice set by 0.04%.

Other results produced from this analysis showed that the cost variable caused the highest direct elasticities in the bus and rail alternatives. A one percentage increase in the cost attribute for bus and rail independently, representing a 1% decrease in the cost of the trip, could result in a 0.31% increase in rail and 0.27% in bus being chosen relative to other modes in the choice set. However, if such cost savings were made to the car alternative, a cross elasticity or decrease of 0.21% in the probability of bus and 0.17% of rail being chosen, would be experienced. Moreover, the time attribute similarly produced statistically significant elasticity findings given a 1% decrease in trip times. For instance, in rail, a 0.29% increase in probability was estimated, and a 0.25% increase in bus. The frequency variable produced less statistically significant but still positive results as a result of reductions in headways and improvements made to the reliability and punctuality of the service, with increases of 0.07% in the likelihood of rail and 0.06% of bus being produced. These behavioural findings demonstrate that sustainable mode choices are more elastic to changes made to the time and cost attributes, signifying that incentives that aim to improve these trip characteristics could be most effective in encouraging a shift to public transport in the GDA.

Table 4.10 Elasticities from a 1% change in the frequency, time and cost attributes (Model 1c)

Elasticities			
Frequency	Bus	Car	Rail
Bus	0.057	-0.044	-0.044
Car	0	0	0
Rail	-0.035	-0.035	0.066
Time	Bus	Car	Rail
Bus	0.251	-0.198	-0.198
Car	0	0	0
Rail	-0.160	-0.160	0.289
Cost	Bus	Car	Rail
Bus	0.270	-0.214	-0.214
Car	0	0	0
Rail	-0.173	-0.173	0.311

'What if' simulations were run in NLOGIT (Econometric Software Inc., 2016) using new attribute level values in Model 1d in Table 4.11. These models offer the capability of using an estimated model to test how changes in an attribute value impact upon choice probabilities and market shares in choice alternatives (Ryley et al., 2014; Hensher et al., 2005). In this way, the analyst can aid transport planners and support policymakers in the examination of the impact of socio-economic and transport-related variables on future passenger demand for certain modes (Carroll, et al., 2017; Onsel et al., 2013). The use of What if simulations is useful in reference to the aims of this study, as they can generate projected modal shares in future years given new demands for alternative modes. The findings from this analysis found that changing the time and cost attributes separately, produced statistically significant results in terms of switching behaviour from the car to bus and rail. For example, for the time attribute, increasing the reduction in travel time from the 35% upper attribute level value presented in the SP scenarios to 50%, led to a 6.85% reduction in the mode share of SOVs, resulting in 95 people opting to switch to public transport. The cost attribute, which was also set to a 50% value, led to 7.24% of the sample opting to switch to the bus (4.06%) and rail (3.18%). A stepwise sensitivity analysis of the effect of the additional increase to the attributes level values for time and cost were tested in the what if simulations, and it was determined that modal shares were more sensitive to change when set at the 50% value than more subtle changes such as 40% or 45%. As a result of this, 50% was the value used in the what if simulations, which was sense checked against the proposed changes to the bus network in the GDA as part of the Bus Connects project (Bus Connects, 2017). The results produced from this analysis are set in the context that the car alternative is excluded from a decrease in trip time or cost, meaning that it is a 'status quo' alternative or held constant and that the current trip times and costs of commuting by car are only considered.

Table 4.11 Simulation of new values for the time and cost attributes (Model 1d)

Alternatives	Base Share		Scenario		Choice share changes	
***Time*- 50% reduction in travel time**						
	N	% Share	N	% Share	N	% Share
Bus	595	42.93	648	46.76	53	3.83
Car	312	22.51	217	15.66	-95	-6.85
Rail	479	34.56	521	37.58	42	3.02
***Cost* - 50% reduction in travel cost**						
Bus	595	42.93	651	46.98	56	4.06
Car	312	22.51	212	15.26	-100	-7.24
Rail	479	34.56	523	37.74	44	3.18

4.3.4 Cross tabulation results of policy measures included in the SP survey (Model 1e)

Table 4.12 presents the results of cross tabulation analyses and chi-square tests of various socio-demographic variables collected from the survey crossed with responses from a question, which asked the respondents to state which policy measures would attract them most to public transport. This question acted as a measure of the receptivity of these policy measures and as a means of examining the socio-demographic characteristics of respondents who favoured certain incentives. The results of this analysis determined that the gender and age variables were statistically significant with p-values of 0.009 and 0.035, respectively, below alpha (0.05), and chi-square values of 15.302 and 26.276. Marital status was also found to be significant at 90%.

These results determined that both males and females within the 35-54 age cohort in the sample were more interested in more frequent services as a pull factor to use public transport, followed by discounted or cheaper tickets. In addition to this, married individuals, with no children/ dependents, owning one to two vehicles were similarly interested in these incentives resulting trip time and cost savings. Likewise, popular amongst the sample were reliable services which link closely with more frequent services as a major factor in the consideration to use public transport. The least popular policy amongst the respondents was the need for more information, with those with two or more children and one car available showing more interest in this measure.

Table 4.12 Cross tabulations and chi-square results (Model 1e)

	More frequent services		Nicer vehicles		Reliable services		More information		Better stop locations		Discounted tickets		Total	
Gender[a]	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Male	61	61.6	7	58.3	34	56.7	5	100.0	9	28.1	44	55.7	160	55.7
Female	38	38.4	5	41.7	26	43.3	0	0.0	23	71.9	35	44.3	127	44.3
Total	99	100.0	12	100.0	60	100.0	5	100.0	32	100.0	79	100.0	287	100.0
Age[b]														
18-34 years old	27	26.7	5	41.7	14	23.3	1	20.0	7	21.9	26	32.9	80	27.7
35-54 years old	50	49.5	6	50.0	34	56.7	3	60.0	14	43.8	46	58.2	153	52.9
55-64 years old	20	19.8	1	8.3	10	16.7	1	20.0	5	15.6	6	7.6	43	14.9
65+ years old	4	4.0	0	0.0	2	3.3	0	0.0	6	18.8	1	1.3	13	4.5
Total	101	100.0	12	100.0	60	100.0	5	100.0	32	100.0	79	100.0	289	100.0
Marital status[c]														
Single	42	42.0	5	41.7	22	37.3	2	40.0	11	35.5	40	52.6	122	43.1
Married	52	52.0	3	25.0	33	55.9	3	60.0	17	54.8	31	40.8	139	49.1
Separated or Divorced	6	6.0	4	33.3	4	6.8	0	0.0	3	9.7	5	6.6	22	7.8
Total	100	100.0	12	100.0	59	100.0	5	100.0	31	100.0	76	100.0	283	100.0
Number of children/ dependents[d]														
None	47	47.0	9	75.0	23	38.3	2	40.0	18	56.0	41	51.9	140	48.6
One	18	18.0	0	0.0	12	20.0	0	0.0	4	12.5	6	7.6	40	13.9
Two or more	35	35.0	3	25.0	25	41.7	3	60.0	10	31.3	32	40.5	108	37.5
Total	100	100.0	12	100.0	60	100.0	5	100.0	32	100.0	79	100.0	288	100.0
Number of cars owned[e]														
One	59	43.1	7	53.8	39	52.0	4	57.1	17	39.5	53	56.4	179	48.5
Two or More	57	41.6	4	30.8	27	36.0	1	14.3	20	46.5	22	23.4	131	35.5
None	21	15.3	2	15.4	9	12.0	2	28.6	6	14.0	19	20.2	59	16.0
Total	137	100.0	13	100.0	75	100.0	7	100.0	43	100.0	94	100.0	369	100.0

[a] Gender result: significant ($p<0.009$, chi-square = 15.302, 5 degrees of freedom).
[b] Age result: significant ($p<0.035$, chi-square = 26.276, 15 degrees of freedom).
[c] Marital status result: significant ($p<0.068$, chi-square = 17.311, 10 degrees of freedom).
[d] Number of children/ dependents result: not significant ($p<0.205$, chi-square = 13.344, 10 degrees of freedom).
[e] Number of cars owned result: not significant ($p<0.196$, chi-square = 13.520, 10 degrees of freedom).
[f] Living location result: not significant ($p<0.963$, chi-square = 6.794, 15 degrees of freedom).

4.3.5 Base Model 2a (Active Modes Model)

Model 2 investigates the effect of offering infrastructural improvements and time savings on the modal choice of walking and cycling in the GDA, in addition to addressing the perceived risk of taking these modes by reducing speed limits on certain routes. To provide some initial context to this model, Table 4.13 details the choice proportions of respondents that selected each of the different modes in Model 2. The car (drive alone) option was marginally more popular than walking and cycle, with over a third of respondents choosing it, followed by 33.14% and 31.78% opting for the walk and cycle alternatives respectively.

Table 4.13 Model 2 sample proportions

Choice	Observation Count	Survey %	Census 2016 Count	Census 2016 (GDA) (%)
Car	563	35.08	441,147	61.31
Walk	532	33.14	217,912	30.29
Cycle	510	31.78	60,454	8.40
Total	1,605	100.00	719,513	100.00

In this model, the context for the SP scenario was that respondents were offered a mode choice decision for a short distance trip (i.e. between 2-4kms, a distance that is generally deemed suitable for walking and cycling (Census, 2016; Caulfield, 2014)). Considering this distance, the respondents were then asked which of the following three modes: walk, cycle or car, would they most likely choose given policy incentives assigned to the walking and cycling alternatives only.

The base Model 2a results, presented in Table 4.14, show a low pseudo rho-squared of 0.013, which suggests that this base model does a poor job at fitting the MNL model to the sample dataset and explaining the variances in the data. This finding is mirrored through the low coefficients and high p-value of 0.064, which marginally exceeds the level of alpha (0.05), meaning that we cannot reject the null hypothesis that the estimated model is no better than the constants only model. Thus, the assumption in Base Model 2a was that the policy scenarios provided to the respondents were not sufficient to ultimately entice those to shift from the car to more sustainable modes of transport, in this case walking and cycling, which is itself a difficult task. The coefficients of the infrastructure and time variables for the walk and cycling alternatives (i.e. *Walkinfra* and *Cycletime)* were, however, only significant at 80%, with a positive coefficient sign, which while it is relatively low, it still demonstrated intuitive results, in that improvements made to walking infrastructure and reductions made to cycle times would increase the utility of walking and cycling as the attribute levels increased. Naturally, as cycling trip times decreased and as more improvements were made to walking infrastructure, the higher the likelihood was of the respondents choosing these modes.

Table 4.14 Base Model Output for Model 2a

Observations N = 1605			
	Variable	Coefficient	Z-stat
Walkinfra	Infrastructure	0.0040*	1.17
Walktime	Time	-0.0143	-0.42
Walkadjs	Adj. Traffic Speed	0.0023	0.83
Cycleinfra	Infrastructure	0.0009	0.27
Cycletime	Time	0.0404*	1.17
Cycleadjs	Adj. Traffic Speed	0.0020	0.74
Log Likelihood -1582.020			
Constants only log-likelihood (LL) -1584.138			
AICc 3180.0			
Pseudo Rho Squared 0.013			
Prob. Chi-squared 0.064			

* Significant at 80% confidence, ** Significant at 90% confidence, *** Significant at 95% confidence, **** Significant at 99% confidence

4.3.6 Extended Model 2b

Table 4.16 presents the results from the extended model including the socio-demographic variables, coded in reference to Table 4.6. As there were many predictors included in the extended model output, the model was reduced to exclude the variables that were non-significant, thus the results presented are the predictors that appeared statistically significant alongside the base attributes tested. Table 4.16 shows that there were many statistically significant socio-demographic coefficients, which in turn improved the performance of the model from the base model (Model 2a). The improvements in modal fit and the statistical quality of the model were validated through lower log-likelihood and AICc values and a p-value below alpha. A comparison of these statistical indicators is provided in Table 4.15. The log-likelihood value for the estimated model was -992.623, which was an improvement on the log-likelihood of the base comparison model (-1582.020), indicating that the model fit better with the socio-demographic data from the sample. As a result of the differences in log-likelihood, there was a notable increase in the pseudo rho-squared in the extended model (0.064) suggesting an improvement in the goodness of fit of the model as it rose from the base model value of 0.013. The AICc of the model was 2041.2, in contrast to the AICc of the base model (3180.0), meaning that the extended model provided a better trade-off of goodness of fit and quality of the statistical model than the base model. The 0.000 p-value for the extended model was sufficiently below alpha (0.05), which permitted the null hypothesis to be rejected as a greater extent of the variation in the model was explained by means of the addition of the predictor variables.

Table 4.15 Comparison of model fit and performance indicators for Model 2b

Indicator	Base Model 2	Extended Model 2a
Log-likelihood (LL)	-1582.020	-992.623
AICc	3180.0	2041.2
Pseudo Rho-squared	0.013	0.064
P-value (chi-squared)	0.064	0.000

With reference to the parameter estimates in Table 4.16, the results indicated, that the *Walkinfra* variable increased to statistical significance of 90%, and the coefficient was positive explaining that as the percentage of evenly surfaced, widened footpaths, separated from traffic increased, the utility of the walking mode also increased. In relation to the predictors, women were more likely to walk to work or education than men, supported by the negative coefficient, statistically significant at 99%, and older age groups were more likely to walk than younger age cohorts, suggested by the positive sign and also statistically significant at 99%. Furthermore, the coefficients for possessing a driver's licence, owning more than one car and having free parking available at your place of work or college/ University were all negative and statistically significant at 99% to 95%, suggesting that the chances of those individuals opting to walk to work or education was reduced, which made intuitive sense and corresponded to the results from Table 4.9. The *Walklive* variable was statistically significant, yet only at 80% significance, with a negative sign, which again can be considered as low, however it does initiatively show that those living in closer proximity to the Dublin city centre showed a higher probability of walking to work or education than those living in the outer suburbs.

For the cycling alternative, the case was largely similar, though in addition to this, the results also suggested that those not in full time employment, i.e. the unemployed, students, the retired etc., were more likely to cycle to work or education, based on the 0.1416 coefficient. It was stated in the survey that if the respondent was not currently in employment or studying, that they should respond in accordance to how they used to travel when they were employed or a student. Finally, individuals with no children were found to be more likely to commute by bike, through examining the negative *Cyclechil* coefficient, statistically significant at 90%.

Table 4.16 Extended Model Output Model 2b

Observations N = 1605			
	Variable	Coefficient	Z-stat
Walkinfra	Infrastructure	0.0077**	1.74
Walktime	Time	-0.0124	-0.28
Walkadjs	Adj. Traffic Speed	0.0027	0.78
Walkgen	Gender	-0.2778****	-3.17
Walkage	Age	0.2374****	3.30
Walkedu	Education	0.0912***	2.19
Walklive	Living location	-0.0907*	-1.30
Walklic	Licence	-1.3091****	-6.02
Walkown	Car Ownership	-0.3765****	-3.27
Walkpark	Free Parking	-0.3800***	-1.98
Cycleinfra	Infrastructure	0.0021	0.49
Cycletime	Time	0.0363	0.84
Cycleadjs	Adj. Traffic Speed	0.0028	0.83
Cycleedu	Education	0.0907***	2.22
Cycleemp	Employment Status	0.1416****	3.76
Cyclechil	No. of children	-0.1109**	-1.66
Cyclelic	Licence	-0.5030***	-2.26
Cyclepark	Free Parking	-0.5168****	-2.80
Log Likelihood -992.623			
Constants only LL -1060.040			
AICc 2041.2			
Pseudo Rho Squared 0.064			
Prob. Chi-squared 0.000			

* Significant at 80% confidence, ** Significant at 90% confidence, *** Significant at 95% confidence, **** Significant at 99% confidence

4.3.7 Elasticity and simulation results Model 2c and 2d

Table 4.17 displays the direct and cross elasticity results from Model 2c as a consequence of a 1% change in the infrastructure, time and adjacent traffic speed attributes presented in this model. The results from this analysis showed that given a one percent increase in the time attribute, equivalent to a 1% decrease in the time of a cycling trip, a direct elasticity or an increase in the probability of choosing the cycling alternative by 0.034% would result. If the 1% increase in time was isolated to the walking alternative, it would increase the likelihood of it being chosen by 0.033%, *ceteris paribus*. Yet if there was such a decrease in the time of a car trip, as expected, both the cycling and walking modes would experience a cross elasticity or decrease in the probability of each being chosen by 0.016% and 0.016% respectively. Alternatively, if a 1% change was made to the infrastructure attribute, i.e. an extra 1% increase in the incidence of fully segregated cycle tracks or the availability of well-lit, evenly surfaced and widened footpaths, separated from other traffic, then the outcome of this would be a 0.067% and 0.066% increase in probability of cycling and walking being chosen.

However, elasticities associated with the adjacent traffic speed attribute produced the most statistically significant results in Model 2c, as an increase of 0.108% and 0.111% in the likelihood of walking and cycling being chosen would occur given an additional 1% rise in the percentage of the trip with a 30km/h or lower speed limit. In terms of the cross elasticities for the adjacent traffic speed attribute, reductions of 0.054% in the likelihood of walking and 0.052% in cycling being selected would ensue, from a 1% increase in the car alternative only.

Table 4.17 Elasticities from a 1% change to the infrastructure, time and adjacent traffic speed attributes (Model 2c)

Elasticities			
Infrastructure	Car	Walk	Cycle
Car	0	0	0
Walk	-0.033	0.066	-0.033
Cycle	-0.032	-0.032	0.067
Time	Car	Walk	Cycle
Car	0	0	0
Walk	-0.016	0.033	-0.016
Cycle	-0.016	-0.016	0.034
Adjacent traffic speed	Car	Walk	Cycle
Car	0	0	0
Walk	-0.054	0.108	-0.054
Cycle	-0.052	-0.052	0.111

'What if' simulations of the impacts of changing the actual attribute level values (opposed to percentage changes) on mode shares, were conducted in Model 2d, the results of which are presented in Table 4.18. Through analysing the results of modifying the various attributes, it was found that the effect of changing the infrastructure attribute value to 80% produced statistically significant results. This scenario examined the impact of adding a further 10% (on top of the modelled 60%) improvement in the percentage of walking or cycling routes with evenly surfaced, widened paths, separated from traffic. In other words, the infrastructure attribute level is increased and then modelled for its consequence on modal share and choice proportions. The findings from this analysis in Table 4.18, showed that the 80% value for the infrastructure attribute translated into 32 individuals switching from the 'driving alone' car mode to the walk and cycle modes. These 32 choices that shifted, were equivalent to 2.24% of the sample and from this, 1.09% switched to cycling and 1.14% to walking. A simulation of the time attribute was similarly conducted, where an extra two minutes were shed from the trip time (i.e. 8 mins reduction in trip time). The results from this found that a modal shift of 1.14% of respondents shifting way from solo driving to walking and cycling could be achieved. From Table 4.18 we can also observe that from modifying the infrastructure variable, that the car steps from being the most chosen alternative in the base case to the third most preferred alternative, with walking attracting the highest modal share in the simulated scenario at 34.26%.

Table 4.18 Simulation of new value for the Instructure attribute (Model 2d)

Alternatives	Base Share		Scenario		Choice share changes	
***Infrastructure* - 80% increase pedestrian and cycling infrastructure**						
	N	% Share	N	% Share	N	% Share
Car	506	35.07	474	32.83	-32	-2.24
Walk	478	33.12	494	34.27	16	1.14
Cycle	459	31.81	475	32.90	16	1.09
***Time* - 8 mins reduction in travel time**						
Car	506	35.07	490	33.92	-16	-1.14
Walk	478	33.12	486	33.71	8	0.58
Cycle	459	31.81	467	32.37	8	0.56

4.3.8 Cross Tabulation results of policy measures included in the SP survey (Model 2e)

In parallel with Model 1e, cross tabulations and chi-square tests were also conducted in reference to a question in the survey which asked respondents to identify the policy measure that would attract them most to cycle to work if distance was not an issue and if they already owned a bicycle. The results from this analysis, shown in Table 4.19, found that improved cycle routes or cycling infrastructure was most attractive as an incentive for cycling, with loans to purchase a bicycle being the least popular measure amongst the sample. The socio-demographic variables of the number of children/ dependents and number of cars available to a household, were found to be statistically significant in relation to this question with p-values of 0.051 and 0.046, respectively. It was determined from this that those with no children or dependents and one to two cars available to the household were most interested in improved cycle routes as an incentive to cycle to work or education.

Both males and females, who were married, and within the 35-54 age group agreed that improved cycling infrastructure, followed by less traffic on the roads, were the measures that were most important to them in the decision to commute by bike to work or education.

Table 4.19 Cross tabulations and chi-square results (Model 2e)

	Improved cycle routes		Bicycle facilities and security		Less traffic on the roads		Loan to buy a bicycle		Financial incentives		N/A		Total	
Gender[a]	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Male	76	56.7	20	54.1	46	60.5	5	62.5	18	50.0	37	44.7	203	54.0
Female	58	43.3	17	45.9	30	39.5	3	37.5	18	50.0	47	55.3	173	46.0
Total	134	100.0	37	100.0	76	100.0	8	100.0	36	100.0	85	100.0	376	100.0
Age[b]														
18-34 years old	35	25.7	12	32.4	19	25	4	50.0	12	33.3	26	30.6	108	28.6
35-54 years old	73	53.7	21	56.8	42	55.3	3	37.5	19	52.8	41	48.2	199	52.6
55-64 years old	20	14.7	3	8.1	13	17.1	1	12.5	4	11.1	14	16.5	55	14.6
65+ years old	8	5.9	1	2.7	2	2.6	0	0.0	1	2.8	4	4.7	16	4.2
Total	136	100.0	37	100.0	76	100.0	8	100.0	36	100.0	85	100.0	378	100.0
Marital status[c]														
Single	58	43.6	15	40.5	31	41.9	3	37.5	14	40.0	33	38.8	154	41.4
Married	64	48.1	18	48.6	39	52.7	4	50.0	18	51.4	47	55.3	190	51.1
Separated or Divorced	11	8.3	4	10.8	4	5.4	1	12.5	3	8.6	5	5.9	28	7.5
Total	133	100.0	37	100.0	74	100.0	8	100.0	35	100.0	85	100.0	372	100.0
Number of children/ dependents[d]														
None	70	51.5	1	35.1	35	46.1	2	25.0	17	48.6	33	39.3	170	45.2
One	20	14.7	7	18.9	6	7.9	4	50.0	8	22.9	14	16.7	59	15.0
Two or more	46	33.8	17	45.9	35	46.1	2	25.0	10	28.6	37	44.0	147	39.1
Total	136	100.0	37	100.0	76	100.0	8	100.0	35	100.0	84	100.0	376	100.0
Number of cars owned[e]														
One	78	46.4	22	51.2	45	47.4	4	30.8	37	51.9	43	41.0	219	46.0
Two or More	65	38.7	15	34.9	29	30.5	3	23.1	22	42.3	46	43.8	180	37.8
None	25	14.9	6	14.0	21	22.1	6	46.2	3	5.8	16	15.2	77	16.2
Total	168	100.0	43	100.0	95	100.0	13	100.0	52	100.0	105	100.0	476	100.0

[a] Gender result: not significant ($p<0.401$, chi-square = 5.122, 5 degrees of freedom).
[b] Age result: not significant ($p<0.941$, chi-square = 7.548, 15 degrees of freedom).
[c] Marital status result: not significant ($p<0.989$, chi-square = 2.647, 10 degrees of freedom).
[d] Number of children/ dependents result: significant ($p<0.051$, chi-square = 18.232, 10 degrees of freedom).
[e] Number of cars owned result: significant ($p<0.046$, chi-square = 18.547, 10 degrees of freedom).

4.3.9 Base Model 3a (Smarter Car Use Model)

The final of the three models is Model 3, that included smarter and more sustainable alternatives to SOVs, namely: carpooling and car-sharing as alternatives. This model is particularly important in the context of this study as it directly relates to the sustainable usage of the private car in order to encourage car-shedding behaviour, by means of reducing the number of people driving alone to work, rendering the car of less importance for commuting proposes. Table 4.20 shows that a majority of the sample (48.41%) chose carpool in the SP experiment, with the remaining two options (car and car-share) shared with 26.79% and 24.80% of the respondents selecting these modes respectively.

Table 4.20 Model 3 sample proportions

Choice	Observation Count	Survey %	Census 2016 Count	Census 2016 (GDA) (%)
Carpool/ passenger in a car	777	48.41	176,265	28.55
Car-share	398	24.80	N/A	N/A
Car	430	26.79	441,147	71.45
Total	1,605	100.00	617,412	100.00

The base model results for Model 3a in Table 4.21, show that all the parameter coefficients were positive, statistically significant and the chi-squared probability value (0.000) satisfactorily below alpha to warrant a rejection of the null hypothesis that the policy incentives do not increase the utility of the carpool and car-share alternatives. The most statistically significant coefficients, based on the size preference of the coefficients, were in reference to the cost attribute (*Carpcost* and *Carscost*), which showed a positive sign suggesting that as carpooling and car-sharing became increasingly cheaper modes, the utility of these modes also increased and hence the likelihood of individuals choosing them also increased. The convenience and time attributes in this model, were also statistically significant at 99% and 95% and 90%, and positive, meaning that as carpooling and car-sharing became more convenient to use and time efficient, the likelihood of individuals choosing these modes increased.

Table 4.21 Base Model Output for Model 3a

Observations N = 1605			
Variable		Coefficient	Z-stat
Carpconv	Convenience	0.0109****	3.24
Carptime	Time	0.0128**	1.91
Carpcost	Cost	0.0179****	2.65
Carsconv	Convenience	0.0131****	3.33
Carstime	Time	0.0171***	2.18
Carscost	Cost	0.0192***	2.45
Log Likelihood -1393.401			
Constants only LL -1414.195			
AICc 2802.8			
Pseudo Rho Squared 0.015			
Prob. Chi-squared 0.000			

* Significant at 80% confidence, ** Significant at 90% confidence, *** Significant at 95% confidence, **** Significant at 99% confidence

4.3.10 Extended Model 3b

The extended Model 3b improved upon the base model results, by producing a higher pseudo rho-squared value of 0.074, in contrast to the base model value of 0.015, suggesting that the extended model was a more precise representation of the data with the inclusion of the socio-demographic variables. A comparison of the log-likelihood and AICc values, shown in Table 4.22, supports the improvement in model fit, as the extended model produced a log likelihood figure of -856.938 and AICc of 1773.9, which were higher than the base comparison log-likelihood value of -1393.401 and AICc of 2802.8. This demonstrating that the extended model was of better statistical quality and presented higher goodness of fit to the data than the base model.

Table 4.22 Comparison of model fit and performance indicators for Model 3b

Indicator	Base Model 2	Extended Model 2
Log-likelihood (LL)	-1393.401	-856.938
AICc	2802.8	1773.9
Pseudo Rho-squared	0.015	0.074
P-value (chi-squared)	0.000	0.000

The extended Model 3b output in Table 4.23 showed that all the beta coefficients were statistically significant to various significance levels. Several predictor variables in the model produced noteworthy results with gender, age and education level being statistically significant at 99% and 95% for both the carpool and car-share alternatives. The negative gender coefficients indicated that women, were more likely than men to carpool and car-share, whereas the positive coefficients for age and education levels suggested that individuals within higher age cohorts and higher levels of educational attainment were more likely to carpool and car-share than younger males with lower levels of education. Those living in areas in the outer suburbs or peripheral locations of the GDA showed higher probability of choosing to carpool, dictated by a positive coefficient sign. In addition to this, owing to the negative *Carpmari* coefficient, it was found that single people were more likely to carpool than married individuals. Yet those working in closer proximity to Dublin city centre and in full-time employment, were more likely to car-share, at 95% and 90% statistical significance, perhaps given the greater availability of car-sharing vehicles closer to Dublin city centre. Finally, akin to Models 1b and 2b, possessing a driving license and owning more than one car, reduced the chances of those commuting by carpool and car-sharing to work or education, given the negative coefficients for these variables.

Table 4.23 Extended Model Output for Model 3b

Observations N = 1605			
Variable		Coefficient	Z-stat
Carpconv	Convenience	0.0131****	3.06
Carptime	Time	0.0126*	1.47
Carpcost	Cost	0.0246****	2.86
Carpgen	Gender	-0.2023***	-2.23
Carpage	Age	0.3678****	4.68
Carpedu	Education	0.1824****	4.38
Carplive	Living location	0.1904***	2.25
Carpmari	Marital Status	-0.2210***	-2.01
Carplic	Licence	-0.9395****	-3.91
Carpown	Car Ownership	-0.3005****	-2.71
Carsconv	Convenience	0.0098***	1.97
Carstime	Time	0.0187**	1.86
Carscost	Cost	0.0209***	2.07
Carsgen	Gender	-0.3260****	-3.08
Carsage	Age	0.2589****	2.89
Carsedu	Education	0.0836**	1.65
Carswork	Working location	-0.2381***	-2.27
Carsempl	Employment Status	-0.0952**	-1.72
Carschil	No. of Children	0.1786***	2.16
Carslic	Licence	-0.5606***	-2.05
Carsown	Car Ownership	-0.3135***	-2.40
Log Likelihood -856.938			
Constants only LL -925.384			
AICc 1773.9			
Pseudo Rho Squared 0.074			
Prob. Chi-squared 0.000			

* Significant at 80% confidence, ** Significant at 90% confidence, *** Significant at 95% confidence, **** Significant at 99% confidence

4.3.11 Elasticity and simulation results Model 3c and 3d

The results of the direct and cross elasticities of Model 3c, shown in Table 4.24, analysed the impact of a 1% change in the three attributes that this model incorporated (convenience, time, cost) on choice probabilities. In parallel to the attributes in the public transport model (Model 1), trip cost and time were similarly sensitive to attribute level changes in Model 3c. Trip cost was statistically significant with a direct elasticity or increase in the probability of car-sharing being selected, of 0.34% and 0.23% for carpooling. However, if this change were to be applied to either carpooling or car-sharing only, then this would negatively affect the likelihood of the mode with no such change. For example, if a 1% decrease in the cost of car-sharing occurred, this would result in a cross elasticity of -0.22% in carpooling being chosen, and if the cost of carpooling was altered, car-sharing would undergo a 0.11% reduction in probability, thus lowering its utility overall. Comparable effects are noticed for the time and convenience attributes as increases of 0.27% and 0.185% in the probability of car-sharing and carpooling are recorded for the time attribute, and increases of 0.26% and 0.17% for these modes from changes to the convenience variable.

Therefore, from this analysis it was found that policies that financially incentivise carpooling and car-sharing were found to be most effective in increasing the likelihood of these modes being chosen, hence encouraging a mode shift to these modes.

Table 4.24 Elasticities for a 1% change in the conveniences, time and cost attributes (Model 3c)

Elasticities			
Convenience	Carpool	Car-share	Car
Carpool	0.173	-0.180	-0.180
Car-share	-0.094	0.260	-0.094
Car	0	0	0
Time	Carpool	Car-share	Car
Carpool	0.185	-0.180	-0.180
Car-share	-0.093	0.272	-0.093
Car	0	0	0
Cost	Carpool	Car-share	Car
Carpool	0.231	-0.228	-0.228
Car-share	-0.118	0.341	-0.118
Car	0	0	0

The 'what if' simulation results for Model 3d, shown in Table 4.25, found that a high percentage of the sample were estimated to switch from the SOV alternative to the smarter and more sustainable usage of the private car alternatives (carpooling and car-sharing). This was a statistically significant finding in the context of this study and it strengthens the rationale to engage with commuters in the GDA and encourage car-shedding behaviour, without sacrificing the real benefits of owning a private vehicle, e.g. comfort, freedom, independence and status. This is particularly evident with the cost attribute, that was modified from a 35% reduction in trip cost to 50%, the results of which revealed that 107 individuals could switch to carpool and car-share given this extra cost saving. Of these 107 individuals, it was estimated that 72 could switch to carpool and 35 to car-share, which translated into 5.34% and 2.61% of the sample respectively. Changes made to the time and convenience attributes also produced noteworthy findings, as 6.49% of the sample were estimated to switch, 4.33% to carpooling and 2.15% to car-sharing when time was set to a 50% attribute level value. Finally, 6.3% of respondents were predicted to shift to smarter modes as a consequence of a 60% reduction access and wait times associated with carpooling and car-sharing, of which 4.32% would shift to carpooling and 1.98% to car-sharing.

Table 4.25 Simulation of new values for the time and cost attributes (Model 3d)

Alternatives	Base Model		Scenario		Choice share changes	
***Convenience* - 60% reduction and access or wait times**						
	N	% Share	N	% Share	N	% Share
Carpool	652	48.40	710	52.73	58	4.32
Car-share	334	24.80	361	26.77	27	1.98
Car	361	26.80	276	20.50	-85	-6.30
***Time* - 50% reduction in travel time**						
Carpool	652	48.40	710	52.74	58	4.33
Car-share	334	24.80	363	26.95	29	2.15
Car	361	26.80	274	20.31	-87	-6.49
***Cost* - 50% reduction in travel cost**						
Carpool	652	48.40	724	53.75	72	5.34
Car-share	334	24.80	369	27.41	35	2.61
Car	361	26.80	254	18.84	-107	-7.96

4.3.12 Comparison of means analysis

In addition to the MNL modelling, elasticity and simulation analyses in Model 3, a comparison of means test was conducted to further identify the policy incentives that were most effective in determining mode choice between carpooling and car-sharing in the SP experiment. Table 4.26 shows the results of the comparison of means analysis between various socio-demographic variables and an attitudinal question from the survey that asked respondents to state the importance of various policy measures included in the experiment in their decision to either carpool or car-share. This question was measured on a Likert scale of: important (1), neutral (0) and unimportant (-1) (Carroll, et al., 2017). The policy measures tested in this analysis, numbered 1 to 6, were grouped based on the attribute that the policy corresponded to in the SP study. These policies are listed as follows:

Convenience Policies:

Policy 1: Help to find a carpool partner/ sign-up to a car-share scheme

Policy 2: Guaranteed ride home (i.e. free taxi home if let down by carpool members)

Financial Policies:

Policy 3: Financial incentives/ rewards for carpooling or car-sharing provided by employer

Policy 4: Free road tolls

Travel time Policies:

Policy 5: Free parking (on-street and private)

Policy 6: Availability of HOV lanes

Upon viewing the results of this test, Table 4.26 identified that for gender, Policy 5 (free parking) was highest in terms of the mean value generated for both male and female respondents, which was followed by Policy 4 (free road tolls), with a slightly higher value for males. Help finding a carpool partner or a car-share scheme (Policy 1) was found to be the least popular amongst the sample, in other words it was seen as being of lesser importance in the decision to carpool or car-share to work or education. The mean values for the other socio-demographic variables: age, marital status, number of children and cars and living location; indicated that free parking and road tolls were similarly most important in the decision to carpool or car-share. Specifically, the 35-54 and 55-64 age cohorts were influenced to a greater extent by Policies 4 and 5, than any of the other age groups tested. Furthermore, single people, living in the outer suburbs of the GDA, with no children and one car available, were seen to be more interested in these policies than other socio-demographic groups analysed. Financial assistance from employers in the form of cost subsidies (Policy 3) were comparably found to be popular policies, though to a lesser extent than free parking and tolls (Carroll, et al., 2017). Overall, this analysis offers a strong indication that policies which result in cost savings for the commuter could be most appropriate as an incentivisation tactic to encourage commuters in the GDA to switch away from SOVs and to uptake either carpooling or car-sharing.

Table 4.26 Comparison of means analysis (Model 3e)

Variables		Importance of policy measures in the decision to carpool/ car-share					
		Convenience Policies		Financial Policies		Travel time Policies	
		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
Gender		Mean	Mean	Mean	Mean	Mean	Mean
Male		0.12	0.29	0.47	0.54	0.66	0.41
Female		0.14	0.32	0.41	0.46	0.63	0.42
Total		0.13	0.31	0.44	0.49	0.65	0.42
Age		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
18-34		0.06	0.30	0.46	0.44	0.57	0.46
35-54		0.18	0.32	0.42	0.54	0.67	0.42
55-64		0.05	0.23	0.50	0.47	0.71	0.41
65+		0.26	0.44	0.42	0.37	0.58	0.30
Total		0.13	0.31	0.44	0.49	0.64	0.42
Marital status		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
Single		0.13	0.35	0.46	0.51	0.71	0.47
Married		0.14	.29	0.45	0.49	0.62	0.41
Separated or Divorced		0.10	0.20	0.30	0.43	0.40	0.27
Total		00.13	0.30	0.44	0.49	0.64	0.42
Number of children		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
None		0.15	0.31	0.45	0.46	0.65	0.42
One		0.05	0.28	0.48	0.53	0.59	0.43
Two or more		0.14	0.31	0.41	0.51	0.65	0.42
Total		0.13	0.31	0.44	0.49	0.64	0.42
Number of cars available		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
None		0.09	0.28	0.38	0.54	0.67	0.45
One		0.08	0.33	0.48	0.58	0.74	0.47
Two or more		0.19	0.31	0.43	0.43	0.55	0.39
Total		0.12	0.32	0.45	0.52	0.66	0.44

Living location		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
Dublin city centre		0.15	0.25	0.51	0.61	0.66	0.53
Inner suburbs		0.16	0.29	0.40	0.56	0.64	0.41
Outer suburbs		0.17	0.42	0.56	0.56	0.71	0.50
Commuter town or Rural area		0.06	0.27	0.37	0.32	0.59	0.34
Total		0.13	0.31	0.44	0.49	0.64	0.42

4.3.13 Non-SP survey questions

A number of other non-SP questions were also included in the survey, which asked the respondents to reflect on how they answered the choice scenarios. Respondents were first questioned on which of the attributes (time, cost, frequency, adjacent traffic speed, convenience, infrastructure) tested in the SP scenarios, influenced their mode choice most. As shown in Table 4.27, it was found that a third of the sample felt that cost was most influential in their mode choice decision, followed by 29% for convenience and 26% for time. However, adjacent traffic speed was least popular as a trip characteristic, with only 0.22% of the sample feeling that it influenced their choice.

Table 4.27 Attributes in SP scenarios that most influenced mode choice

Attributes	Total	%
Time	120	26.09
Cost	150	32.61
Frequency	40	8.69
Adjacent Traffic Speed	1	0.22
Convenience	135	29.35
Infrastructure	14	3.04
Total	460	100.00

In a similar vein, the sample were also asked which of the following factors was most important to them when commuting to work or University: a flexible schedule, convenient to use, fast, comfortable, cheap, protected from the weather, and control over time. The results from this question, displayed in Table 4.28, showed that convenience was the dominant aspect of consideration for commuters in the GDA, with over a quarter of (27%) of respondents choosing it, followed by 19.5% of respondents opting for a quick service, while only 4.6% of the sample felt that being protected from the weather was an issue in their daily commute.

Table 4.28 Factors of importance when commuting

Factors	Total	%
Flexible schedule	58	12.86
Convenient to use	124	27.49
Quick	88	19.51
Comfortable	34	7.54
Cheap	55	12.20
Protected from the weather	21	4.66
Control over time	71	15.74
Total	451	100.00

Finally, the respondents were asked, how difficult would it be for them to commute by the modes examined in the survey, which was measured on a Likert scale of 'Very Easy' to 'Very Difficult'. This question aimed to elicit the perceived difficulty of accessing modes in the GDA, and the reasons for such difficulty were similarly collected in a follow-up question. The results from this question, presented in Table 4.29, showed that the train and Luas were the most difficult modes to take across the modes surveyed. Half of the sample stated that the Luas was 'very difficult' to take to work or education, while over 40% felt that taking the train was very difficult. Over a third of the sample also felt that commuting on foot was very difficult. On the contrary, the results showed that the bus was an easy mode to take with over a quarter of the sample stating this, and relative to the other modes tested in this question, it was found that walking was the easiest mode to take when commuting in the GDA, based on 22% of respondents selecting that it was 'very easy' or easier than cycling, bus or rail.

Table 4.29 Perceived difficulty of commuting by different modes

	Very Easy		Easy		Neutral		Difficult		Very Difficult		Total
	N	%	N	%	N	%	N	%	N	%	N
Walk	101	22.05	71	15.50	54	11.79	64	13.97	168	36.68	458
Cycle	77	17.04	84	18.58	73	16.15	108	23.89	110	24.34	452
Bus	86	18.98	116	25.61	99	21.85	84	18.54	68	15.01	453
Train	39	8.55	58	12.72	70	15.35	101	22.15	188	41.23	456
Luas	37	8.22	56	12.44	59	13.11	75	16.67	223	49.56	450

A number of issues were highlighted as reasons as to why certain modes were perceived to be difficult to take to work or education in the GDA. These reasons were elicited from a follow-up question in the survey, some of the comments from which are set out in Figure 4.2:

"[There is] *no connection of modes in* [the] *area and it would take too long, too many bus/train changes"*.

"There are no stops near my house or job!".

"The public transport is a bother to get to and isn't very often".

"I don't live near a Luas stop".

"I live in a rural area of Wicklow".

"I don't cycle at 80 years".

"Luas/train is unavailable, walking/ cycling is impossible, and the bus is inconvenient as it is very expensive & takes much longer".

"Bad stop locations".

"Have children to get to school not locally".

"Work involves driving".

"Fares too high, dangerous for cycling".

Figure 4.2 Reasons for perceived difficulty of taking different modes

4.4 Policy Implications

The results produced from the SP survey and analysed by means of discrete choice modelling in this chapter demonstrate the sample's sensitivity to changes made to various key trip characteristics, and the statistical significance of certain socio-demographic predictors. This research method provides a method of policy appraisal and pre-evaluation to assess the level of success of a range of policy incentives that encourage car-shedding behaviour. The SP survey examined in this study was utilised as a forecasting tool to measure the relative market elasticity and market share (probability) for a range of alternative modes in the GDA given several hypothetical scenarios presented in a choice context where a trade-off must be made (Hess and Daly, 2010). By analysing the elasticities, 'what if' simulations, cross tabulations and comparison of means results from the survey, it was established that policy measures leading to cost and time savings were most popular, relative to the other policies tested, as a technique of shedding solo car commuting trips in the GDA (Carroll, et al., 2017). The estimated behavioural change observed from the MNL model parameter coefficients, market elasticities, simulation model share outputs and comparison of means results indicated that the cost attribute was statistically significant across the three models conducted. This suggested that incentives such as reduced fares, free parking, exemptions from road tolls and cost subsidies provided by employers for public transport, carpoolers and car-sharers, would be the more appropriate policy instruments to implement in order to encourage a modal shift from SOVs to these alternative modes. Furthermore, greater priority assigned to active modes and public transport in addition to the provision of segregated infrastructure were also found to be strong pull factors in terms of encouraging shedding behaviour for commuting purposes.

However, as low rho^2 and regression coefficients were generated in the base models, it is noted that care needs to be taken when interpreting these coefficients from the base model, as they are less valuable when considering the statistical relationship between the policy attributes and modal choice in the experiment. This was particularly the case in Model 2a (Table 4.14) where low coefficients were produced. Yet, it was found that by adding additional independent variables such as gender, age, availability of free parking etc, in the extended model, the statistical power of the results increased and better represented the stated choices made in the experiment.

The findings determine that even in the absence of disincentives applied to solo drivers, that commuters in the GDA can potentially be encouraged to travel more sustainably to work or education when presented with a suitable stimulus. 'These results will be of interest to policymakers who may be reluctant to penalise solo motorists, especially in areas where no viable alternatives to the car exists but wish to stimulate car-shedding behaviour' (Carroll et al., 2017). Therefore, this study effectively acts as a policy appraisal tool for analysing behavioural responses to choice situations not revealed in the market.

4.5 Conclusions

This experiment was conducted with the principal aim of analysing the impact of strategically designed policy plans on the commuting population of the GDA, through evaluating the behavioural repercussions of such policy implementation. The tool most commonly applied to experiments in this field of research, was determined from the literature (Train, 2009; Hensher, et al., 2005; Louviere, et al., 2000) to be a SP survey, that incorporated these policies into hypothetical choice scenarios. The results produced in this experiment are set in the context of EU emission reduction directive deadlines for 2020 and 2030, the first of which has been accepted as being unattainable, as Ireland is currently not on track to meet its 2020 commitments (Irish Times, 2017).

In analysing the results of this survey, it was found that individual commuters do need a proper incentive to disrupt, in some cases, long-standing commuting habits. Nevertheless, if such incentives can lead to tangible time and cost savings for the commuter, then this is estimated to result in some sustainable mode choice behaviour. The choice scenarios were constructed to ask the respondents to deliberate on the attributes that were of real importance to them and from this they were prompted to make trade-offs between three modes of transport in each scenario. If the respondent was not attracted by the incentives presented or if, given their socio-demographic characteristics, the sustainable modes were not able to be realistically considered, then the status-quo ‘drive alone’ option was included as a no-choice alternative, for no incentives nor disincentives were applied to it. Yet, from examining the results it was found, with the exception of Base Model 2a (active modes), that the sample responded positively to the experiment, to the extent that the car alternative was placed second or even third in order of preference. This indicated that there is evidence for investing more attention to providing commuters with more enticements to switch to other modes. It also suggests that operators of public transport services as well as bike sharing and car-sharing providers may benefit from influencing government authorities to consider increasing their budget for measures discussed here.

The research examined in this chapter will be also used to inform parameter changes made to the National Transport Authority’s (NTA) Eastern Regional Model (ERM), which provides a ‘comprehensive representation of travel patterns across the GDA and is a suitable tool for the testing and appraisal of the 2035 GDA Strategy’ (NTA, 2015). The policy incentives tested in the SP survey will be further assessed using this four-stage transportation model to produce real life mode share estimates following implementation of the range of car-shedding measures, as a means of determining trip making behaviour in the GDA. The policies modelling here are represented as proxies in the ERM to explore the effect of introducing them in various scenarios akin to those analysed in this chapter. The work described here will be examined in Chapter 5

CHAPTER 5: MODELLING THE IMPACTS OF POLICY INCENTIVES ON MODE SHARES AND EMISSIONS

5.1 Introduction

This chapter examines the travel demand modelling of the policy scenarios that were assessed in the SP experiment, discussed in Chapter 4. These policies were represented in the NTA[5] Regional Modelling System (RMS) for Ireland, which predicts all-day travel demand and patterns for all modes of transport and 'allows for appraisal of a wide range of potential future transport and land use alternatives' (NTA, 2017b). More specifically, the Eastern Regional Model (ERM) was consulted, which considers the modelling area of the GDA and the Leinster province. However, in accordance with the findings from the SP experiment in Chapter 4, only the GDA, discussed in Section 5.2, will be considered in the results produced from the ERM in this study.

The ERM model was chosen to complement the results of the SP analysis and to provide detailed policy evaluation of the potential 'real life' impacts of incentives that encourage car shedding behaviour. The outputs from the ERM were then used to produce mode share and emission reduction estimates, to measure the behavioural and environmental impacts of implementing the policy incentives. The rationale for using the NTA Regional Modelling System (RMS) in this thesis was based on an extensive review of a range of economic, environmental, land-use and transportation models available in Ireland, which was one of the main deliverables of the Greening Transport project (Carroll, et al., 2016). The review determined that the NTA model was the most suitable transportation model for the aims of this study.

Ultimately, this chapter builds upon the results explored in Chapter 4 and offers further empirical evidence, which examines the effect of policy incentives in encouraging a reduction in SOV trips, that may provide valuable recommendations for policymakers. Such recommendations could be considered in encouraging a sustainable shift from private car use to alternative modes such as public transport, active modes (walking and cycling), and sustainable usage of the private car through carpooling and car-sharing. The results of this work were presented in Carroll et al. (2018).

[5] The NTA is a 'statutory non-commercial body, which operates under the aegis of the DTTAS' (NTA, 2018). The functions of the NTA include transportation planning and modelling, procurement of PT services, taxi regulation, management of the Rural Transport Programme.

Section 5.2 of this chapter provides context to the modelling system in which the ERM is a central component. The methodological structure of the four stage model (FSM) in the ERM is discussed in-depth in this section, where specific attention is devoted to the mathematical framework of the mode and destination choice and assignment stages of the model. In Section 5.3 the methodology employed for representing the policy incentives in the ERM is examined, where the model parameter changes made to the active, PT and road networks are delineated in reference to the ERM structure. In addition to this, the methodology used to calculate the CO_2, NO_x, and $PM_{2.5}$ emissions and the monetary savings from these emissions are outlined. Section 5.4 then presents the mode share results produced from each of the policy scenarios in the 2012 Base Scenario and 2035 GDA Strategy in the ERM, while Section 5.5 provides the emissions estimations results and the monetary savings generated from the emissions reductions.

5.2 The Regional Modelling System (RMS)

The NTA's RMS is Ireland's chief national transport modelling framework tool, providing a vital instrument for policy and project appraisal to transport planners and modellers, urban planners and policymakers. It comprises of the National Demand Forecasting Model (NDFM), five large-scale multi-modal regional transport models and a suite of appraisal modules. Figure 5.1 illustrates these modelling areas.

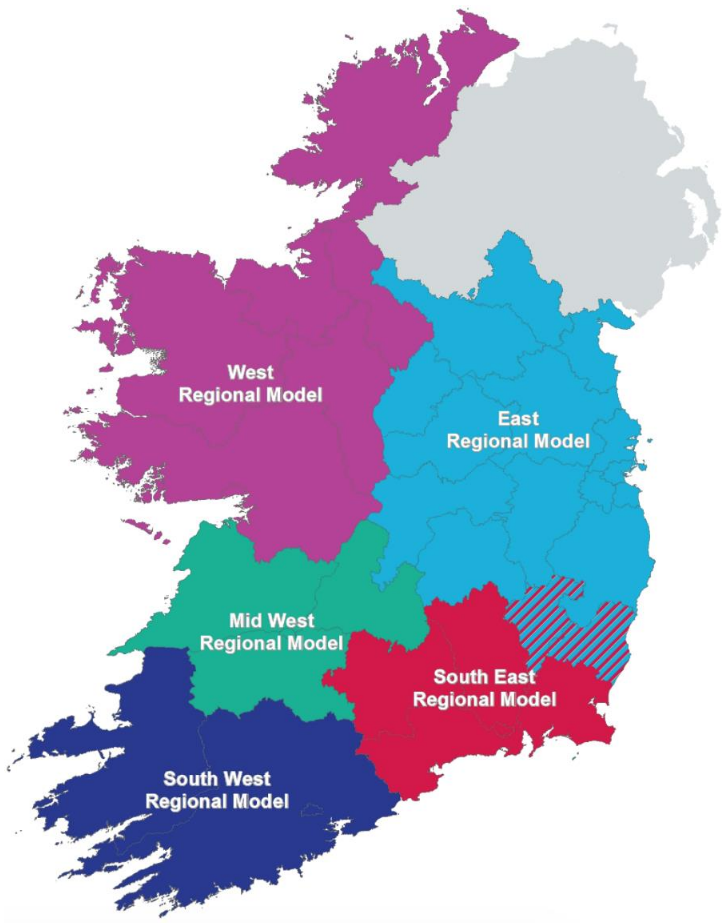

Figure 5.1 Regional Model Areas (NTA, 2017b)

These models are used primarily to accurately predict and forecast mode choice behaviour and complex travel patterns, by modelling all day travel demand. These models are valuable tools that can be utilised as a means of assessing the response of travellers to various transport policies and schemes by analysing the potential changes to travel demand and flows on certain routes in the network. The main features of the models are: that they provide comprehensive coverage of the country through the use of five independent models, they offer an in-depth depiction of the road, PT and active modes networks and have the capability to estimate demand for modes on these networks. The regional models also consider four main journey purposes (employer business travel, commuting trips, education trips, other), four time periods (AM, Lunch Time (LT), School Run (SR), PM, and Off-Peak (OP)), and finally they can 'predict change in trip destination and mode choice through changes to traffic conditions, transport provision and/ or policy' (NTA, 2017b).

5.2.1 Eastern Regional Model (ERM)

For the purposes of this thesis the ERM was utilised, thus, from this point onward the ERM will be the only model referred to in this chapter. The ERM is represented based on a zoning system that is linked to the Census disaggregated structure of Census Small Areas (CSAs), with the zonal boundaries of the GDA defined according to the CSAs. The ERM zoning system includes 1,854 zones in total, which are broken down as follows:

Table 5.1 Zoning structure of the ERM[6]

Zones	GDA Sector codes (see Figure 5.2)
Dublin zones: 1,315 (Dublin City Council (DCC), Fingal CC, South Dublin CC, Dun Laoghaire-Rathdown CC)	A1, A2, B1, B2, C1, C2, D1, D2, E1, E2, F1, F2
Buffer zones: 529 (Kildare, Meath, Wicklow)	A3, B3, C3, D3, E3, F3
External zones to the GDA: 6	Grey area in Figure 5.2
Special Use Zones: 3 (Dublin Airport, Dublin Port, Dun Laoghaire Port)	Included in sectors: A2, F1
Northern Ireland zones: 1	North most area of Figure 5.2

These 1,854 zones are aggregated to form three concentric bands that radiate from Dublin City outwards in the GDA, that represent the different zone segments or sectors in Figure 5.2. These segments are entitled the Outer Hinterland, Outer Metropolitan Area and the Inner Metropolitan Area of the GDA.

[6] Only zones within the GDA i.e. Dublin zones, Buffer zones and Special Use Zones, will be considered in the modelling results presented in this study, as the GDA was selected as the study area for this thesis.

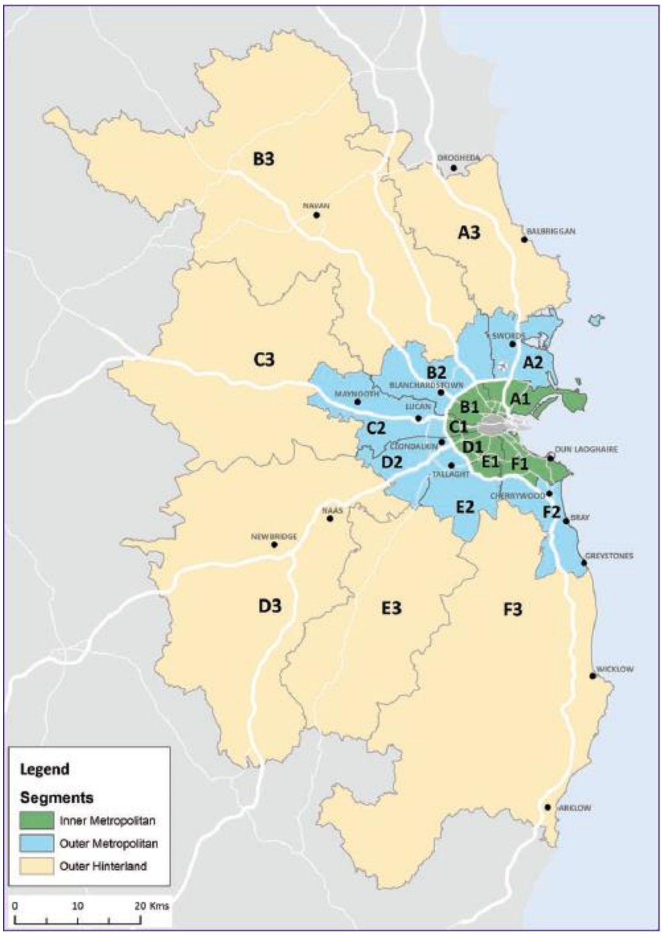

Figure 5.2 Map of GDA Sectors (NTA, 2016)

5.2.2 Modelled Years

The Base Model Scenario in the ERM is 2012, based on data from the 2011 POWSCAR[7] (Place of work, school or college – Census of anonymised records) (CSO, 2012) and the NHTS (NTA, 2013a) datasets. The year 2012 was used in this thesis, as it was based on the latest available Census of Ireland data. In 2018 the base year will be updated to accommodate the 2016 Census results. The 2012 Base Scenario was used as the foundation for the various parameter changes made in the ERM, as well as acting as a base case/ comparison year in the examination of the effect that the policy changes have on mode share if implemented.

The 2035 NTA Transport Strategy for the GDA (NTA, 2016) is the forecast scenario that was modelled in this study. The 2035 Strategy 'provides a framework for the planning and delivery of transport infrastructure and services in the GDA over the next two decades' (NTA, 2016).

[7] Specialised geo-coded Census database that is only available to bone fide researchers (CSO, 2011).

The key elements that the 2035 GDA strategy proposes are:
- Reducing traffic congestion, particularly in relation to bottlenecks and PT priority along busy routes
- Avoiding further increases in private car mode shares and added support to schemes that aim to reverse this trend, with particular attention assigned to short distance and commuter trips
- Addressing issues of pedestrian priority and the walkability of urban areas
- Accelerate and maintain increases in the mode share of active modes
- Reducing the risk associated with cycling and preventing the number of road accidents involving cyclists by investing in the GDA Cycle Network Plan (NTA, 2016; NTA, 2013b)

The array of policy incentives/ interventions explored in the SP study in Chapter 4, were tailored to represent the objectives set out in this strategy. However, it must be also noted that the ERM model parameter changes made in this study, were modifications made over/ beyond the infrastructure projects already planned in the 2035 Strategy.

The large transport infrastructure projects contained in the 2035 GDA Strategy, include:
- Heavy Rail: A DART (Dublin Area Rapid Transit) expansion to the north and west of the GDA

- Light Rail: A new Metro line (Metrolink) from the Dublin city centre to Dublin airport, and two new tram (Luas) lines

- Bus: The Bus Connects project: proposes to develop a number of initiatives on bus corridors in the GDA that aim to make bus journeys faster, more reliable and more frequent (Bus Connects, 2017). A key feature of this project is the focus on the development of the Core Bus Network – representing the most important bus routes in the Dublin area, serving high frequency and passenger volumes. The introduction of a Bus Rapid Transit (BRT) service will be included as part of Bus Connects, which will consist of a service delivering higher speeds through improved road infrastructure and enhancements to the quality of service by means of fast boarding/ alighting and appropriate vehicles (NTA, 2016)

- Cycling: An expansion of the GDA cycle network and development of more segregated facilities are planned to address cycle lane continuity along routes and to address cyclist safety

- Walking: Reducing traffic signalling times for pedestrians at crossings in Dublin City Centre, thus leading to shorter wait times. Provision of dedicated pedestrian crossings, footpath widening, in addition to providing better surfacing and removal of street clutter (NTA, 2016)

5.2.3 ERM modelling characteristics

The ERM models a selection of transport modes that are each estimated independently, these modes are:

- Privately owned cars (disaggregated in line with the Census by driver and car passenger)
- Public Transport: Bus, Rail (Heavy - Irish Rail, Light – Luas), Metro and BRT (not included in the 2012 Base Scenario, but considered in 2035 GDA Strategy)
- Park and Ride
- Active Modes (Walking and Cycling)
- Light Goods Vehicles (LGV) and Other Goods Vehicles (OGV)

These modes are modelled for five distinct time periods in the ERM to capture all-day travel demand, these periods are:

- AM Peak (07:00-10:00)
- Lunch Time LT (Morning Inter-peak 1) (10:00-13:00)
- School Run SR (Afternoon Inter-peak 2) (13:00-16:00)
- PM Peak PM (16:00-19:00)
- Off-Peak OP (19:00-07:00)

However, for each of these time periods a single peak/ representative hour is defined to represent the time period.

Four main journey purposes are similarly considered in the model:

- Employer business travel (EMP)
- Commute trips (COM)
- Education trips (EDU)
- Other trips (OTH) (e.g. recreation, shopping, visiting relatives, etc.)

The commute and education purposes will be the main focus of the analysis in this chapter, as the policies tested are targeted at encouraging a shift in commuting practices i.e. shifts from the private car to alternative modes for work and education trips. However, the mode share output for all trip purposes were also analysed for comparison purposes and are discussed in this chapter, in Section 5.4.

The overall model structure of the ERM is based on the traditional Four Stage Model (FSM) (i.e. Trip Generation, Trip Distribution, Mode Choice and Trip Assignment), which is commonly used to estimate demand and trip making behaviour in a transport network. The trip generation stage of FSM takes place in the NDFM, which is followed by the Full Demand Model (FDM) where the distribution, mode choice and assignment stages are run in a sequential process.

A key feature of the FSM is the iterative process that takes place between trip distribution and trip assignment, where generalised costs generated from the trip assignment stage are fed back to the trip distribution and mode choice stages until a point of equilibrium between trip patterns and costs is achieved. When an equilibrium is met after a number of iterations, the model is then said to have converged. The FSM is usually utilised at the planning stage of a transportation project where infrastructural and/ or policy schemes are appraised for their impacts on a network (Transport and Infrastructure Council, 2016). Hence, the ERM was consulted to complement the findings from the SP experiment and to simulate the effects of introducing a range of policy incentives on mode shares in the GDA.

5.2.4 The National Demand Forecasting Model (NDFM) (Trip Generation)

The NDFM estimates the total quantity of 'daily travel demand produced and attracted to the 1,854 Census Small Areas (CSA)' in the ERM (NTA, 2017b). Socio-demographic data such as population, data on land-use and employee numbers are linked between trip generations and attractions for origin and destination (O-D) pairs (NTA, 2017b).

The NDFM is composed of several sub-models:

- The Planning Data Adjustment Tool (PDAT), where the relevant planning data that is fed into the NDFM, which is updated in accordance with new land-use developments
- The Car Ownership & Car Availability Model, which labels households based on their car ownership status, and identifies households as car available or not available, and whether there are more, equal to or less cars than the number of adults in the household
- The National Trip End Model (NTEM) 'converts planning data into person trips' (NTA, 2017b)
- The Regional Model Strategic Integration Tool (RMSIT) then takes account of trip making behaviour in urban sites on the island to determine inter-regional travel demand (NTA, 2017b)

In this study, the NTEM is consulted as it feeds trip end matrices into the Mode and Destination Choice (MDC) model to calculate utilities for each trip purpose at each of the five time periods, which is delineated later in Section 5.2.6.

5.2.5 RMS Full Demand Model (Trip Distribution)

NDFM produces trip end matrices and trip making patterns for various modes that are then passed onto the Full Demand Model (FDM), which consists of two main modules: the Choice Model and the Assignment Model (see Figure 5.3). These two models run in an iterative process until equilibrium is achieved between travel demand and generalised cost. The FDM, as the name suggests, estimates the travel demand by modelling trip making behaviour, using observed travel data from the POWSCAR and NHTS datasets:

- POWSCAR provides origin (home) and destination (place of work or education) trips by employment type, education level, and time of departure (up to 9:30 am).
- NHTS data provide records of trip making behaviour of households (persons aged 4 and over) including origin and destination, departure time, arrival time, distance, purpose, and main mode. Trips are also segmented by trip-maker attributes such as age, gender, income range etc.

The demand model requires input data on generalised travel costs, travel distances, and journey times, thus, trips from POWSCAR and NHTS are matched to the zone systems and networks of the regional models to obtain estimates of these variables. This model then produces trip matrices as outputs from behavioural models representing travel choices such as mode and destination decisions (NTA, 2017b).

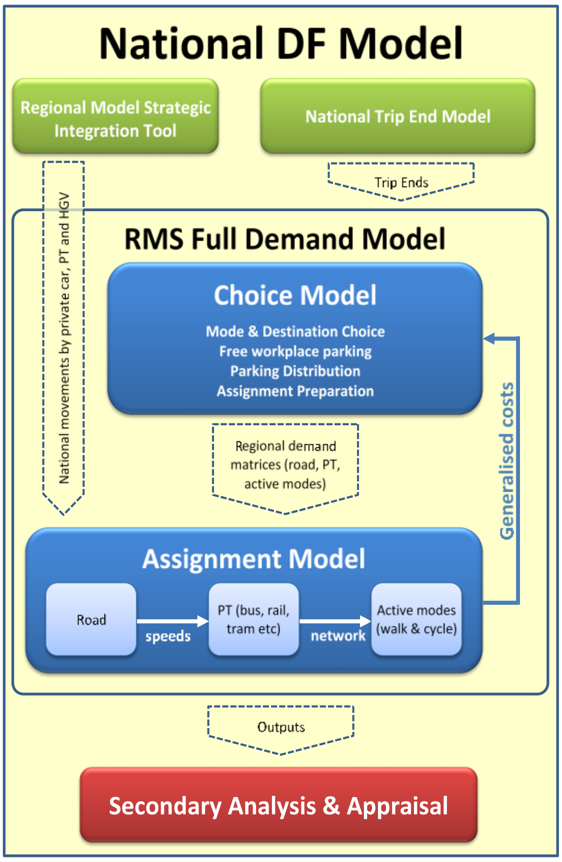

Figure 5.3 Regional Modelling System Structure (NTA, 2017b)

5.2.6 Mode and Destination Choice (MDC) Model

The Mode and Destination Choice Model is central to the modelling conducted in the FDM as it replicates mode choice behaviour of travellers for different journey purposes at different times of the day (NTA, 2017b). The MDC will hereafter be referred to as the Choice Model for clarity and to avoid confusion. Free workplace parking and parking distribution, a key determinant of the mode choice of private cars in the GDA, is also accounted for in the estimation of mode shares. The NHTS provides 'data on whether free or paid parking spaces are available for car trips' (NTA, 2017b), which is used to indicate the presence of an attractor zone in the demand model. This data is utilised in the choice model to calculate an alternative mode split based on new mode choices owing to the presence or absence of free workplace parking. In other words, the choice model estimates the proportion of trips that have access to free parking separately to trips with paid parking and using these proportions it calculates the mode shares in each case.

Mathematical framework of the Choice Model

The mathematical structure of the choice model is based on a hierarchical MNL model, as illustrated in Figure 5.4. The first two branches of the tree represent the choice of destination, which then for each destination option has a number of mode choices such as: car, public transport, park and ride and active modes, where there is then a secondary mode split between the cycle and walk mode choices for that specific destination.

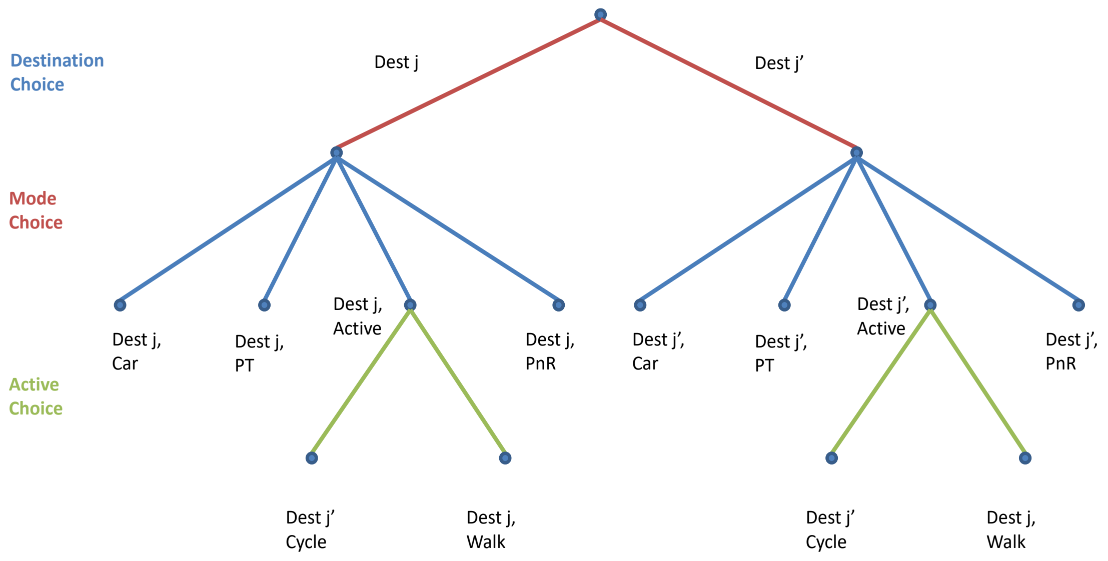

Figure 5.4 Hierarchical structure of mode and destination choice model (NTA, 2017d)

The mathematical formula used to calculate the probability of making a choice is the same as Equation 3.5, presented in Chapter 3, Section 3.3.1:

Equation 5.1

$$Pn = \frac{e^{\lambda V_n}}{\sum_{n \epsilon N} e^{\lambda V_n}}$$

where:

$\lambda < 0$ is the relevant spread parameter

V_n is the utility of choice n

N is the subset of choices considered

The mode choice utility equation, which is a function of the generalised cost (the weighted sum of the costs of taking that mode) is calculated as follows:

Equation 5.2

$$V_{ij} = \alpha U_{ij} + \beta \ln(U_{ij}) + ASC_M$$

where:

V_{ij} is the deterministic component of utility

$U_{ij} = \frac{1}{\lambda} ln\left(\sum_{m \in M} e^{\lambda U_{mij}}\right)$ is the generalised cost (see Table 5.2)

ASC_m is the alternative specific constant

α, β are the estimated parameters (NTA, 2017d)

For example, the utility of active mode choices is the 'composite cost of the utilities at the lower levels' of the hierarchical tree in Figure 5.4 (NTA, 2017d), which is written as follows:

Equation 5.3

$$U_{active\ ij} = \frac{1}{\lambda_{act}} \ln\left(\sum_{m \in M} k e^{\lambda_{act} U_{mij}}\right)$$

where:

$U_{active\ ij}$ is the composite cost of active modes

U_{mij} is the utility of walking or cycling

M is the active mode choice set

$\lambda_{act} < 0$ is the active mode choice spread parameter

The generalised costs (*U*) for walk and cycle are time matrices produced from the active modes assignment model, discussed in Section 5.2.7. While the generalised costs for private cars and PT modes consist of multiple components listed in Table 5.2, which can be calculated using Equations 5.4 and 5.5:

Equation 5.4

Car Generalised Cost (U): Time (IVT) + (Distance x CPK/CPM) + (Tolls/CPM)

Equation 5.5

PT Generalised Cost (U): Time (Walk time, Wait time, Transit time, Boarding penalties) + (Fare, Transfer penalties)

Table 5.2 Generalised cost components for car and public transport modes

Car Generalised Cost (U)	**Public Transport Generalised Cost (U)**
In Vehicle Time (IVT)	Perceived Walk Time (Actual Access + Egress walk time)
Travel Distance	Perceived Initial Waiting Time (Based on Service Headways)
Travel cost: Cents per Minute (per time period and user class) Cents per Kilometre (per trip purpose & user class) Tolls	Boarding Penalties (15mins for Rail, 10mins for other modes)
	Perceived Fare (divided by Value of Time)
	Perceived Transit Time (Transit time x IVT factor)
	Perceived Transfer Wait Time
	Transfer Penalties (min) (Mode-specific)

The overall model process employed to produce the choice matrices is illustrated in Figure 5.5, whereby cost matrices and trip ends are firstly fed into the choice model from NTEM. These are then used to estimate the utility of each destination choice, followed by the modes specific to the destination, in reference to the hierarchical structure of the model (see Figure 5.4). The calculations set out in Equations 5.4 and 5.5 are then used to generate the composite cost of travel. When the utilities for the modes are calculated the composite costs are then utilised in the distribution function to distribute the trips amongst the associated destinations. The trip distribution matrices are fed into CUBE Voyager's[8] (Citilabs, 2017) Fratar[9] analysis module of the software where the production and attraction trip ends are matched with each other (NTA, 2017d). The mode split for each mode, disaggregated by time period, trip purpose, user class and car available and car unavailable categories, produced in matrices, are then weighted based upon on the availability of free workplace parking. The final outputs produced are in the form of various matrix files, which are then passed onto the assignment models.

[8] A computer software program developed by Citilabs, used to build complex regional transport models enabling large scale demand forecasting

[9] A growth factor method of trip distribution used for predicting future O-D matrix trips (Ceha, Ohta, 1997)

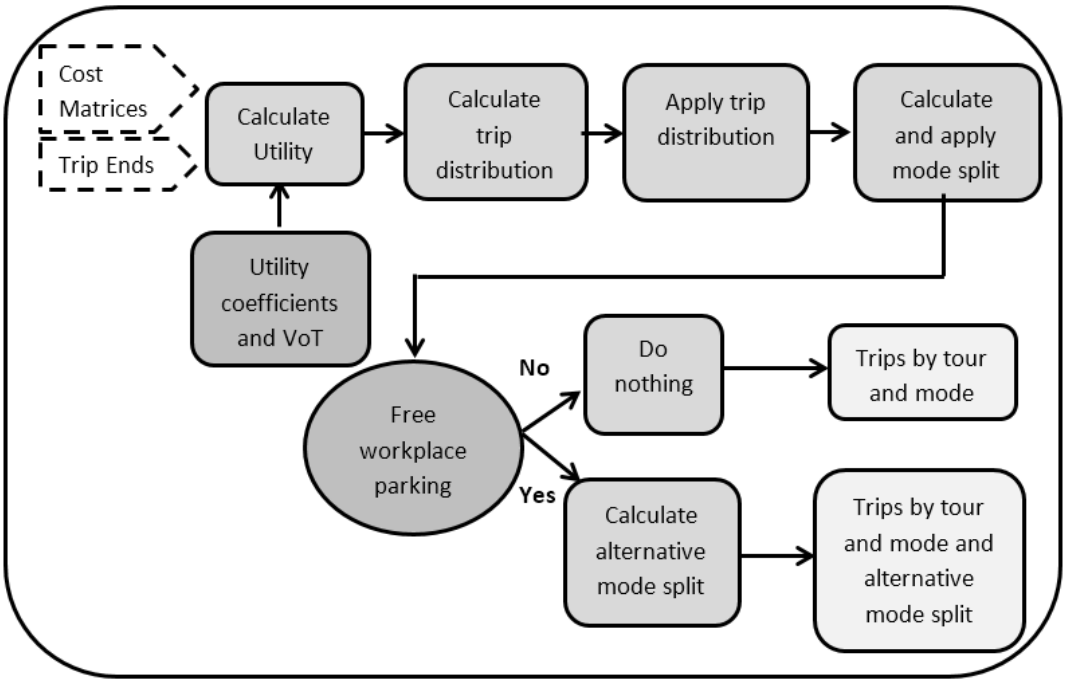

Figure 5.5 Mode and destination choice model process (NTA, 2017d)

The Assignment Models of the FDM (Road, PT and Active Modes) (see Figure 5.3) then receive the movements of modes from the RMSIT and assign them to their corresponding networks to determine route choice and the new generalised cost for O-D pairs.

Finally, the secondary analysis and appraisal modules are utilised to produce an assessment of the impacts of transport plans and schemes in the ERM. The outputs from the FDM, such as generalised costs, demand and flows are used here to produce economic, safety, environmental, health, accessibility and social inclusion impacts to create policy appraisal recommendations.

5.2.7 Active, PT and Road Assignment Models (Trip Assignment)

The fourth and final stage of the FSM is trip assignment, where an equilibrium between demand and supply in the network is met. At this stage, demand produced from the choice model is assigned to the mode-specific network. In order for new mode shares to be estimated, as a result of policy changes or new transport plans being introduced, the associated parameter changes must first be made at the assignment stage before the generalised costs can then be passed back to the choice model to produce new mode choice estimates. At the assignment stage, there are three separate assignment models: the Active Modes, PT and Road assignment models.

The Active Modes and PT assignment models assign traveller demand for active modes and passenger demand for PT services, generated from the Full Demand Model (FDM), to the Active and PT networks (i.e. the supply) (NTA, 2017c).

Whereas, the Road assignment model assigns demand from vehicle O-D matrices to the road network, defined based on specific road characteristics coded into the SATURN[10] network model (Akins, 2017). The assignment models are structured with three defined elements, the interrelationship between supply and demand, and the actual assignment of this demand to the services in the respective networks.

The supply component of the model is composed of the road, rail, cycle and walk networks, and in the PT model mode-specific data such as the headways, fares, road capacities and routes are added to determine the generalised costs.

The demand component of the assignment model considers the trip making behaviour between O-D pairs, e.g. from home (origin) to place of work/education (destination), to determine traveller/passenger/vehicle volumes in the model. In other words, this component of the model distinguishes the estimated demand for these trips so that they can be assigned to their respective networks in the model.

In the final component of the model, the process of trip assignment itself takes place. Here, the characteristics of the active modes, PT and road networks, outlined in the supply component, are used as criteria to define the routes where the O-D trips must be assigned to in the network. The assignment model produces estimates of passenger flows on links in the network for operational analysis and calculates the generalised costs of travel, such as wait times, IVT and fares for economic appraisal (NTA, 2017b).

5.3 Parameter Modifications in the ERM

5.3.1 Changes to the active mode network

In this thesis, the cycle network in the active modes assignment model, shown in Figure 5.6, was firstly modified to take account for the proposed provision of improved cycle infrastructure in the GDA, as examined in the SP survey. In the regional modelling system (RMS) of the NTA, levels of cycling infrastructure provision are represented by coded cycle speeds in the model, with higher speeds signifying higher levels cycle lane segregation, which will be discussed in more detail in Section 5.3.5.

[10] A computer software program developed by Akins, used in strategic highways assignment, traffic management and demand forecasting

Thus, in order to represent an improvement in cycling infrastructure, coded cycle speeds were increased in line with the SP policy scenarios, on certain links in the network to act as a proxy for the provision of segregated cycle lanes. Pedestrian speeds coded in a comparable fashion, also examined further in Section 5.3.5, were similarly increased to account for walking mode improvements, such as signalling changes and widening footpaths (i.e. more street space assigned to pedestrians to increase the flow of pedestrians) and decluttering footpaths to remove obstacles that may hinder pedestrian flows.

5.3.2 Changes to the PT network

In the PT Assignment Model, also illustrated in Figure 5.6, headways were reduced as a direct modelled proxy for increased PT service frequency in the network for all routes in the GDA serviced by bus operators: Dublin Bus (Dublin Bus, 2018) and Bus Eireann (Bus Eireann, 2018); and rail operators for the DART and the Luas: Irish Rail (Irish Rail, 2018) and Transdev (Transdev, 2018). In addition to this, fares associated with these services, which are coded in the CUBE Voyager scripting language, were also modified to represent staged decreases in the cost of bus and rail services. These parameter changes acted as proxies for improvements made to bus and rail service frequency, leading to shorter wait times, and lower trip costs for PT commuters.

The assignment model runs in a CUBE Voyager module through a two-step process to allot trips to their respective routes. The first step (enumeration) calculates all reasonable routes between zone O-D pairs in addition to the probabilities of certain routes being chosen. The second step (evaluation) uses choice models to allocate trips to these routes based on the ‘probabilities of use’, considering crowding and fares (NTA, 2017c).

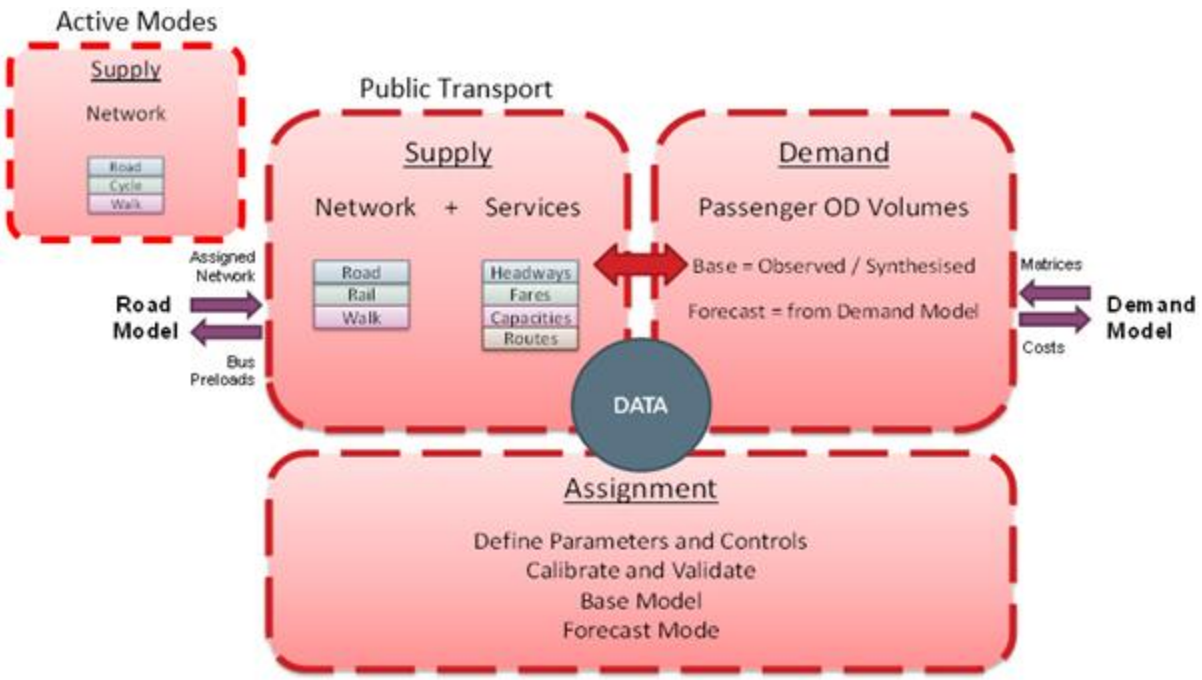

Figure 5.6 Active and PT Model structure (NTA, 2017a)

5.3.3 Changes to the road network (i.e. car occupancy level values)

In the road assignment model, shown in Figure 5.7, car-sharing and carpooling are not explicitly modelled as discrete modes. Carpooling is however, represented by modifying the car occupancy level values or car user to car driver values. Thus, in order to account for increases in carpooling behaviour for commuting purposes in the GDA, it was decided to code an increased car occupancy value for private vehicles in the ERM model for commute and education trip purposes, as a proxy for individuals responding to carpooling incentives such as: free tolls, free parking, high occupancy vehicle (HOV) lanes and financial rewards. The road assignment model is somewhat different to the active and PT assignment models as the supply and demand components of the model draw upon more detailed road and highway data. For example, the supply component of the road model is determined by the road network which includes link and junction capacities, link speeds, vehicle restrictions and tolls, coded in a SATURN network model (Akins, 2017). The demand for the road model is defined as a series of vehicle O-D matrices prepared using data from POWSCAR and Dublin City Council's (DCC) SCATS[11] (DPER, 2018) dataset. When the supply and demand data is fed into the model the O-D vehicle trips are assigned to the road or highway network to determine route choice and the generalised costs for motorised road vehicles.

[11] The Sydney Coordinate Adaptive Traffic System is an intelligent transport system which utilises data collected from traffic cameras and induction loops installed in the network for vehicle counting and to control the timing of traffic signalling

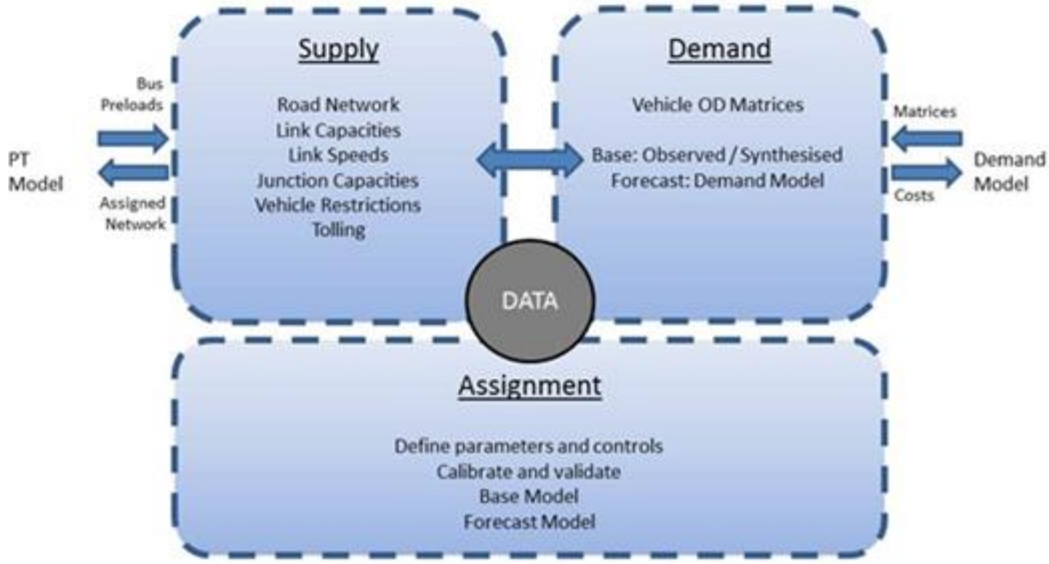

Figure 5.7 Road Model structure (NTA, 2017e)

5.3.4 Methodology

As discussed in Sections 5.1 and 5.2, the objective of this work was to more accurately predict the potential real life responsiveness of commuters in the GDA to a range of policy incentives by employing the NTA's ERM. To achieve this aim, a number of scenarios were devised to simulate the introduction of the policy interventions explored in the SP experiment in Chapter 4, and to capture the effect of these policies on mode share estimates.

To account for the attribute levels included in the SP study, three overarching modelling scenarios were examined: a Do Nothing/ Base, a Do Something, and a Do Maximum scenario. In each of these scenarios, changes to the network were introduced in multiple model runs. The organisational structure of the parameter changes made in the ERM are outlined in Table 5.3:

Table 5.3 Policy incentives and model parameter changes

Modes	Policy Incentives/ Measures	Effects of Incentives on trip attributes			Justification for model changes
		Infrastructure	**Time**		
Cycling	Increase cycle lane continuity, incidence of fully segregated cycle lanes Priority given to cyclists over motorists at junctions	% increase in the incidence of fully segregated cycle lanes	% reduction in trip time from improved cycling infrastructure		Increase in cycle speeds on certain links act as a proxy for an increase in segregated cycle infrastructure
Walking	Improved pedestrian priority at junctions, signalling changes, greater amount of street space assigned to pedestrians	Reclaiming street space for pedestrians, priority over motorised traffic	% reduction in trip times from shorter wait times at junctions and crossings, reduction in pedestrian congestion		Increase in pedestrian speeds acts as a proxy for pedestrian priority at junctions.
		Frequency	**Time**	**Cost**	
Bus/Rail	Scheduling improvements to ensure reliability, punctuality and increased frequency of services Reduction in bus and rail fares	% improvement in frequency of PT services (% reductions made to headways of PT modes)	% reduction in door-to-door trip times due to reduced wait times	% reduction in trip cost from lower fares	Reduction in PT headways and fares acts as a proxy for changes in service efficiency affecting time and cost parameters. Adjustment to headways also acts a proxy for improvements in service frequency.
		Convenience	**Time**	**Cost**	
Carpool/ Car-sharing	Free on-street and private parking for high occupancy vehicles (HOVs) and car-share members HOV lanes, exemption of road tolls Other optional incentives: guaranteed ride home for carpoolers and car-sharers, cost subsidies or rewards for carpooling/ car-sharing	% reduction in access and/ or wait time from home to place of work or education	% reduction in trip times	% reduction in trip costs from sharing the cost of the carpool or through avoiding high car ownership costs	Increase in the modelled occupancy level values to account for an increase in the mode share of carpooling as a result of the range of policy incentives/ interventions implemented

As outlined in Table 5.3, the model parameter changes are all mode-specific in order to analyse the impact of the introduction of these policy measures independently, holding all else constant, which required a separate model run for each mode-specific policy.

It must be emphasised that in order to make the necessary model parameter modifications a certain level of understanding, training and competence in Transportation Modelling was required to be demonstrated to the NTA, in accordance with the NTA Model Access Protocol. This was to ensure that comprehension the capabilities of the model and the CUBE Voyager scripting language, in addition to SATURN network coding was attained prior to making any model changes (Akins, 2017).

5.3.5 Active Modes Scenarios

Active mode parameter modifications were made to represent improvements made to walking and cycling infrastructure, leading to reductions in trip time and the perceived level of risk of these modes. The demand of walking and cycling, produced from the FDM is assigned separately reflecting the difference in the pedestrian and cycling networks. Walk trips are assigned to the shortest distance route, assuming a constant walk speed of 5.1 km/h, and cycle trips are assigned based on the quickest journey time based on available route infrastructure, e.g. segregated cycleways (NTA, 2017a). The active modes model employs as simple 'All or Nothing' shortest path approach, with no capacity or 'speed-flow' effects, i.e. 'the speed on the links is not affected by the number of pedestrians or cyclists using that link' (NTA, 2017a). All or Nothing assignment refers to when travel times on links are defined beforehand, thus the shortest paths between origin and destination are already determined. The trips are then assigned accordingly to links with the shortest trip times (Ortúzar and Willumsen, 2011).

Pedestrian Speeds

Network pedestrian speeds in the model are set based on fixed assumptions for walking. In the active modes model, the average coded walk speeds differ by age, where three age categories are defined, and average walk speeds are calculated based on NHTS (2012) data. The age cohorts considered and associated average walk speeds calculated in the ERM model are:

- 0 to 20 years: 4.9km/h;
- 20 to 60 years: 5.1km/h; and
- Over 60 years: 4.4km/h (NTA, 2017a).

To account for improvements made to pedestrian priority and more street space being assigned to pedestrians, as detailed in Table 5.3, the coding of pedestrian speeds were accordingly modified. In line with the Do Something and Do Maximum scenarios, 25% and 35% increases in pedestrian speeds were applied to represent greater pedestrian priority, thus simulating a minimisation of wait times for pedestrians at junctions due to signalling changes implemented, in addition to the de-cluttering and widening of footpaths. These percentage increases were applied to the default 5.1km/h constant pedestrian speed coded in the active modes assignment model.

The value changes that were coded and read into the scripting language of CUBE Voyager are set out in Table 5.4:

Table 5.4 Adjusted pedestrian speeds modelled

Base Constant Ped. Speed (km/h)	Adjusted Do Something Ped. Speed (km/h)	Adjusted Do Maximum Ped. Speed (km/h)
5.1	6.38	6.89

An example of the CUBE scripting of pedestrian speeds is displayed in Appendix B of this thesis.

Cycle Speeds

In order to represent improvements in cycle infrastructure, modifications were similarly made to cycling speeds on certain links in the cycle network that correspond to little or no cycling infrastructure. In the ERM, the quality of service of cycle infrastructure or 'cycle friendliness' is modelled in terms of changes in cycling speeds. The base cycle speed (corresponding to links without any cycling infrastructure) is set to a minimum of 12km/h, with the maximum cycling speed set to 20km/h, which represents links with the fully segregated cycle infrastructure/ lanes or greenways. These speeds are calculated based on data from the National Household Travel Survey (2012). A list of the full range of modelled cycle speeds in the ERM cycling network, based on the quality of service grading system is displayed in Table 5.5:

Table 5.5 Cycle speeds based on quality of service data (NTA, 2017a)

Grade	Quality of Service	Modelled Cycle Speed (km/h)
A+	High quality well maintained surface, no manholes, gullies or other ironworks	20
A	High quality well maintained surface, with manholes, gullies	19.2
B	Surface with deteriorating surface or poorly maintained with debris evident	18.4
C	Undulating, cracked, generally an unsatisfactory ride experience	17.2
D	Very poor ride quality with severe undulations, concrete aprons, very poorly maintained surface. Unsuitable and needs action	15.2

Calibrated mandatory and advisory cycle speeds[12] are also included in the cycle speeds database in the model, which are set according to specific types of available cycling road infrastructure. These are listed in Table 5.6:

Table 5.6 Cycle speeds based on link characteristics (NTA, 2017a)

Grade	Type of Infrastructure	Mandatory Cycle Speed (km/h)	Advisory Cycle Speed (km/h)
B1	Bus Lane (no cycle lane)	12.8	12.6
C1	Cycle Track – separated from road	19.5	17.6
C2	Cycle Track – immediately adjacent	15.2	14.4
C3	Cycle Lane (even within Bus Lane)	15.2	14.4
G1	Cycle Trail or Greenway	19.5	17.6
S1	Shared with Traffic	12.8	12.6
S2	Shared Space (with pedestrians)	12.8	12.6

[12] Mandatory and advisory cycle speeds were used in the NTA Active Mode Model calibration in reference to data from the NTA's journey planner application and the Census.

To represent the Do Something and Do Maximum policy scenarios in the ERM cycling network, 40% and 60% increases in the cycle speeds were applied on links below the 15.2 km/h default/ average cycle speed, in reference to Table 5.5 and 5.6. In other words, cycling speeds were increased on links, indicated by Tables 5.5 and 5.6, to have poor or little cycle infrastructure in place. The new cycle speed values were first calculated in an Microsoft Excel worksheet and then applied to specified links that met the low cycle speed criteria. The new cycle speeds were then coded as an into CUBE Voyager so that the ERM could interpret these new values. An example of these new calculated cycle speeds and the structure of the coding based on defined links in the cycle network is provided in Appendix B.

5.3.6 Public Transport Scenarios

Headways

In the ERM, the frequency of PT services operating in the GDA are represented by coded headways for all bus and rail operators in the ERM in the PT network, for each time period. Thus, for the PT scenarios, changes to the coded headways of the main commuter bus and rail services operating in the GDA were applied in the supply component of the PT assignment model (see Section 5.3.2). In order to modify such headways value, a macro enabled Microsoft Excel worksheet was utilised to ensure that only selected services were modified (i.e. commuter services only operating in the GDA as opposed to the eastern region as a whole: Dublin Bus, Bus Eireann, DART and Luas). When these change to headways were performed, a new PT input file was generated, which would then be read in by the model within CUBE Voyager application. This input file contains detailed information concerning PT services, such as: the PT routes in consideration, a definition of the operator, in addition to wait and crowding curves. This file also contains a large amount of in-depth data associated with the services modelled, namely: the operating company, route type (i.e. circular/ linear), service type (i.e. stopping/ express), the headway values for modelled time periods (AM, LT, SR, PM Peaks), a short and long text description of the serviced routes, and the sequence of nodes serviced along the route.

In line with the Do Something and Do Maximum scenarios, it was decided to reduce PT headway by 25% in the Do Something scenario and by 35% in the Do Maximum scenario, as a proxy for increased service frequency for bus and rail services in the GDA, which consequently reduces PT wait times. An example of some of the Dublin Bus operated routes and the headways for each of the four time periods (AM [1], LT [2], SR [3], PM [4]) are listed in Table 5.7. These new headway values were then coded into CUBE Voyager to be run in the ERM. An example of this coding is supplied in Appendix B of this thesis.

Table 5.7 Headways input file example (Source: CUBE Voyager)

NAME	LONGNAME	HEADWAY[1]	HEADWAY[2]	HEADWAY[3]	HEADWAY[4]
2481	Dublin Bus: 11: Blackthorn Road to Saint Pappin's Road	20	26	30	16
2482	Dublin Bus: 120: Rathbourne Avenue to Elgin Road	30	0	0	0
2483	Dublin Bus: 120: The Gate Hotel to River Road	8	10	10	9
2484	Dublin Bus: 120: Merrion Road RDS to River Road	0	0	0	30
2486	Dublin Bus: 120: Rathbourne Avenue to Marlborough Street	9	10	10	7
2490	Dublin Bus: 122: Ashington Park to Errigal Road (Brandon Road)	12	18	20	11
2491	Dublin Bus: 122: Drimnagh Road (Our Lady's Hospital for Sick Children) to Ashington Gardens	11	20	20	11
2492	Dublin Bus: 123: Kilnamanagh Road to Griffith Avenue (Malahide Road)	10	10	10	11
2493	Dublin Bus: 123: Griffith Avenue (Malahide Road) to Kilnamanagh Road	11	10	11	10
2494	Dublin Bus: 130: National Lottery Head Quarters to Clontarf Castle	11	10	10	9
2495	Dublin Bus: 130: Saint John The Baptist Cemetery to Marlborough Street	9	10	10	10
2496	Dublin Bus: 13: Harristown Bus Depot to Business Park Bus Terminus	36	36	26	30
2497	Dublin Bus: 13: Harristown Bus Garage to Business Park Bus Terminus	45	36	36	45
2498	Dublin Bus: 13: Saint James Hospital to James Street	45	36	36	45
2499	Dublin Bus: 13: Harristown Bus Depot to Cuisine de France	0	0	0	61
2500	Dublin Bus: 13: Harristown Bus Garage to Cuisine de France	61	0	61	0
2501	Dublin Bus: 13: Business Park Bus Terminus to Harristown Bus Depot	26	26	36	36
2502	Dublin Bus: 13: Business Park Bus Terminus to Harristown Bus Garage	61	45	26	36
2503	Dublin Bus: 13: Cuisine de France to Harristown Bus Garage	45	61	0	61
2505	Dublin Bus: 140: Saint Margaret's Road to Upper Rathmines Road	12	18	20	13
2506	Dublin Bus: 140: Palmerston Park to Saint Margaret's Road	15	20	20	13
2507	Dublin Bus: 142: Wendell Avenue to UCD Sports Centre	45	0	0	0
2508	Dublin Bus: 142: UCD Sports Centre to Coast Road	0	0	0	45
2509	Dublin Bus: 145: Slip Road Stillorgan Dual Carriageway to Outside Heuston Train Station	0	0	0	60
2510	Dublin Bus: 145: Donnybrook Road to Outside Heuston Train Station	0	0	61	61

The modelled headways, shown in Table 5.7, are based on the number of services that operate in each time period (i.e. AM Peak: 07:00 – 10:00, Lunch Time/ Inter-Peak 1: 10:00 – 13:00, School Run/ Inter-Peak 2: 13:00 – 16:00, PM Peak: 16:00 – 19:00), calibrated in reference to National Household Travel Survey (NHTS) data and the respective table tables of each operator. With a single assigned 'peak hour' defined based in the mid-point timetabled in the network.

Fares

In addition to headways, trip costs (i.e. fares) were also reduced as an added measure to represent the policy incentives explored in the SP survey to encourage a modal shift to PT from private car commuting in the GDA. The fare 'systems'/ structures modelled in the ERM for Dublin Bus, Bus Eireann, DART and Luas are considered as operator specific as each has a different fare structure (i.e. stage/ zone based versus number of stations or stops travelled). A description of the fare systems modelled for each service/ operator, which include boarding penalties and a distance based - cost per km tariff, are set out in Table 5.8. Furthermore, independent fare system coding is used for school services to account for discounted school fares. Akin to the headways/ frequency coding, 25% and 35% decreases in bus and rail fares for the operators specified in Table 5.8 were coded into the model. The CUBE Voyager coding used for modifying the values represented in the fare systems modelled in the ERM is shown in Appendix B.

Table 5.8 Fare systems for PT modes modelled (NTA, 2017b)

Mode	Fare System
DART, Luas	Defined as a station-to-station matrix to account for modelled fares to stations in the DART/ Luas network. The fare values represent average prices for different ticket types (2012 fares are taken from 2011 prices).
Dublin Bus	A stage-based fare structure was used to represent the Dublin Bus fare system.
Bus Eireann	A distance-based fare model was used to represent Bus Éireann services based on ticket sales and journey data for key routes.

5.3.7 Carpooling Scenario

To account for an increase in those opting to carpool to work or education in the GDA in response to the range of policy incentives listed in Table 5.3, modifications to the 'car user to car driver' values in the ERM were made. In other words, changes to the values defined for car occupancy levels in the model were made to represent increases in carpooling activity, informed by the results produced from the SP experiment. For the purposes of this study, only the car occupancy level values for commute and education trip purposes were modified, as the policy incentives that were considered were targeted specifically at those commuting to work and education as opposed to other trip purposes such as shopping, recreational and visiting relatives.

In accordance with the Do Something and Do Maximum scenarios, the car occupancy level values for the commute and education trip purposes in the ERM were modified by 25% and 35%, respectively. The modified values, which were coded into CUBE Voyager, are listed in Table 5.9.

Table 5.9 Car Occupancy values for the Base, Do Something and Do Maximum scenarios

User Class (time periods)		Base Value	Do Something	Do Maximum
COM AM	Commute trips (07:00 – 10:00)	1.13	1.41	1.53
COM LT	Commute trips (10:00 – 13:00)	1.11	1.39	1.50
COM SR	Commute trips (13:00 – 16:00)	1.11	1.39	1.50
COM PM	Commute trips (16:00 – 19:00)	1.10	1.38	1.49
COM OP	Commute trips (19:00 – 07:00)	1.10	1.38	1.49
EDU AM	Education trips (07:00 – 10:00)	15.38	19.23	20.76
EDU LT	Education trips (10:00 – 13:00)	10.55	13.19	14.24
EDU SR	Education trips (13:00 – 16:00)	10.55	13.19	14.24
EDU PM	Education trips (16:00 – 19:00)	10.55	13.19	14.24
EDU OP	Education trips (19:00 – 07:00)	10.55	13.19	14.24

The coding script written into CUBE Voyager is shown in Appendix B of this thesis.

5.3.8 Emissions Estimation

In order to estimate the emissions savings or changes in emissions as a result of implementing the range of policy scenarios tested in this study, the recommended approach outlined in the Department of Transport, Tourism and Sport's (DTTAS) Common Appraisal Framework (CAF) Report (2016) was adopted. The CAF provides guidance in evaluating a range of aspects related to the transport sector in Ireland including economic appraisal, risk and uncertainty analysis, cost-benefit analysis, in addition to recommending approaches for project assessment, monitoring and implementation. The purpose of the CAF is to 'develop a common framework for the appraisal of transport investments that is consistent with the Irish Public Spending Code (PSC), to assist scheme promoters in constructing robust and comparable business cases for submission to Government' (DTTAS, 2016). One of the central factors included in the CAF project appraisal criteria is related to evaluating the impact of transport on the environment, such as air, noise, and ecological pollution and architectural impacts. In reference to air quality, the CAF recommends the following approach for estimating road-based emissions, outlined in Figure 5.8:

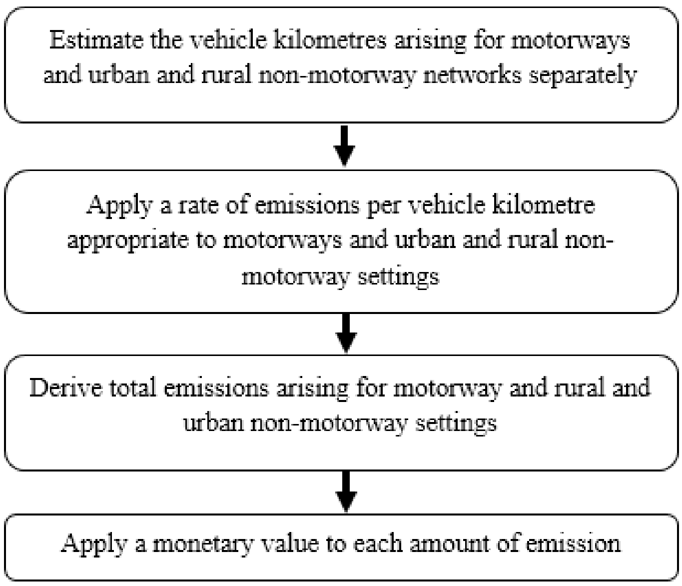

Figure 5.8 CAF recommended method for evaluating road-based emissions (DTTAS, 2016)

Under this approach, estimation of Carbon Dioxide (CO_2), Mono-nitrogen oxides (NO_x), and Particle matter ($PM_{2.5}$) are considered, by applying the following equation (CAF, 2016; McNamara, 2012):

Equation 5.6

$$CO_2 = \sum (EF_i * VKM)$$

where:

VKM is the number of vehicle kilometres travelled for motorised modes modelled

EF_i are the emissions factors, estimated in kilograms per kilometre

The vkms travelled were calculated based on the distance of each link in the network and the load of the user classes travelling on the links, per time period (AM, LT, SR, PM). These results were generated from SATURN (Atkins, 2017), and Cube Voyager (Citilabs, 2017) for the following user classes: car employer business, car commute, car education, car other, bus and rail. Factors were first applied to the vkms for each of the peak hours to estimate the passenger car unit (PCU) kms for bus and rail. Hour-to-period factors were then applied to calculate vkms for all modes in the time periods. These factors are outlined in Tables 5.10 and 5.11. When the PCU and Hour-to-Period vkms were calculated, the emissions factors (*EF*), included in the 2016 CAF report (DTTAS, 2016), were applied to the vkms to estimate the daily mode specific emissions for private cars and buses in kilograms per kilometre for the 2012 Base Scenario and 2035 GDA Strategy scenarios. 'The emission factor is, in principle, a universally-applicable parameter specific to a particular vehicle type, where activity data is specific to a particular region' (EPA, 2007). The factors for private vehicles and bus, listed in Table 5.12, were sourced from the default values contained in the COPERT 4 (Computer Programme to calculate Emissions for Road Traffic) (Emisia, 2018) road transport emissions model in the Irish context. The CO_2 emission factor for DART was obtained from a European Research project (PEACOX: Brazil, et al., 2013), and the Luas emissions factor was developed by the Veolia Transport Group Eco-Efficient Travel Assessment Methodology (Luas, 2017). The factors for DART and Luas are also included in Table 5.12. For private cars, separate factors were applied to petrol cars and diesel cars, based on a fuel split in the private car fleet of 53.6% diesel and 46.4% petrol, which was outlined in the National Mitigation Plan (DCCAE, 2017). A decision was made, in discussion with the NTA, to employ consistent emissions factors both the 2012 and 2035 scenarios due to the unavailability of reliable forecast emissions factors for the PT modes analysed.

Table 5.10 PCU factor for PT modes (Bus and Rail)

Mode	PCU Factor
Public Service Vehicle (PSV) i.e. Public Transport	3.0

Table 5.11 Hour-to-period factors per time period

Time Period	Car	PT
AM	2.09	2.17
LT	3.00	3.00
SR	2.63	3.00
PM	2.35	2.50

Table 5.12 Emission factors in kilograms per kilometre (Luas, 2017; DTTAS, 2016; Brazil, et al., 2013)

Vehicle Category	CO_2	NO_x	$PM_{2.5}$
Petrol Car	0.1923	0.0001	0.000002
Diesel Car	0.1811	0.0007	0.000035
Bus	1.1393	0.0092	0.000081
DART	0.0110		
Luas	0.0706		

Applying a monetary value to the emissions estimation is outlined as the final stage in the approach set out by the CAF, see Figure 5.8 (DTTAS, 2016). In view of this, the CAF provides a range of emissions values per emission type to calculate the cost of road transport emissions. These values that were employed in this thesis to estimate the potential cost savings generated from emissions reductions are shown in Table 5.13:

Table 5.13 Monetary values for emissions (DTTAS, 2016)

Emissions Type	Emission Value (€ per tonne)
CO_2	€13.22
NO_x	€5,851
$PM_{2.5}$	€200,239

5.4 ERM Mode Share Results

This section outlines the mode share changes estimated from the ERM following the stepwise introduction of parameter modifications in the model. The parameter changes are in accordance with the Do Something and Do Maximum scenarios, set out in Section 5.3. Separate tables are provided for the 2012 Base Scenario results and the 2035 GDA Strategy results, which compare the mode shifts from the Base/ Do Nothing scenario to the Do Something and Do Maximum scenarios. Only trips made within the GDA segments outlined in Figure 5.2 will be considered in the analysis of mode shares. The behavioural responses measured as a result of introducing the policy incentives are analysed from changing mode shares, calculated from the total number of trips taken by each mode, firstly for all trip purposes and then for the commute purpose alone. Section 5.5 will then examine the emission savings or changes in emissions estimated from changes in vkms travelled by different modes, in addition to the cost savings associated with the changes in emissions.

Figure 5.9 sets out the order in which the modelling results will be presented for each of the modelled scenarios (PT, active mode and smarter car use) in this section:

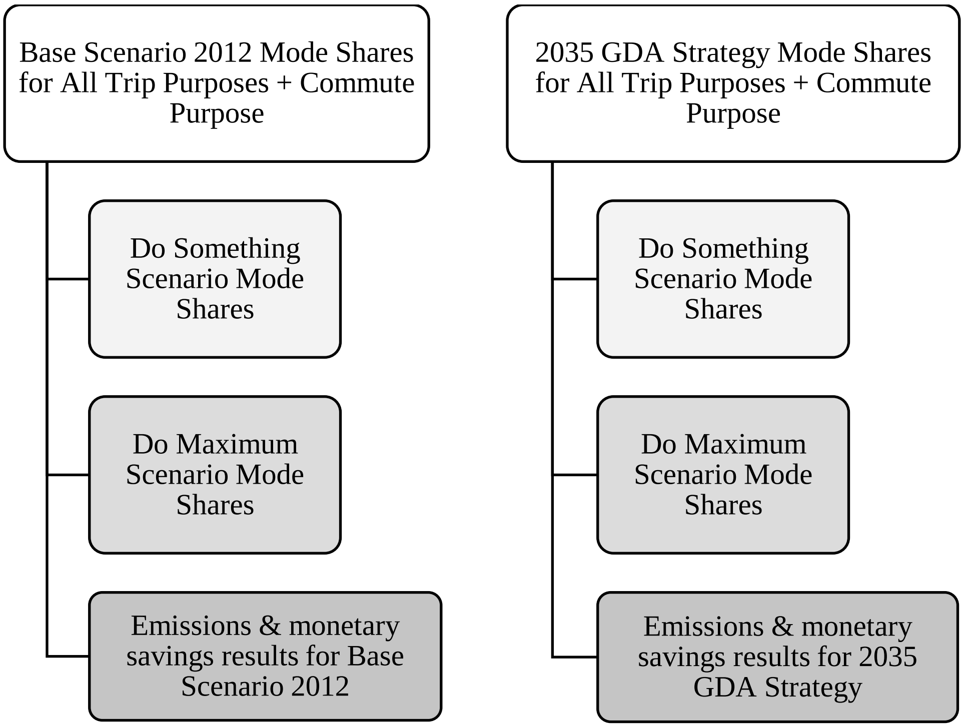

Figure 5.9 Order of model results presented in Sections 5.4 ad 5.5

5.4.1 Active Modes Changes Output

The alterations made to the walking and cycling network in the ERM were centred on increases to pedestrian and cycling speeds as proxies for improvements made to infrastructure for pedestrians and cyclists in addition to increasing pedestrian and cycling priority at junctions. The results set out in Table 5.14 show the mode shares in the GDA produced from the ERM based changes in the 2012 Base Scenario, the results produced from the 2035 GDA Strategy are then shown in Table 5.15.

In the 2012 Base Scenario Do Something scenario, shown in Table 5.14, the 25% increase in pedestrian speeds and 40% increase in cycle speeds, resulted in a 4.42% increase in the mode share of walking for all trip purposes. This was as a result of improving cycling and pedestrian infrastructure (i.e. addressing pedestrian and cyclist priority at junctions, increasing the incidence of widened and decluttered footpaths, and fully segregated cycle lanes). Of this increase 1.33% came from private cars, 2.12% from PT and 0.97% from cycling. The mode share of walking then increased further by 1.53% in the Do Maximum scenario, bringing the share to 29.85%, with 1.91% of private car users, 2.81% of PT users and 1.23% of cyclists switching to walking. The key result from this particular model run was that the largest decrease in the mode share of private cars, for all trip purposes, was achieved at 1.91%. This suggested that investing in pedestrian infrastructure in particular, could be an effective means of encouraging a mode shift away from private car usage in the GDA.

By isolating commute trips estimated in the model, it was also possible to observe the mode choice behaviour of commuters in the GDA. The mode share for private cars was markedly higher for commute trips at 72.89% for the Base scenario, which marginally fell to 72.08% in the Do Something scenario. Walking was found to have the only increase across the modes, with an increase of 2.38% in the Do Something scenario and 3.17% in the Do Maximum scenario. Of this 3.17% increase in the Do Maximum scenario, 1.67% came from PT, 0.76% from cyclists and 0.75% came from private car users shifting to walking. These results showed, given infrastructure improvements made in both the pedestrian and cycling network, that pedestrians could be more sensitive to such changes than cyclists, represented by the mode share increases for walking and decreases for cycling. Which suggested that, if walk trip times were reduced due to shorter wait times at junctions, and wider and de-cluttered footpaths, cyclists (who were also incentivised) along with PT users and private car drivers, would be attracted to mode shift to walking.

Table 5.14 Active modes (walking and cycling) changes output for the 2012 Base Scenario

All Trip Purposes (2012 Strategy)					
Base Scenario		Do Something Scenario 25% increase in Ped. speeds and 40% increase in cycle speeds		Do Maximum Scenario 35% increase in Ped. speeds and 60% increase in cycle speeds	
No. of Trips:	5,048,523	No. of Trips:	5,050,470	No. of Trips:	5,050,691
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	62.23	60.90	-1.33	60.32	-1.91
PT	9.69	7.57	-2.12	6.88	-2.81
Walk	23.90	28.32	+4.42	29.85	+5.95
Cycle	4.18	3.21	-0.97	2.95	-1.23
Total	100.00	100.00		100.00	
Commute Trip Purpose (Base Scenario 2012)					
Base Scenario		Do Something Scenario 25% increase in Ped. speeds and 40% increase in cycle speeds		Do Maximum Scenario 35% increase in Ped. speeds and 60% increase in cycle speeds	
No. of Trips:	1,046,797	No. of Trips:	1,047,419	No. of Trips:	1,047,515
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	72.89	72.08	-0.81	72.14	-0.75
PT	10.58	9.58	-1.00	8.91	-1.67
Walk	12.78	15.16	+2.38	15.95	+3.17
Cycle	3.75	3.19	-0.57	3.00	-0.76
Total	100.00	100.00		100.00	

The mode share output from the 2035 GDA Strategy model runs, shown in Table 5.15, comprised of the introduction of large public transport projects such as Metro North, new Luas lines and the Bus Connects project (see Section 5.2.2). This increase in the availability of PT modes was reflected in the Base Scenario mode shares, which showed a mode split of 58.40% for Car, 16.18% for PT, 22.18% for Walk, and 3.24% for Cycle. This equated to an increase in the mode share of PT of 6.49%, from the 2012 Base Scenario to the 2035 GDA Strategy. The share of private cars in 2035 was also found to be noticeably lower when compared to 2012, in response to the range of projects introduced in the period of the 2035 strategy, as this mode share fell by 3.83%, from 62.23% to 58.40% during this period.

However, the aim of the changes in the active modes scenario was to further incentivise walking and cycling over other modes in the model. This was represented in 2035 mode shares output from the Do Something and Maximum scenarios, shown in Table 5.15, where, the mode share of walking rose by up to 6.30% in the Do Maximum scenario for all trip purposes and 3% for the commute trip purpose only. Pedestrians were again more elastic to changes in speeds than cyclists as there were decreases in the mode shares of cycling of up to 0.96% for all trip purposes and up to 0.51% for the commute trip purpose. Nevertheless, the model modifications made to cycling and pedestrian speeds also came at the cost of a significant mode shift away from PT modes, similarly shown in the 2012 scenario. In the 2035 scenario, reductions in the mode share of PT of up to 4.07% in the Do Maximum scenario for all trip purposes, and up to 2.12% for the commute purpose alone, were estimated. In this scenario, such a significant shift away from PT would not necessarily be a negative consequence given the large increase in the mode shares of walking and reduction in private car trips. Overall, these results showed that the introduction of the active mode incentives outlined in Table 5.3 resulted in a 4.58% increase in the mode share of walking from the Base case scenario 2012 to the Do Maximum 2035 Strategy.

Table 5.15 Active mode changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)					
Base Scenario		Do Something Scenario 25% increase in Ped. speeds and 40% increase in cycle speeds		Do Maximum Scenario 35% increase in Ped. speeds and 60% increase in cycle speeds	
No. of Trips:	5,984,781	No. of Trips:	5,987,783	No. of Trips:	5,991,301
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	58.40	57.68	-0.72	57.07	-1.33
PT	16.18	13.20	-2.98	12.11	-4.07
Walk	22.18	26.83	+4.65	28.48	+6.30
Cycle	3.24	2.29	-0.96	2.35	-0.89
Total	100.00	100.00		100.00	
Commute Trip Purpose (2035 Strategy)					
Base Scenario		Do Something Scenario 25% increase in Ped. speeds and 40% increase in cycle speeds		Do Maximum Scenario 35% increase in Ped. speeds and 60% increase in cycle speeds	
No. of Trips:	1,268,512	No. of Trips:	1,266,550	No. of Trips:	1,266,948
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	68.76	68.20	-0.56	68.26	-0.50
PT	18.75	17.58	-1.17	16.64	-2.12
Walk	10.35	12.59	+2.25	13.35	+3.00
Cycle	2.14	1.63	-0.51	1.76	-0.38
Total	100.00	100.00		100.00	

Mode shares within the Inner Metropolitan Area (see Figure 5.2) of the GDA were also examined in the Active Modes scenarios, as a means of comparison between the mode shares of private cars, considering distances travelled by active modes users (Caulfield, 2014). The table of results for the 2012 Base Scenario and 2035 Strategy are displayed in Appendix C of this thesis.

The 2012 Base Scenario mode share results for the Inner Metropolitan Area of the GDA, estimated that a reduction in the mode share of private cars of up to 2.69% for all trip purposes and 1.01 for the commuting purpose, could be achieved in the Do Maximum scenario. These results were also in response to a 35% increase in pedestrian speeds and a 60% increase in cycle speeds as a result of upgrading active mode infrastructure in this area. The results are notable as they were found to be the highest reductions in the mode share of private cars recorded as part of this study. This suggested, as expected, that incentives for walking and cycling could be most effectively implemented in inner metropolitan areas, where there is higher population density and an accumulation of centres of employment. The policy measures tested in this model run were found to result in an increase of up to an 8.78% in the mode share of walking for all trip purposes and 4.43% for commuting trips. This was shown to increase the mode share of walking to 39.23%. Of this increase in walking, a mode shift of 2.69% came from private cars, 4.26% from PT and 1.84% from cyclists shifting to walking for all trip purposes.

For commuting trips, a 1.01% switch from cars, 2.37% from bus and rail, and 1.05% from cyclists were estimated. The reduction in cycling trips was again found to be an adverse effect of people favouring improvements made to the pedestrian network over improvements in the cycling network.

The walking mode share results estimated in the 2035 GDA Strategy for the Inner Metropolitan Area (see Appendix C) were higher as an increase of 9.28% for all trip purposes and 4.61% for commuting purposes were found. These increases in walking were, however, coupled with large shifts away from PT of up to 6.28% for all trips and 3.07% for commute trips in the Do Maximum scenario. Moreover, it was found that reductions in the mode share of private cars from introducing the active mode policy incentives were projected to be higher in the Inner Metropolitan Area of the GDA in 2035 than in the rest of the GDA, as a 1.85% reduction was found for all trip purposes and a 1.09% reduction for commute trips.

The results generated from the changes to pedestrian and cycling networks were found to be comparable to those produced by O'Fallon, et al. (2004), and Mackett (2001), who determined that an increase in the incidence of cycle lanes did not have a statistically significant impact on cycle mode shares in relation to encouraging a mode shift from SOV use to cycling. These studies concluded that only 2% of car drivers would be willing to shift to cycling given infrastructural improvements made to the cycle network. The mode share findings from the cycle speed only changes, as opposed to both pedestrian and cycle speeds, (see Appendix C), showed that only a 1.05% increase in cycling could be achieved in the GDA across the two modelled years, of which the majority of this modal shift came directly from private car commute trips (1.08%).

5.4.2 Public Transport Changes Output

The network changes applied to the PT (bus and rail) networks were reductions made to service headways and fares, to account for reducing time and cost parameters of travelling by bus or rail in the GDA. In the 2012 Base Scenario, shown in Table 5.16, the changes in the PT network resulted in an increase in PT trips of 1.34% in the Do Something and 2.08% in the Do Maximum scenario. Of this increase in the Do Maximum scenario, 0.52% came from private cars, 1.03% from walking and 0.53% from cycling. These mode shifts were as a result of decreasing headways and fares of bus and rail services in the GDA by 35% as proxies for quicker, more frequent and cheaper PT trips.

The mode shares from commute trips produced a 2.19% increase in the mode share of PT modes in the Do Something scenario, and a 2.87% increase in the Do Maximum scenario. The majority of this mode shift came from private cars where, up to 1.76% switched to PT, followed by cycling at 0.57% and walking at 0.54%. Thus, these findings suggested that reductions made to headways and fares influenced a direct modal shift from private cars to bus and rail services for those commuting to work.

Table 5.16 PT (bus and rail) changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)					
Base Scenario		Do Something Scenario 25% decrease in headways and fares		Do Maximum Scenario 35% decrease in headways and fares	
No. of Trips:	5,048,523	No. of Trips:	5,047,423	No. of Trips:	5,064,850
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	62.23	61.95	-0.28	61.71	-0.52
PT	9.69	11.03	+1.34	11.77	+2.08
Walk	23.90	23.22	-0.68	22.87	-1.03
Cycle	4.18	3.80	-0.38	3.65	-0.53
Total	100.00	100.00		100.00	
Commute Trip Purpose (Base Scenario 2012)					
Base Scenario		Do Something Scenario 25% decrease in headways and fares		Do Maximum Scenario 35% decrease in headways and fares	
No. of Trips:	1,046,797	No. of Trips:	1,046,850	No. of Trips:	1,046,765
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	72.89	71.41	-1.48	71.13	-1.76
PT	10.58	12.77	+2.19	13.45	+2.87
Walk	12.78	12.44	-0.34	12.24	-0.54
Cycle	3.75	3.39	-0.36	3.18	-0.57
Total	100.00	100.00		100.00	

The 2035 GDA Strategy results, outlined in Table 5.17, showed smaller increases in PT mode shares than the 2012 scenario. However, these increases were made in addition to the higher mode share of PT in 2035 given the range of PT projects included in the strategy. For all trips, the PT mode share grew to 17.37% in the Do Maximum scenario, representing a 1.19% increase. Yet, only 0.07% of this shift came from private cars, as larger shifts were found from cycling and walking to PT with reductions of 0.82% and 0.30%, respectively. The PT mode share for commuters (second half of Table 5.17) resulted in an increase of up to 1.42% in the Do Maximum scenario. The share of PT for commute trips represented the highest mode share for PT across all of the runs conducted in this research at 20.17%. The majority of this shift came from private cars at 0.99%. Overall, the results presented in this scenario showed an increase in PT of 7.68% from the 2012 Base case scenario to the Do Maximum scenario in the 2035 forecast.

Table 5.17 PT changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)					
Base Scenario		Do Something Scenario 25% decrease in headways and fares		Do Maximum Scenario 35% decrease in headways and fares	
No. of Trips:	5,984,781	No. of Trips:	5,987,610	No. of Trips:	5,986,137
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	58.40	58.53	+0.13	58.33	-0.07
PT	16.18	16.82	+0.64	17.37	+1.19
Walk	22.18	21.62	-0.56	21.36	-0.82
Cycle	3.24	3.03	-0.21	2.94	-0.30
Total	100.00	100.00		100.00	
Commute Trip Purpose (2035 Strategy)					
Base Scenario		Do Something Scenario 25% decrease in headways and fares		Do Maximum Scenario 35% decrease in headways and fares	
No. of Trips:	1,268,512	No. of Trips:	1,266,159	No. of Trips:	1,266,313
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	68.76	67.90	-0.86	67.77	-0.99
PT	18.75	19.82	+1.06	20.17	+1.42
Walk	10.35	10.25	-0.10	10.11	-0.24
Cycle	2.14	2.04	-0.10	1.95	-0.19
Total	100.00	100.00		100.00	

5.4.3 Carpooling changes Output

Mode share changes based on increasing private car occupancy level values are unique in comparison to the other parameter changes tested in the ERM. In this case an increase in the mode share of private cars would be a relatively positive outcome, if such an increase were accompanied by reduced vkms travelled by private cars. Decreases in vkms travelled by private cars would account for more commuters shifting to carpooling as a mode, as opposed to driving alone. Akin to the other parameter changes in this study, there were two levels of change, one in the Do Something scenario: a 25% increase in car occupancy levels, and the second: a 35% increase in occupancy levels in the Do Maximum scenario. The Do Something scenario results for the 2012 Base Scenario, outlined in Table 5.18, showed a 0.61% increase in the private car mode share for all trips, with shifts away from other modes, i.e. -0.28% for PT, -0.23% for walk, and -0.10% for cycle. The private car mode share then increased further by an extra 0.17% in the Do Maximum scenario to bring the mode share up to 63.01%. In this scenario the largest shift came from PT at 0.38%, followed by walking at 0.27%, and finally 0.13% from cycling. For commute trips, the mode share changes were not as high as for all trip purposes, meaning that those travelling for other trip purposes were also attracted to carpooling as a mode, given the incentives offered (i.e. free tolls and parking, HOV lanes, etc.).

For commute trips, the increase in private car trips was estimated to be 0.21% in the Do Something scenario, and 0.58% in the Do Maximum scenario. These increases were facilitated by marginal reductions in the mode shares of other modes, with the highest shift coming from PT at 0.47% in the Do Maximum scenario.

Table 5.18 Carpooling changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)					
Base Scenario		Do Something Scenario 25% increase in car occupancy values		Do Maximum Scenario 35% increase in car occupancy values	
No. of Trips:	5,048,523	No. of Trips:	5,048,587	No. of Trips:	5,049,031
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	62.23	62.84	+0.61	63.01	+0.78
PT	9.69	9.41	-0.28	9.31	-0.38
Walk	23.90	23.67	-0.23	23.63	-0.27
Cycle	4.18	4.08	-0.10	4.05	-0.13
Total	100.00	100.00		100.00	
Commute Trip Purpose (Base Scenario 2012)					
Base Scenario		Do Something Scenario 25% increase in car occupancy values		Do Maximum Scenario 35% increase in car occupancy values	
No. of Trips:	1,046,797	No. of Trips:	1,047,407	No. of Trips:	1,047,289
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	72.89	73.10	+0.21	73.47	+0.58
PT	10.58	10.39	-0.19	10.10	-0.47
Walk	12.78	12.75	-0.03	12.73	-0.05
Cycle	3.75	3.76	0.01	3.70	-0.06
Total	100.00	100.00		100.00	

Changes made to car occupancy level values in the 2035 GDA Strategy, presented in Table 5.19, resulted in higher modal shifts to private cars than in the 2012 Base Scenario. In the Do Something scenario, for all trips, a mode shift to private car use of 1.19% was found, based on the 25% increase in car occupancy values. In the Do Maximum scenario this figure increased to 1.83%, based on the 35% increase in car occupancy values. More pedestrians were estimated to shift to carpooling (0.84%) in the Do Something scenario than the Do Maximum. In the Do Maximum scenario 1.12% of PT users were estimated to shift away from bus and rail use to private car usage. For commute trips, the private car mode share changes were broadly in line with those for all trip purposes, though fewer pedestrians and cyclists were likely to shift to private cars than in the results for all trips, and finally, 1.75% of PT commuters were estimated to switch to the car given the carpooling incentives offered in Table 5.3.

Table 5.19 Carpooling changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)					
Base Scenario		Do Something Scenario 25% increase in car occupancy values		Do Maximum Scenario 35% increase in car occupancy values	
No. of Trips:	5,984,781	No. of Trips:	5,984,605	No. of Trips:	5,986,252
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	58.40	59.59	+1.19	60.23	+1.83
PT	16.18	16.13	-0.05	15.06	-1.12
Walk	22.18	21.34	-0.84	21.65	-0.53
Cycle	3.24	2.94	-0.30	3.06	-0.18
Total	100.00	100.00		100.00	
Commute Trip Purpose (2035 Strategy)					
Base Scenario		Do Something Scenario 25% increase in car occupancy values		Do Maximum Scenario 35% increase in car occupancy values	
No. of Trips:	1,268,512	No. of Trips:	1,266,467	No. of Trips:	1,266,514
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	68.76	69.79	+1.03	70.57	+1.81
PT	18.75	18.04	-0.71	17.00	-1.75
Walk	10.35	10.19	-0.16	10.31	-0.04
Cycle	2.14	1.98	-0.16	2.12	-0.02
Total	100.00	100.00		100.00	

Overall, a mode shift to private cars of up to 1.83% was found as a result of introducing incentives to make shared car usage more attractive, represented by a modification to car occupancy values in the ERM. However, in order to verify that those switching to this mode were not entirely SOV trips, it was necessary to analyse the vkms travelled from the base scenario in comparison to the Do Something and Do Maximum scenarios modelled. The vkms results for all scenarios in the 2012 Base Scenario and the 2035 GDA Strategy are presented in Table 5.20. These results showed, in the 2012 scenario, that a daily reduction up to 1,264,019kms in Car Commute trips and 17,285kms in Car Education trips could be achieved as result of increasing the car occupancy level by 35% in the Do Maximum scenario. In the 2035 Strategy the vkm reductions were slightly lower at 1,186,072kms for commute trips and 7,420kms for education trips in the Do Something scenario, before rising again in the Do Maximum scenario.

These results suggested that, while there were notable increases in the mode share of private cars of 1.81%, as a result of making modifications to car occupancy level values in the ERM, this increase was accompanied by lower vkms travelled. This in turn suggested that those who mode shifted to the private car, were likely to be carpoolers and not those opting to commute in SOVs. Thus, the results in this scenario found that a sustainable mode shift, in the form of smarter usage of the private car (i.e. carpooling), could be achieved by offering incentives, that result in time and cost savings, such as free parking, free road tolls and HOV lanes etc., to commuters in the GDA.

Table 5.20 Daily (AM-PM Peaks) vehicle kilometres travelled from the Carpooling scenarios in the 2012 Base Scenario and 2035 GDA Strategy

2012 Base Scenario	Base	Do Some		Do Max	
	Km (‘000)	Km (‘000)	Diff. from base (km)	Km (‘000)	Diff. from base (km)
Car Employer's Business	1,575	1,599	+23,765	1,604	+29,158
Car Commute	6,814	5,832	-981,824	5,550	-1,264,019
Car Education	102	89	-12,953	85	-17,285
Car Other	9,779	9,925	+146,547	9,962	+183,425
Bus	174	174	-5	170	-4,317
DART	185	179	-6,548	175	-9,683
Luas	184	176	-7,804	175	-9,000
2035 GDA Strategy	Base	Do Some		Do Max	
	Km (‘000)	Km (‘000)	Diff. from base (km)	Km (‘000)	Diff. from base (km)
Car Employer's Business	1,680	1,774	+94,927	1,885	+205,962
Car Commute	8,881	7,695	-1,186,072	10,226	+1,344,698
Car Education	94	87	-7,420	121	+26,421
Car Other	10,354	10,769	+415,250	1,321	+489,092
Bus	1,361	1,345	-16,187	1,321	-40,110
DART	1,009	905	-103,687	888	-120,582
Luas	311	277	-33,952	271	-39,471

5.4.4 Optimal Car-shedding Model Output

The stepwise parameter modifications up to this point have tested the behavioural response of the population of the GDA to a range of policy incentives, that were run in isolation of each other. Each of these parameter changes aimed to make alternative modes more attractive to potential commuters, by introducing time and cost savings, enhancements to the convenience of taking the mode and addressing issues of risk and safety in taking active modes. To examine the overall impact of introducing these policy measures together, each of the model parameter modifications were then run in tandem with each other in one model run for each scenario. An overview of all the modifications included in the ‘Optimal Car-shedding’ model runs for both the 2012 Base Scenario and 2035 GDA Strategy is as follows:

- Do Something scenario: 25% increase in pedestrian speeds and 40% in cycle speeds, 25% decrease in PT headways and fares, and 25% increase in car occupancy level values
- Do Maximum scenario: 35% increase in pedestrian speeds and 60% in cycle speeds, 35% decrease in PT headways and fares, and 35% increase in car occupancy level values

The Optimal Car-shedding model results for the 2012 Base Scenario, shown in Table 5.21, highlight the sensitivity of the changes made to pedestrian speed, given the large increases in the mode share of walking for all trips amid the other parameter changes made to cycling, PT and private car occupancy. Increases in the mode share of walking of 3.62% in the Do Something scenario, and 4.86% in the Do Maximum scenario were estimated. While time and cost savings and enhancements to the convenience of cycling, PT and carpooling were made, these improvements did not elicit elastic behavioural responses like the increases in pedestrian speeds were estimated to. For instance, in the Do Something scenario there were reductions in the mode share of PT of 1.31%, in cycling of 1.26%, and in private cars of 1.06%. In the Do Maximum scenario, shifts away from other modes to walking were evenly spread with the highest shift coming from PT at 1.69%.

For commute trips, in the Do Maximum scenario there was a marginal increase of 0.22% in the mode share of private cars, signifying a minor shift to carpooling as a result of offering incentives such as free parking, HOV lanes and cost subsidies for opting to carpool. The walking mode share for commute trips also increased, by up to 2.40% across the two scenarios, with mode shifts coming from cycling (1.38%) and PT modes (1.24%).

Table 5.21 Optimal Car-shedding model output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)					
Base Scenario		Do Something Scenario All parameter changes		Do Maximum Scenario All parameter changes	
No. of Trips:	5,048,523	No. of Trips:	5,048,984	No. of Trips:	5,048,563
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	62.23	61.17	-1.06	60.63	-1.60
PT	9.69	8.38	-1.31	8.00	-1.69
Walk	23.90	27.52	+3.62	28.76	+4.86
Cycle	4.18	2.92	-1.26	2.61	-1.57
Total	100.00	100.00		100.00	
Commute Trip Purpose (Base Scenario 2012)					
Base Scenario		Do Something Scenario All parameter changes		Do Maximum Scenario All parameter changes	
No. of Trips:	1,046,797	No. of Trips:	1,047,772	No. of Trips:	1,047,855
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	72.89	72.87	-0.02	73.11	0.22
PT	10.58	9.83	-0.75	9.34	-1.24
Walk	12.78	14.61	+1.83	15.18	+2.40
Cycle	3.75	2.69	-1.07	2.37	-1.38
Total	100.00	100.00		100.00	

The results from the 2035 GDA Strategy model runs, presented in Table 5.22, showed that there was a higher increase in the mode share of walking than in the 2012 Base Scenario results. An increase in the mode share of walking of 5.10% was estimated in the Do Maximum scenario, with the majority of the modal shift coming from PT at 3.66% and cycling at 1.11%. There was also a marginal shift away from private cars of 0.33% in the Do Maximum scenario. These results once again highlighted the sensitivity of the mode share of pedestrians to the policy incentives offered (i.e. pedestrian priority at junctions, widened and decluttered footpaths). For commute trips, a similar trend in mode shares was found, with the main difference being an increase in the mode of the private cars of up to 1.67%, which suggested that more commuters would be willing to mode shift away from PT and cycling to carpooling and walking in the 2035 strategy.

Table 5.22 Optimal Car-shedding model output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)					
Base Scenario		Do Something Scenario All parameter changes		Do Maximum Scenario All parameter changes	
No. of Trips:	5,984,781	No. of Trips:	5,985,290	No. of Trips:	5,988,037
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	58.40	58.45	+0.06	58.07	-0.33
PT	16.18	13.37	-2.81	12.52	-3.66
Walk	22.18	26.04	+3.86	27.28	+5.10
Cycle	3.24	2.14	-1.10	2.13	-1.11
Total	100.00	100.00		100.00	
Commute Trip Purpose (2035 Strategy)					
Base Scenario		Do Something Scenario All parameter changes		Do Maximum Scenario All parameter changes	
No. of Trips:	1,268,512	No. of Trips:	1,267,187	No. of Trips:	1,267,591
Modes	Mode Share %	Mode Share %	% diff. from Base	Mode Share %	% diff. from Base
Car	68.76	69.95	+1.20	70.43	+1.67
PT	18.75	16.30	-2.45	15.20	-3.55
Walk	10.35	12.27	+1.92	12.86	+2.51
Cycle	2.14	1.48	-0.66	1.52	-0.62
Total	100.00	100.00		100.00	

To demonstrate if there was an actual increase in carpooling or simply just in SOV trips, the daily vkms travelled in the 2035 GDA Strategy, presented in Table 5.23, were consulted. These results, produced from SATURN, showed that a daily reduction of up to 1,209,651kms for commute trips and 16,928kms for education trips in the Do Something scenario, and a saving of up to 1,603,672kms and 22,981kms for commute and education trips, respectively, in the Do Maximum scenario. In this way, these results accounted for a reduction in private car usage for commute and education trips, which was found to firstly be as a result of mode shifting behaviour away from private cars and secondly, from reduced vkms travelled as a result of more commuters being incentivised to carpool.

Table 5.23 Daily (AM-PM Peaks) vehicle kilometres travelled from Optimal Car-shedding model in the 2012 Base Scenario and 2035 GDA Strategy

2012 Base Scenario	Base	Do Some		Do Max	
	Km ('000)	Km ('000)	Diff. from base (km)	Km ('000)	Diff. from base (km)
Car Employer's Business	1,575	1,569	-5,463	1,562	-12,915
Car Commute	6,814	5,824	-990,049	5,533	-1,281,217
Car Education	102	79	-23,279	72	-30,546
Car Other	9,779	9,801	+22,291	9,787	+8,304
Bus	174	207	+32,707	284	+110,166
DART	185	185	-5,213	180	-6,168
Luas	184	184	-20,535	163	-23,482
2035 GDA Strategy	Base	Do Some		Do Max	
	Km ('000)	Km ('000)	Diff. from base (km)	Km ('000)	Diff. from base (km)
Car Employer's Business	1,680	1,750	+70,327	1,755	+75,303
Car Commute	8,881	7,672	-1,209,651	7,278	-1,603,672
Car Education	94	77	-16,928	71	-22,981
Car Other	10,354	10,672	+317,798	10,719	+365,094
Bus	1,361	1,438	+77,074	1,494	+133,064
DART	1,009	897	-111,894	847	-161,811
Luas	311	234	-76,811	226	-84,789

5.5 Emissions Estimation Results

To ultimately appraise the performance of the range of policy incentives suggested in this study, a technical evaluation of the emissions from transport with the behavioural changes (i.e. mode shares) required to achieve the emissions savings was conducted (Greening Transport, 2017). As delineated in Section 5.3.5, the vkms travelled results taken from SATURN (Akins, 2017), were used to estimate daily emissions in kilograms per kilometre, produced from the various scenarios modelled by applying the mode specific emissions factors for CO_2, NO_x, $PM_{2.5}$ gases (see Table 5.12).

5.5.1 Active Mode Emissions Results

The emissions results from the 2012 Base Scenario Active Modes scenario presented in Table 5.24, show that daily emissions savings of 10.93 tonnes, (hereafter abbreviated to 't'), of CO_2, 0.03t of NO_x, and 0.0011t of $PM_{2.5}$ for car other user class trips could be achieved in the Do Maximum scenario, as a result of introducing the active mode policy incentives set out in Table 5.3. These emissions savings were accompanied by other emission reductions for private cars, for example, for private car use in work/ business travel, savings of 4.94t of CO_2, 0.011t of NO_x and 0.0005t of $PM_{2.5}$ were estimated in the Do Maximum scenario. However, as a consequence of the mode shifting behaviour from PT to active modes in this scenario, associated emissions reductions from bus, DART and Luas were similarly found. Bus, for example, experienced the largest reduction in vkms, which in total was found to be a saving of 16.44t of CO_2, 0.13t of NO_x and 0.0012t of $PM_{2.5}$ being emitted daily relative to the base total of emissions estimated. DART and Luas were also found to have lower CO_2 emissions, but to a lesser extent than bus.

Table 5.24 Active mode changes daily emissions output for the 2012 Base Scenario

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	293.45	290.31	-3.14	288.51	-4.94
Car Commute	1,269.41	1,280.72	+11.31	1,284.37	+14.96
Car Education	19.15	17.38	-1.77	16.74	-2.41
Car Other	1,821.77	1,817.18	-4.59	1,810.84	-10.93
Bus	199.10	185.19	-13.91	182.66	-16.44
DART	2.04	1.86	-0.18	1.79	-0.25
Luas	13.02	11.18	-1.84	10.58	-2.44
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.643	0.636	-0.007	0.632	-0.011
Car Commute	2.78	2.80	0.02	2.81	+0.03
Car Education	0.042	0.038	-0.004	0.037	-0.005
Car Other	3.99	3.98	-0.01	3.96	-0.03
Bus	1.61	1.47	-0.14	1.48	-0.13
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.0309	0.0306	-0.0003	0.0304	-0.0005
Car Commute	0.1338	0.1350	-0.0012	0.1354	-0.0016
Car Education	0.0020	0.0018	-0.0002	0.0017	-0.0003
Car Other	0.1920	0.1915	-0.0005	0.1909	-0.0011
Bus	0.0142	0.0132	-0.001	0.0130	-0.0012

The monetary savings associated with these emissions savings from the car user classes in the 2012 Base Scenario, were calculated using the CAF (DTTAS, 2016) recommended approach, which was set out in Table 5.13. These findings are presented in Table 5.25:

Table 5.25 Monetary savings from car user class emissions reductions in the 2012 Base Scenario

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car other	CO_2: 10.93t	144.49
	NO_x: 0.03t	175.53
	$PM_{2.5}$: 0.0011t	220.26
Car Employment/ Business	CO_2: 4.94t	65.31
	NO_x: 0.011t	64.36
	$PM_{2.5}$: 0.0005t	100.119
	Total (€)	770.07

In the 2035 GDA Strategy, the emissions results shown in Table 5.26, estimated that for car education trips in the Do Maximum scenario, in total 2.01t of CO_2, 0.01t of NO_x would be saved daily from encouraging a mode shift away from car use to walking and cycling. However, like in the 2012 Base Scenario results, incentivisation of active modes resulted a decrease in usage of PT as these modes remained constant or unaffected by the policies in this scenario.

This fall in PT usage led to a daily reduction of 205.42t in CO_2, 1.66t in NO_x and 0.015t in $PM_{2.5}$, for buses in the GDA. The reductions in emissions from buses along with other reductions in emissions from DART and Luas, were in accordance with the reductions in the mode share of PT examined in Section 5.4.2.

Table 5.26 Active mode changes daily emissions output for the 2035 GDA Strategy

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	312.96	317.87	+4.91	316.17	+3.21
Car Commute	1,654.59	1,669.11	+14.52	1,668.67	+14.08
Car Education	17.65	16.32	-1.33	15.64	-2.01
Car Other	1,928.89	1,952.66	+23.77	1,946.58	+17.69
Bus	1,551.32	1,408.33	-142.99	1,345.89	-205.43
DART	11.10	9.73	-1.37	9.35	-1.75
Luas	21.97	17.61	-4.36	16.36	-5.61
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.69	0.70	+0.01	0.69	0.00
Car Commute	3.62	3.66	+0.04	3.65	+0.03
Car Education	0.04	0.04	0.00	0.03	-0.01
Car Other	4.22	4.28	+0.06	4.26	+0.04
Bus	12.54	11.38	-1.16	10.88	-1.66
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.03	0.03	0.00	0.03	0.00
Car Commute	0.17	0.18	+0.01	0.18	+0.01
Car Education	0.002	0.002	0.00	0.002	0.00
Car Other	0.20	0.21	+0.01	0.21	+0.01
Bus	0.11	0.10	-0.01	0.10	-0.01

The daily cost savings that were calculated as a result implementing the range of policies in the 2035 GDA Strategy, are shown in Table 5.27:

Table 5.27 Monetary savings from car user class emissions reductions in the 2035 GDA Strategy

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car Education	CO_2: 2.01t	26.57
	NO_x: 0.01t	58.51
	$PM_{2.5}$: 0.00t	00.00
	Total (€)	85.08

5.5.2 PT Emissions Results

The changes in emissions produced from the PT scenarios in the 2012 Base Scenario are presented in Table 5.28. These emissions were based on variations in vkms, as a result of modifications made to headways and fares in the ERM. The results from Table 5.28 show that reductions of 431.58t in CO_2, 0.95t in NO_x and 0.046t in $PM_{2.5}$ could be attained for commute trips in the GDA in Do Something scenario. These emissions savings were higher than those recorded in the 2012 Base Scenario of the Active Modes scenario, which represented the reduction in vkms for car commute trips as a result of PT modes being incentivised. Car trips for employment or business purposes also produced emissions reductions in this scenario, with 37.02t of CO_2, 0.08t of NO_x and 0.004t of $PM_{2.5}$ being saved in the Do Something scenario. In the Do Maximum scenario, the emissions generated for the car user classes were lower than in the Do Something scenario, with the exception of car other trips. However, in response to mode shifting behaviour from active modes and private cars to PT in this scenario, a resultant rise in emissions for bus, train and Luas was subsequently found, which was expected given the higher frequency of service in order to meet the shorter headway times modelled in the network.

Table 5.28 PT changes emissions daily output for the 2012 Base Scenario

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	293.45	256.43	-37.02	290.54	-2.91
Car Commute	1,269.41	837.83	-431.58	1,258.36	-11.05
Car Education	19.15	507.29	+488.14	18.23	-0.92
Car Other	1,821.77	1,811.48	-10.29	1,805.98	-15.79
Bus	199.10	236.36	+37.26	324.61	+125.51
DART	2.04	2.38	+0.34	2.55	+0.51
Luas	13.02	14.56	+1.54	15.46	+2.44
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.64	0.56	-0.08	0.64	0.00
Car Commute	2.78	1.83	-0.95	2.76	-0.02
Car Education	0.04	1.11	+1.07	0.04	0.00
Car Other	3.99	3.97	-0.02	3.95	-0.04
Bus	1.61	1.91	+0.30	2.62	+1.01
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.031	0.027	-0.004	0.031	0.00
Car Commute	0.134	0.088	-0.046	0.133	-0.001
Car Education	0.002	0.053	+0.051	0.002	-0.00
Car Other	0.192	0.191	-0.001	0.190	-0.002
Bus	0.014	0.017	+0.003	0.023	+0.009

The daily emissions savings recorded for the car commute and employment use purposes in the 2012 Base Scenario were then used to estimate the following daily cost savings:

Table 5.29 Monetary savings from car user class emissions reductions in the 2012 Base Scenario

User Class	Daily Emissions Savings (t)	Daily Monetary Savings (€)
Car Commute	CO_2: 431.58t	5,705.48
	NO_x: 0.95t	5,558.45
	$PM_{2.5}$: 0.046t	9,210.99
Car Employment/ Business	CO_2: 37.02t	489.40
	NO_x: 0.08t	468.08
	$PM_{2.5}$: 0.004t	800.96
	Total (€)	22,223.36

In the 2035 GDA Strategy there were relativity minor reductions in emissions over the base scenario, given the mode shift to PT between the 2012 Base Scenario and 2035 Strategy with the inclusion of Metro North, Bus Connects and DART and Luas expansions. However, Table 5.30 shows that in addition to these infrastructural changes, the policy incentives tested in this study were found to result in an added reduction of 1.19t of CO_2, 0.002t of NO_x and 0.0001t of $PM_{2.5}$ a day for car business use trips, and 0.11t of CO_2, 0.001t of NO_x and 0.0001t of $PM_{2.5}$ for car education trips, in the Do Maximum scenario. These two car user classes were the only ones to experience a reduction in emissions over the two scenarios modelled (i.e. Do Something, Do Maximum) in this scenario, which represented the difficulty in encouraging a further reduction in car mode shares over that already achieved in the 2035 GDA Strategy, as discussed in Section 5.2.2.

Table 5.30 PT changes emissions daily output for the 2035 GDA Strategy

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	312.96	312.92	-0.04	311.77	-1.19
Car Commute	1,654.59	1,660.75	+6.16	1,657.34	+2.75
Car Education	17.65	17.77	+0.12	17.54	-0.11
Car Other	1,928.89	1,944.70	+15.81	1,937.90	+9.01
Bus	1,551.32	1,977.00	+425.68	1,977.00	+425.68
DART	11.10	11.67	+0.57	11.77	+0.67
Luas	21.97	20.73	-1.24	22.10	+0.13
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.685	0.685	0.00	0.683	-0.002
Car Commute	3.62	3.64	+0.02	3.63	+0.01
Car Education	0.039	0.038	+0.001	0.038	-0.001
Car Other	4.22	4.26	+0.04	4.24	+0.02
Bus	12.54	15.98	+3.44	15.98	+3.44
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.0330	0.0330	0.00	0.0329	-0.0001
Car Commute	0.174	0.175	+0.001	0.175	+0.001
Car Education	0.0019	0.0019	0.00	0.0018	-0.0001
Car Other	0.203	0.205	+0.002	0.204	0.001
Bus	0.11	0.14	+0.03	0.14	+0.03

However, these emissions reductions calculated in the 2035 scenarios modelled in this study were still found to result in the following daily monetary savings for CO_2, NO_x, and $PM_{2.5}$:

Table 5.31 Monetary savings from car user class emissions reductions in the 2035 GDA Strategy

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car Employment/ Business	CO_2: 1.19t	15.73
	NO_x: 0.002t	11.70
	$PM_{2.5}$: 0.0001t	20.02
Car Education	CO_2: 0.11t	1.45
	NO_x: 0.001t	5.85
	$PM_{2.5}$: 0.0001t	2.02
	Total (€)	56.77

5.5.3 Carpooling Emissions Results

The 2012 Base Scenario emission results for the carpooling scenario tested in this study are presented in Table 5.32. These results show the effect of incentivising car users in the GDA to take up carpooling through various policy measures that lead to short trip times and costs and an enhancement in the convenience of carpooling, by increasing the occupancy of private cars. These findings are a representation of how individuals in the GDA could make more sustainable use of the car and in this way also help to reduce emissions from shared-use trips. Table 5.32 shows that in the Do Maximum scenario, 235.47t of CO_2, 0.88t of NO_x and 0.025t of $PM_{2.5}$ could be saved from car commute trips as a result of increasing occupancy levels of private vehicles by 35%. While the same model parameter modifications were made to education trip purposes, this resulted in lower daily emissions savings of 3.22t in CO_2, 0.01t in NO_x and 0.0002t in $PM_{2.5}$. As the incentives offered in the Carpooling Model resulted in mode shifting behaviour from PT and active modes to private car use in the form of carpooling, this as intended, also had the effect of reduced emissions being produced from PT from a decrease in bus and rail use and in vkms travelled. The PT emissions savings are also presented in Table 5.32, of which Luas trips were found to decrease more in the Do Something scenario, and Bus trips led to more emissions reductions in the Do Maximum scenario.

Table 5.32 Carpooling changes daily emissions output for the 2012 Base Scenario

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	293.45	297.88	+4.43	298.88	+5.43
Car Commute	1,269.41	1,086.51	-182.9	1,033.94	-235.47
Car Education	19.15	16.74	-2.41	15.93	-3.22
Car Other	1,821.77	1,849.07	+27.3	1,855.94	+34.17
Bus	199.10	199.09	-0.01	194.18	-4.92
DART	2.04	1.97	-0.07	1.94	-0.1
Luas	13.02	12.47	-0.55	12.39	-0.63
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.64	0.65	+0.01	0.85	+0.21
Car Commute	2.78	2.38	-0.40	3.66	-0.88
Car Education	0.04	0.03	-0.01	0.05	+0.01
Car Other	3.99	4.05	+0.06	5.25	+1.26
Bus	1.6095	1.6094	-0.0001	2.6241	+1.0146
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.0309	0.0314	0.0005	0.0315	+0.0006
Car Commute	0.1338	0.1145	-0.0193	0.1090	-0.0248
Car Education	0.0020	0.0018	-0.0002	0.0017	-0.0003
Car Other	0.192	0.195	+0.003	0.196	+0.004
Bus	0.0142	0.0142	0.00	0.0138	-0.0004

The cost savings associated with the emission savings for car commute and education trips in the 2012 Base Scenario are presented in Table 5.33.

Table 5.33 Monetary savings from car user class emissions reductions in the 2012 Base Scenario

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car Commute	CO_2: 235.47t	3,112.91
	NO_x: 0.88t	5,148.88
	$PM_{2.5}$: 0.025t	5,005.97
Car Education	CO_2: 3.22t	42.57
	NO_x: 0.01t	58.51
	$PM_{2.5}$: 0.0002t	40.04
	Total (€)	11,408.88

In the 2035 GDA Strategy, a similar trend in emissions reductions was found in car commute and education trips. Table 5.34 shows that up to 220.95t of CO_2, 0.48t of NO_x and 0.023t of $PM_{2.5}$ could be saved in the Do Something scenario as a result of increasing occupancy levels of the commuter user class by 25% in the GDA. This is in addition to 1.38t of CO_2, 0.003t of NO_x and 0.0002t of $PM_{2.5}$ being saved for education trips in the same scenario. However, in the Do Maximum scenario no such savings were recorded for private car trips, suggesting that increasing the occupancy level of private cars by 35% could result in a daily increase, rather than decrease, in vkms travelled for private cars. This is line with the vkms findings presented in Table 5.19 in Section 5.4.3. In parallel with the 2012 Base Scenario scenarios, the associated reduction in PT vkms resulted in emissions savings for bus, train and Luas, as shown in Table 5.34, with bus trips found to produce the highest emissions reductions.

Table 5.34 Carpooling changes daily emissions output for the 2035 GDA Strategy

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	312.96	330.65	+17.69	351.33	+38.37
Car Commute	1,654.59	1,433.64	-220.95	1,905.08	+250.49
Car Education	17.65	16.26	-1.38	22.57	+4.92
Car Other	1,928.89	2,006.24	+77.35	2,020.00	+91.11
Bus	1,551.32	1,532.87	-18.45	1,505.62	-45.70
DART	11.10	9.96	-1.14	9.78	-1.32
Luas	21.97	19.57	-2.40	19.18	-2.79
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.69	0.72	+0.03	0.77	+0.08
Car Commute	3.62	3.14	-0.48	4.17	+0.55
Car Education	0.039	0.036	-0.003	0.049	+0.01
Car Other	4.22	4.39	+0.17	4.42	+0.20
Bus	12.54	12.39	-0.15	12.17	-0.37
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.033	0.035	+0.002	0.037	+0.004
Car Commute	0.17	0.15	-0.023	0.20	+0.03
Car Education	0.0019	0.0017	-0.0002	0.0024	+0.0005
Car Other	0.203	0.211	+0.008	0.213	+0.01
Bus	0.110	0.109	-0.001	0.107	-0.003

The emissions savings for the car commute and education trips were found to produce the following daily monetary savings as a result of implementing the CAF (DTTAS, 2016) approach:

Table 5.35 Monetary savings from car user class emissions reductions in the 2035 GDA Strategy

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car Commute	CO_2: 220.95t	2,920.95
	NO_x: 0.48t	2,808.48
	$PM_{2.5}$: 0.023t	4,605.50
Car Education	CO_2: 1.38t	18.24
	NO_x: 0.003t	17.55
	$PM_{2.5}$: 0.0002t	40.05
	Total (€)	10,410.77

5.5.4 Optimal Car-shedding Model Emissions Results

The emissions savings produced as a result of running all of the ERM parameter modifications, as opposed to analysing the results of one scenario in isolation, for both the 2012 Base Scenario and 2035 GDA Strategy, are presented in Tables 5.36 and 5.38. These results considered increases in pedestrian and cycle speeds, decreases in PT headways and fares, as well as increases in car occupancy levels, that were all run in conjunction with each other.

The findings from the 2012 Base Scenario, presented in Table 5.36, found that 238.67t of CO_2, 0.52t of NO_x and 0.025t of $PM_{2.5}$ could be saved for car commute trips in GDA in the Do Maximum scenario. These savings were accompanied by other reductions of 5.69t in CO_2, 0.01t in NO_x and 0.001t in $PM_{2.5}$ for car education trips. In accordance with the vkms results for the all changes scenario, shown in Table 5.23, in Section 5.4.4, the emissions savings demonstrated that while there was a minor decrease in the mode share of private cars in this scenario (see Table 5.21), this was also inclusive of more commuters and students opting to carpool rather than drive alone to work or education.

Table 5.36 Optimal Car-shedding Model daily emissions output for the 2012 Base Scenario

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	293.45	292.43	-1.02	291.04	-2.41
Car Commute	1,269.41	1,084.98	-184.43	1,030.74	-238.67
Car Education	19.15	14.82	-4.33	13.46	-5.69
Car Other	1,821.77	1,825.92	4.15	1,823.32	+1.55
Bus	199.10	236.36	37.26	324.61	+125.51
DART	2.04	1.98	-0.06	1.97	-0.07
Luas	13.02	11.57	-1.45	11.37	-1.66
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.64	0.64	0.00	0.64	-0.01
Car Commute	2.78	2.38	-0.40	2.26	-0.52
Car Education	0.04	0.03	-0.01	0.03	-0.01
Car Other	3.989	3.998	+0.009	3.992	+0.003
Bus	1.61	1.91	+0.30	2.62	1.01
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.0309	0.0308	-0.0001	0.0307	-0.0002
Car Commute	0.134	0.114	-0.02	0.109	-0.025
Car Education	0.0020	0.0016	-0.0004	0.001	-0.001
Car Other	0.1920	0.1925	+0.0005	0.1843	-0.0077
Bus	0.0142	0.0168	+0.0026	0.0231	+0.0089

The cost savings estimated for the daily emissions reductions recorded in 2012 Base Scenario are presented as follows:

Table 5.37 Monetary savings from car user class emissions reductions in the 2012 Base Scenario

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car Commute	CO_2: 238.67t	3,155.21
	NO_x: 0.52t	3,042.52
	$PM_{2.5}$: 0.025t	5,005.97
Car Education	CO_2: 5.69t	75.22
	NO_x: 0.01t	58.51
	$PM_{2.5}$: 0.001t	200.24
	Total (€)	11,537.67

In the 2035 GDA Strategy results, shown in Table 5.38, emissions savings of 298.74t of CO_2, 0.65t of NO_x and 0.031t of $PM_{2.5}$ for car commute trip purpose were estimated. These findings were in addition to emissions reductions of 4.28t of CO_2, 0.007t of NO_x and 0.0004t of $PM_{2.5}$ for car education trips in the Do Maximum scenario. When comparing the car user class emissions results produced from the 2012 Base Scenario and 2035 GDA Strategy, it was found that there were higher CO_2 emissions savings estimated in the projected 2035 scenario, but lower NO_x and $PM_{2.5}$ emissions savings than that found in the 2012 scenario.

Table 5.38 Optimal Car-shedding Model daily emissions output for the 2035 GDA Strategy

CO_2 Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	312.96	326.07	+13.11	326.99	+14.03
Car Commute	1,654.59	1,429.25	-225.34	1,355.85	-298.74
Car Education	17.65	14.49	-3.16	13.37	-4.28
Car Other	1,928.89	1,988.09	+59.20	1,996.90	+68.01
Bus	1,551.32	1,639.13	+87.81	1,702.92	+151.60
DART	11.10	9.87	-1.23	9.32	-1.78
Luas	21.97	16.55	-5.42	15.98	-5.99
NO_x Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.695	0.714	+0.019	0.716	+0.021
Car Commute	3.62	3.13	-0.49	2.97	-0.65
Car Education	0.039	0.032	-0.007	0.029	-0.001
Car Other	4.22	4.35	+0.13	4.37	+0.15
Bus	12.54	13.25	+0.71	13.77	+1.23
$PM_{2.5}$ Emissions(t)	Base	Do Some		Do Max	
	Total	Total	Diff. from base	Total	Diff. from base
Car Emp. Business	0.0330	0.0344	+0.0014	0.0345	+0.0015
Car Commute	0.17	0.15	-0.02	0.14	-0.03
Car Education	0.0019	0.0015	-0.0004	0.0014	-0.0005
Car Other	0.2033	0.2096	+0.0063	0.2105	+0.0072
Bus	0.110	0.117	+0.007	0.121	+0.011

The daily cost savings linked to the reductions in emissions in the 2035 GDA Strategy are presented in Table 5.39:

Table 5.39 Monetary savings from car user class emissions reductions in the 2035 GDA Strategy

User Class	Daily Emissions Savings (tonnes)	Daily Monetary Savings (€)
Car Commute	CO_2: 298.74t	3,949.34
	NO_x: 0.65t	3,803.15
	$PM_{2.5}$: 0.031t	6,207.41
Car Education	CO_2: 4.28t	56.59
	NO_x: 0.007t	40.96
	$PM_{2.5}$: 0.0004t	80.09
	Total (€)	14,127.54

5.6 Conclusions

This chapter has set out the rationale for, the methodology behind and results produced from the travel demand modelling of a range of policy incentives that were first tested in the SP study in Chapter 4. The research presented in this chapter was conducted to complement the results produced from the SP experiment and to further appraise the policy scenarios by analysing the real-life impacts of introducing policies that aim to intensify use of active modes, PT and smart car use modes such as carpooling.

Section 5.2 provided an overview of the use of the RMS in Ireland, with particular attention assigned to the ERM in the context of this research. In this section the mathematical framework of the choice model and the structure of the assignment model in the ERM were discussed. Section 5.3 then delineated the methodology for the model parameter changes in each of the mode specific scenarios that were run in accordance with the Do Something and Do Maximum scenarios. This was followed by the methodology for calculating the emissions savings from vkms and the monetary savings estimated from these emissions savings. Section 5.4 presented the mode share results for each of the mode-specific scenarios in the 2012 Base Scenario and 2035 GDA Strategy. These results found that pedestrians in the GDA were most sensitive to parameter changes made in ERM. This was highlighted in the active modes and the optimal car-shedding model results, where walking experienced the largest and, in some cases, the only increase in mode share. In addition to this, it was found in the carpooling model that while there were increases in the mode share of private cars, carpoolers were likely to have been the reason for this increase based on the reduction in vkms travelled results for this scenario. Thus, it was estimated that a sustainable mode shift similarly occurred in this model.

In Section 5.5, the emissions savings calculated based on the CAF (DTTAS, 2016) methodology, were presented. It was found that for various user classes of private cars - fewer emissions were produced, particularly for car commute and education trips. These results were then used to estimate monetary savings associated with the emissions reductions figures, which determined that up to €5,705 from CO_2 reductions, up to €5,558 from NO_x reductions and up to €9,210 from $PM_{2.5}$ reductions, could be saved from daily commutes.

Chapter 6 presents further a discussion of the results produced in this chapter, where findings generated from a MCA and SWOT analysis are examined, in order to identify the most appropriate policy scenario to implement based on the associated advantages and disadvantages of each scenario.

CHAPTER 6: POLICY SCENARIO ANALYSIS

6.1 Introduction

This chapter provides a comparative analysis of the policy scenarios/ plans considered in the SP experiment in Chapter 4 and the transportation modelling in Chapter 5 to determine the most cost effective and realistic policy interventions to implement in order to reduce car use for commuting trips in the GDA. This chapter merges results from the demand modelling and emission estimation into one overall policy evaluation chapter to provide an overall appraisal of the policies experimented with in this thesis, as a basis for the empirical policy recommendations.

While all of the policies tested deliver various levels of potential car-shedding (determined by behavioural indicators, mode shares and a reduction in car trips) emissions and monetary savings, it is acknowledged that due to potential budgetary and behavioural barriers as well as legislative restrictions, not all of the policies would be feasible to implement. Therefore, it was necessary to evaluate them and identify which particular policy scenario would be most suitable based on the results produced, the potential costs, in addition to considering the advantages and disadvantages of each. Accordingly, a Multi Criteria Analysis (MCA) and Strengths, Weaknesses, Opportunities and Threats (SWOT) Analysis of the three policy scenarios were conducted. Section 6.2 of this chapter introduces the methodology used and presents a brief overview of its use in strategic planning and in transportation policy appraisal. Section 6.3 will then include the MCA and SWOT analysis, which will set out how each policy is rated based on the mode share and emissions results of implementing them, in addition to considering the costs and SWOT factors associated with the intervention. Section 6.4 will then ascertain from the analysis, which policy plan has been deemed the most appropriate overall as a policy recommendation and most effective as a stimulus of car-shedding behaviour, given varying financial and regulatory restrictions.

The MCA and SWOT analyses presented in this chapter reflect on the four stage modelling results exclusively as they represent real life estimates of modal share and emissions based on observed data. A separate discussion of the policy implications of the results produced from the stated preference modelling is provided in Chapter 4, Section 4.4.

6.2 Literature on Multi Criteria Analysis and SWOT Analysis

6.2.1 Multi Criteria Analysis

Multi Criteria Analysis (MCA), sometimes referred to as Multi-Criteria Decision Analysis (MCDA), is a methodological process of comparing various attributes of objectives or policies in terms of the outcomes or impacts such as introducing a particular project or policy. It has been a popular project/ policy appraisal method applied in the field of transport since the 1970s, and commonly includes a selection of monetary and non-monetary, quantitative and qualitative criteria considered in one evaluation (Dimitriou, et al., 2016; Rogers and Duffy, 2012; Makie and Preston, 1998; Vincke, 1992). As a result of this, MCA can complement Cost Benefit Analyses (CBA) and incorporate elements of it in the MCA framework, particularly if certain parameters are not monetiseable (DTTAS, 2016). Furthermore, different types of appraisal techniques such as Environmental Impact Assessments (EIA) can also be integrated into a MCA to provide a holistic evaluation of the impact of a policy or project (Dimitriou, et al., 2016). It is particularly useful in the appraisal of environmental policy as it overcomes any inadequacies of tools such as CBA in such an evaluation, as MCA can capture the full range of impacts involved (Macharis, C., Bernardini, A., 2015; Browne and Ryan, 2011). The WebTAG framework is a frequently used example of this, in the field of transport in the UK (Department for Transport, 2017).

MCA is generally used as in performance evaluation or as a measure of effectiveness to determine whether a financial investment is worthwhile or justified, based on the likely impacts or effects of the decision, and in this way, it is helpful in comparing alternate projects to aid prioritisation and policy recommendation. MCA offers valuable guidance in decision making and can influence strategic planning assessments as it can offer a quick and cost-effective method of comparison for shortlisting competing projects (DTTAS, 2016). In the context of Ireland, the Common Appraisal Framework states that, in the accordance with the Irish Public Spending Code, projects costing from €0.5 million should be subject to a detailed appraisal including a MCA to determine the viability of certain business cases inclusive of financial and economic appraisal (DTTAS, 2016). In this way, a MCA was applied to appraise the range of policy scenarios tested in this thesis based on the potential costs of implementing each scenario and the estimated outcomes recorded in this thesis.

6.2.2 SWOT Analysis

SWOT analyses are traditionally employed to aid business, marketing and other private organisations in decision making as a framework for strategic analysis (Gibis, et al., 2001; Koch, 2000), however they are also commonly used by public entities and non-profit organisations in the same way. Strengths consider the use of a policy or resource to effectively meet or achieve a particular objective, for example the pros of introducing a Bus Rapid Transit (BRT) service or a metro line. Weaknesses, however, identify the limitations or drawbacks to a project or measure that will likely hinder progress in achieving an objective such as a lack of funding or demand for the project. Opportunities define favourable prospects afforded by implementing a policy in question, for instance the prospect of reducing car ownership; whereas threats are alerts of the unfavourable risks or hazards of introducing a measure such as limited road capacity issues (Öncel, 2009). SWOT analysis is based on the interrelationship between the internal and external environment, as strengths and weakness relate to the internal environment, while the external environmental is examined by opportunities and threats. Patagiotou (2003) outlines that SWOT analysis is an ideal tool for identifying 'internal strengths in order to take advantage of external opportunities and avoid potential internal threats, while addressing certain weaknesses'. SWOT analysis was first devised in the 1920s in the Harvard Business School, as a method of strategic assessment and has since become a key advancement in strategic thinking (Patagiotou, 2003). SWOT analysis is often also used in the ex-ante strategic evaluation of goods and services, thus, it can be effectively applied in transportation planning and in policy decision making, as it is useful in enabling proactive thinking and aiding the creation of policy recommendations. It is similarly effective in detecting potential second order effects linked to a MCA, to mitigate against unsolicited outcomes.

6.3 Policy Scenario Analysis

In this section a MCA conducted in the context of the policy scenarios tested in this thesis will be presented in Table 6.1. The data included in the MCA was sourced from the best results produced in Chapter 5 overall, as they represent real life estimates of modal share and emissions based on observed data collected from Census and National Household Travel data. As the potential costs of implementing the policies and the monetary savings attained are estimated, these factors were rated from high to low in a comparative review of the policies.

Table 6.2 will then outline a SWOT analysis conducted for the same scenarios. The findings from the SWOT analysis were produced based on reflecting on the potential costs of introducing the policies tested and the benefits and barriers of encouraging car-shedding behaviour, listed in Chapter 2, Table 2.1. First order effects of the policy implementation will be analysed by the MCA, while the SWOT analysis will consider the potential second order effects. The results generated from both the MCA and SWOT analyses, which were formulated from the viewpoint of the author, will then be used to form an overall policy recommendation when considering all of the necessary factors.

Table 6.1 Multi Criteria Analysis of implementing the policy incentives

Mode	Policy	Cost	**Estimated Outcomes** (Source: results produced from Chapter 5)		
			Mode Share Results (%)	**Emissions Results (t)**	**Daily Monetary Savings (€)**
Bus & Rail	% improvement in frequency of services % reduction in trip time % reduction in trip cost	• High: purchase of more buses and trains to meet increase in frequency in the network (based on supported evidence presented Section 6.4)	2012 Base Scenario: 1.76% reduction in car trips 2.87% increase in PT usage 2035 Strategy: 0.99% reduction in car trips 1.42% increase in PT usage	2012 Base Scenario: 431.58t reduction in CO_2 0.95t reduction in NO_x 0.046t reduction in $PM_{2.5}$ 2035 Strategy: 1.19t reduction in CO_2 0.002t reduction in NO_x 0.0001t reduction in $PM_{2.5}$	High 2012 Base Scenario: €22,223.36 2035 Strategy: €56.77
Walking & Cycling	% increase pedestrian and cycling infrastructure % reduction in trip time % reduction in adjacent traffic speed limit to 30km/h	• Low: infrastructural cost provision of cycle lanes is relatively low when compared to the PT measures (supported evidence cited in Section 6.4) • Low: Widening and decluttering of footpaths inexpensive but effective measure • Low: Reducing speed limit regulatory measure	2012 Base Scenario: 1.91% reduction in car trips 5.95% increase in walking trips 2035 Strategy: 1.33% reduction in car trips 6.30% increase in walking trips	2012 Base Scenario: 10.93t reduction in CO_2 0.03t reduction in NO_x 0.001t reduction in $PM_{2.5}$ 2035 Strategy: 2.01t reduction in CO_2 0.01t reduction in NO_x	Low 2012 Base Scenario: €770.07 2035 Strategy: €85.08
Car-sharing & Carpooling	% reduction in convenience due to shorter access and wait times % reduction in trip time (free parking, HOV lanes) % reduction in trip cost (free parking and tolls, cash rewards for carpooling)	• Low: free parking and cash rewards • Medium: offering free tolls could be costly (such incentives has already been introduced for electric car users)	2012 Base Scenario: 0.78% increase in car trips (carpooling) 2035 Strategy: 1.83% increase in car trips (carpooling)	2012 Base Scenario: 235.47t reduction in CO_2 0.88t reduction in NO_x 0.025t reduction $PM_{2.5}$ 2035 Strategy: 220.95t reduction in CO_2 0.48t reduction in NO_x 0.023t reduction in $PM_{2.5}$	High 2012 Base Scenario: €11,408.88 2035 Strategy: €10,410.77

Table 6.2 Policy Scenario SWOT Analysis

Mode	Policy	Strength	Weakness
Bus & Rail	% improvement in frequency of services % reduction in trip time % reduction in trip cost	• Addresses frequency concerns and ensures short service headways, leading to shorter wait times • PT services perceived as better value for money and level of service vs car use, resulting in higher passenger numbers	• Financial limitations may present an obstacle for vehicle procurement, however the Bus Connects (2017) project has secured funding for extensive changes to the bus network of Dublin
		Opportunity	**Threat**
		• Vehicle procurement provides the prospect of obtaining modern, fuel efficient and low-emitting vehicles (e.g. hybrid buses)	• Higher PT volumes could exacerbate congestion without greater provision of continuous bus lanes
Walking & Cycling	% pedestrian and cycling infrastructure % reduction in trip time % reduction in adjacent traffic speed limit to 30km/h	**Strength**	**Weakness**
		• Greater number of cyclists and pedestrians segregated from motorised transport • Addresses perceived risk of walking and cycling and active modes viewed as being safer modes	• Limitation of road space for full segregation of cycling • Public opposition to limitation of road space for motorised vehicles (e.g. Clontarf to Sutton cycle path)
		Opportunity	**Threat**
		• Walkability of urban areas improve, tourism can be benefit, traffic calming, revitalisation of the retail sector • Reduction in respiratory illnesses due to improvements in air quality	• Possibility of a public opposition or backlash to reduction in speed limit in certain areas • If infrastructure does not meet the demand for cycling, road accidents involving cyclists could increase
Car-sharing & Carpooling	% reduction in convenience due to shorter access and wait times % reduction in trip time (free parking, HOV lanes) % reduction in trip cost (free parking and tolls, cash rewards for carpooling)	**Strengths**	**Weaknesses**
		• Car-sharing viewed as a convenient alternative to car ownership, lessening the need to physically own a car • Popular amongst younger-middle aged professionals (i.e. early adopters, see Section 2.3.2) • Financial incentives making shared car use or carpooling a more cost competitive mode versus SOV use for commuting	• Likely insufficient road space to introduce HOV lanes, motorway network already at capacity • Lack of regulatory and economic incentives for new car-sharing operators to enter the market
		Opportunities	**Threats**
		• Reduction in SOV trips and car ownership due to increasing popularity of shared use schemes • Employers could be incentivised to offer more perks to employees who carpool/ car-share by providing tax exemptions for companies who offer such options to their employees.	• Risk that demand may not meet supply of available car-share vehicles in city centre locations

6.4 Overall Policy Recommendations

PT Scenario

The MCA, shown in Table 6.1, determined that while the PT scenario was estimated to have high monetary savings, relative to the other policy scenarios tested, and could result in an attractive shift to PT from SOV usage, comparatively it would be the costliest scenario examined to implement, with high costs associated with increasing the frequency of services and vehicle procurement. This is supported by the cost of vehicle procurement figures supplied by the Department of Transport, Tourism and Sport (DTTAS) (2015), which state that €35,211,194 was spent in total (or €320,101 per vehicle) for the Dublin Bus procurement contract with Volvo Bus UK for the acquisition of 110 double deck buses. The SWOT analysis, outlined in Table 6.2, added further evidence to this claim, in terms of the associated weaknesses and threats of financial constraints and potential network incapability to withstand a radical increase in the number of vehicles in the network leading to traffic congestion. Ultimately, it was considered that from an environmental perspective, if there were no financial limitations the PT scenario could deliver the best emissions and monetary savings from a reduction in private vkms travelled and an increase in bus and rail use, at the cost of possible adverse consequences to the road network. Therefore, to avoid such issues, it is suggested that if this policy plan was selected, it would be advisable to introduce it in stages, first at the Do Something scenario to observe the effect on the road network, where lower increases in frequency would be included, rather than at the Do Maximum scenario.

Active Modes Scenario

In Table 6.1, the MCA outlined that the active mode policies in this scenario would result in the highest mode share reductions, based on SOV trips, and a large increase in walking, in particular. As determined in Chapter 5, pedestrian mode shares were more sensitive or elastic to an increase in infrastructure than the cycling mode share. Thus, it is suggested that pedestrian infrastructure should be prioritised over cycling infrastructure initially. While the associated mode share shift away from private car use did not translate into significant emissions savings, which in turn did not lead to high monetary savings as a result, the MCA did however highlight that the costs associated with increasing pedestrian and cycling infrastructure would be notably lower than the provision of the PT policies. For instance, research conducted by Bushell, et al. (2013) estimate based on results from other sources, that the average infrastructure costs of a bicycle lane are $133,170 per mile or €183,914 per km. While these costs may vary given the type of infrastructure and the level of complexity of building the infrastructure, this figure is much lower than the cost associated with procurement of PT services.

The SWOT analysis, shown in Table 6.2, provided a deeper insight into many of the strengths and opportunities offered from investing in active mode infrastructure, with the main weakness being limited road space for the provision of fully segregated cycle lanes in certain instances. The primary advantage to investing in active modes is addressing the perceived risk of cycling in the GDA, and enhancing the walkability of urban areas, which could benefit the tourism and retail industries. Overall, from these analyses, the active modes scenario was determined to be the most cost-effective policy plan tested relative to the other scenarios examined, as the suggested investment was estimated to provide the best return in terms of a reduction in SOV trips and the advantages of implementing this plan were found to outweigh the disadvantages.

Carpooling and Car-sharing Scenario

The policies considered in incentivising carpooling and car-sharing were found to provide the optimal balance between the costs associated with introducing the measures and the benefits achieved, in addition to the strengths and opportunities, from the SWOT analysis, which outweighed the potential weaknesses and threats to the policy scenario. Firstly, the emissions and monetary savings were found to be the second highest across the three scenarios experimented, which was identified in Table 6.1. The MCA showed that the reduction in emissions and monetary savings were attributed to a fall in SOV vkms travelled and driver only trips (i.e. an increase in carpooling in the GDA). The increase in the private car mode share also reflects this increase in sustainable car use with only marginal mode share reductions in the other modes, see Chapter 5, Table 5.18 and 5.19. Additionally, while not all of the suggested policy measures in this scenario may be feasible to implement (i.e. HOV lanes due to insufficient road space), the majority of the measures tested were found to have more pros than cons to their implementation, as identified in the SWOT analysis. These advantages included car-sharing and carpooling providing the most convenient, comfortable and cost-effective alternative to private car use, potentially leading a reduction in individuals commuting by car to work or education or driving alone. Evidence of the public acceptance carpooling and car-sharing particularly amongst younger-middle aged professionals, whom are also labelled as the early adopters of such modes, is provided in Section 2.3.2, as examined in research conducted by Millard-Ball (2005) and Shaheen and Chan (2015). Hence, based on the MCA and SWOT analyses conducted in this chapter it was found that the smart car use policy scenario provided the ideal equilibrium between the net aggregate costs of introducing the suggested policy incentives and the associated strengths and weaknesses.

6.5 Conclusion

This chapter has provided a review of MCA and SWOT analysis and presented the results of their application in the context of the research produced in this thesis. It was determined from these analyses that there are various reasons to consider each of the three policy scenarios when seeking to encourage car-shedding behaviour in the GDA. However, the existence of high costs, weaknesses and threats to certain scenarios is what categorically set them apart, as policymakers will naturally be most interested in cost effective measures that have limited adverse effects and provide the greatest return on investment.

Therefore, from the findings explored in this chapter and in Chapter 5, it is recommended that the smarter car use policy scenario is the most optimally designed plan of the three tested in terms of its use in reducing SOV trips for commuting purposes. Thus, it is suggested that incentivising intelligent modes like car-sharing and carpooling, could result in the most favourable outcome in terms of reducing SOV trips, also leading to emissions reductions and monetary savings as a result of more individuals opting to make more sustainable usage of private cars by increasing occupancy levels.

The results examined in this chapter similarly highlight the delicate issue of the effects of competition for road space and competition to secure funding amongst sustainable modes, which was explored in terms of different mode shares in each policy scenario. While it is expected that the recommendations provided in this study may not be welcomed by certain parties, such as bus operators, it is suggested that sufficient time and resources be allocated for consultation and discussion among all interested parties and stakeholders prior to any final decisions being made. A prime example of this may be taken from the Bus Connects project[13], where the proposed changes incorporated in the bus network redesign for Dublin were designed in conjunction with representatives from Dublin Bus, Dublin City Council, DTTAS, the NTA and the private consultants contracted for the project: Jarrett Walker and Associates (2018) (Bus Connects, 2017). This example provides evidence of a scenario whereby the affected operators were included and consulted throughout the process to ensure that all relevant stakeholders were fully satisfied with the changes proposed prior the design being finalised. This consultation approach is also suggested for the introduction of the policies offered in this thesis, which could be modified in response to feedback from stakeholders, in order to avoid any opposition from certain operators or service providers.

[13] Bus Connects is a large project, headed by the NTA, which seeks to redesign the current bus network of the Dublin region in order to makes a range of improvements such as increased frequency of bus services, new integrated ticketing technology and new bus livery and stops in addition to lower emitting vehicles (Bus Connects, 2017).

CHAPTER 7: CONCLUSIONS

7.1 Introduction

The principal objective of this thesis was to investigate the behavioural response of introducing a range of policy measures that incentivise alternative modes as a means of encouraging and evaluating a sustainable travel behaviour change. This chapter discusses the implications of the findings generated from this research and the conclusions that are thus drawn. Section 7.2 provides a summary of the main results produced from each chapter in the thesis, while Section 7.3 outlines the impact of and contribution that this research makes to the field of travel behaviour change and transport policy research. Section 7.4 then critically assesses the methodology employed, suggests ways in which it could be improved and highlights opportunities for further studies generated from this research.

7.2 Summary of Research

This section sets out the main findings from each chapter and the contribution that each makes to the thesis as a whole:

Chapter 2 - Literature Review

The policy of car-shedding is discussed in-depth in this chapter where it is differentiated from other similar concepts in the field of transportation policy. The benefits of the car-shedding approach were then set against the main obstacles that hinder a reduction in car trips and thus the encouragement of car-shedding behaviour. Some of the benefits included a reduction in car dependency, greater priority assigned to pedestrians, cyclists and PT modes, a reduction in traffic congestion and its associated economic benefits, and a reduction in emissions produced from private vehicles leading to lower levels of air and noise pollution. Whereas, the barriers limiting these benefits included: institutional and financial barriers that account for a lack of leadership, political accountability and a limitation in financial resources, social-cultural obstacles that result in a lack of belief or trust in car-shedding measures, and physical barriers that limit the ability to improve certain infrastructure due to the geographic landscape or topography. The current incidence of car-shedding in Ireland was then delineated, where it was indicated that there was a 32% decrease in the number of people aged between 17 and 20 holding a full driving licence and an overall decrease of 24% in those aged between 17-29 holding a full licence in the period of 2008 to 2016.

Following this, the principal theoretical and conceptual grounds for examining travel behaviour change were defined, as the concepts of TPB and behavioural economics were discussed in reference to the literature. Chapter 2 also reviewed literature that tested the effect of TDM and mobility management tools in stimulating a reduction in SOV use and an encouragement of alternative mode use. This review identified that research exploring the use of policy incentives as tools for encouraging sustainable transport practices exclusively is under researched in Ireland, and there are few studies that merge SP discrete choice modelling with traditional four-stage transportation modelling (FSM) as a means of policy appraisal. Finally, it was also acknowledged that there is a need for more research in Ireland that considers the emissions associated with a reduction in SOV use and the behavioural change needed to achieve this reduction, in addition to the monetary savings attained from a potential emissions abatement.

Chapter 3 Stated Preference Research Design and Methodology

SP surveying was identified in this chapter as the most suitable tool to explore the behavioural response of introducing a range of transport policy incentives to a sample in the GDA. However, it was acknowledged that using observed or revealed preference data in conjunction with hypothetical SP preferences was the optimal approach to model the utility functions in this study. The formulae utilised in discrete choice methodology in the SP experiment were examined in this chapter, followed by a delineation of how to interpret each of the outputs produced from the MNL model. A definition of the attributes and attribute levels used in the experiment were then outlined in reference to their use in the literature, followed by a description of how the orthogonal main effect fractional factorial research design was employed to randomly assign the choice scenarios amongst the 432 respondents recorded. Finally, the structure of the SP survey and the sampling method were set out, which determined that the gender split of 44.53% males and 55.47% females was in line with the Census 2016 results.

Chapter 4 Stated Preference Experiment

The results of the SP experiment were presented in Chapter 4, where it was found that a greater percentage of the sample were aged between 35 and 44, with a secondary school level of education, married with no children, an annual household income of between €24,999 and €49,999, living in the inner suburbs of Dublin and working in Dublin city centre. These results were similarly found to be an acceptable representation of the population of the GDA based on the Census 2016 results. The observed travel characteristics of the sample determined that 39.5% of the sample travelled by car to work or education, followed by bus at 14% and 11% on foot. The results showed that 41% of the sample commuted more than 8kms to work or education, with an average trip time of 40+ minutes.

The discrete choice modelling results produced from the SP preferences collected in the survey, found that policy incentives offering tangible time and cost savings led to the greatest shift towards sustainable modes across the attributes modelled.

The regression coefficients generated from MNL models suggested that individuals who possessed a driving licence, access to free parking at the workplace or University and access to at least one car per household were less likely to choose PT, active modes or carpooling and car-sharing. Individuals with more than one child also displayed a lower likelihood of choosing these modes, while those with a higher level of education showed a higher probability. Older individuals were more likely to walk and to opt for the train, carpooling and car-sharing, and females showed a higher probability than males to walk or to choose carpooling and car-sharing as modes for commuting purposes.

The elasticity, what if simulations, cross tabulations and comparison of means results similarly produced in the analysis of the survey responses, found that policy incentives that made an improvement to trip time and cost were most effective in encouraging respondents to choose other sustainable modes and consequently reduce car usage.

Chapter 5 Demand Modelling

The travel demand modelling conducted in Chapter 5 showed that various levels of car-shedding behaviour and emissions reductions could be achieved as a result of implementing the three policy scenarios tested in the SP experiment. In the 2012 PT scenario, the results showed that a reduction in private car trips of up to 1.76% could be experienced as a result of a 2.87% shift towards PT modes. This reduction in private car trips was estimated to result in a daily 431.58t reduction in CO_2, a 0.95t reduction in NO_x and a 0.046t reduction in $PM_{2.5}$ emissions from car commutes trips alone. These emissions reductions combined with reductions in car use for education trips would result in a daily saving of €22,223 in the 2012 Base Scenario. The results produced from the 2035 GDA Strategy for this scenario were lower but a reduction in the mode share of private cars of up to 0.99% could be achieved on top of the 3.83% reduction already made between 2012 and 2035. This shift away from private cars lead to an increase in PT of up to 1.42%, which again was over the 6.49% increase in PT made between 2012 and 2035.

The reduction in private car trips was higher in the active modes scenario, where up to a 1.91% reduction was estimated in the 2012 scenario and up to a 1.33% reduction in the 2035 scenario. Pedestrians were however more elastic to changes in infrastructure provision than cyclists, as the results showed a 5.95% increase in the mode share of walking in the 2012 Base Scenario and a 6.30% increase in the 2035 GDA Strategy. Cyclists were, conversely, found to shift to walking given infrastructure improvements, as were PT users, which suggested that cyclists were relatively inelastic to infrastructure improvements made in the experiment.

The 2012 Base Scenario changes in mode shares incentivised by the introduction of the active mode policy plan were then found to result in a reduction of 10.93t in CO_2, 0.03t in NO_x, and 0.001t in $PM_{2.5}$, leading to a daily monetary saving of €770.07.

Finally, the smarter car use policy scenario found that based on incentives offered to carpoolers and car-sharers, an increase of 0.78% in the 2012 Base Scenario and 1.83% in the 2035 GDA Strategy could be experienced, which was represented in lower vkms travelled for private cars following the introduction of the measures. In these scenarios, the increase in carpooling was also accounted for by marginal shifts away from other modes to carpooling. The emissions savings recorded from the shift to carpooling were higher than the active modes scenario savings. The results showed that in the 2012 Base Scenario, a daily reduction of 235.47 in CO_2, 0.88t in NO_x, and 0.025t in $PM_{2.5}$ could be achieved which would result in €11,408 saved per day when combined with the car education trip savings, while the findings from 2035 Strategy, led to a daily saving of €10,410.

Chapter 6 Policy Scenario Analysis

An assessment of the policy plans tested in this thesis was conducted in Chapter 6, where a MCA and SWOT analysis were employed. In the MCA, the costs associated with the policy implementation were compared against the outcomes recorded in terms of modal shifts, emissions and monetary savings. This analysis determined that while the benefits of implementing the PT policies were most attractive, represented in the highest emissions and monetary savings; the cost of this scenario were also the highest, as vehicle procurement to meet the increased PT frequency of service is a costly decision. The active modes scenario was found to have the lowest implementation costs across the three scenarios, as there are lower costs associated with improving pedestrian and cycling infrastructure. In addition to this, the active modes scenario resulted in the highest reduction in private vehicle use, however, this increase did not translate into lower vkms travelled for private cars, as lower emissions reductions were recorded in comparison to the PT scenario.

The carpooling and car-sharing scenario provided the ideal balance between the costs and estimated results of implementing the policies. The costs of free parking and cash rewards were recorded as being relatively low, while the provision of free road tolls would be associated with a medium cost level. The emissions and monetary savings were second highest across the three scenarios in reference to attractive modal shifts to carpooling. Thus, it was determined from the MCA that the smart car use scenario was the most cost-effective plan of the three, as it was estimated to provide an attractive return on investment.

The SWOT analysis then considered the balance of internal strengths and opportunities of each scenario versus the external weaknesses and threats. While the scenarios had appealing strengths and opportunities such as: addressing PT frequency concerns, introduction of a modern low-emitting vehicle fleet, shortening wait times for PT services, carpooling and car-sharing, and improving the perceived risk of walking and cycling, the weaknesses and risks of certain policy scenarios, however, outweighed the advantages. For example, in the PT scenario, financial limitations could restrict the ability to increase service frequency on routes and exacerbate traffic congestion as a result of higher PT volumes, especially at bottlenecks, or a limitation of road space could present an obstacle to providing fully segregated cycle lanes. Nevertheless, in the carpooling and car-sharing scenario only minor weaknesses were estimated to arise, which were namely a lack of regulatory and economic incentives for new car-sharing operators to enter the market, and an insufficiency of road space for HOV lanes.

Hence, the analysis in this chapter determined that the smart car use scenario would present the optimal balance between the costs and outcomes in the MCA, and the pro and con factors in the SWOT analysis. In this way, it was recommended that the policies included in this scenario could be most effective in encouraging car-shedding behaviour from a policy-makers perspective.

7.3 Contribution to Knowledge

It was identified in Section 2.6 in Chapter 2 that there are a number gaps in the existing literature that this research sought to address and opportunities for further research. Thus, from the findings produced in this thesis, this research provides the following contributions to the existing literature in aiding the understanding of the effect of policy incentives in encouraging a reduction in SOV trips:

- The introduction of the car-shedding term to the field of transportation policy provides a notable addition to literature examining sustainable travel behaviour change. The use of policy incentives alone, which seek to reduce SOV trips demonstrate that sustainable mode choice can be stimulated and evaluated without limiting the freedom of modal choice or penalising car users, particularly in cases where no alternatives to the private car exist. This approach is in contrast to other prominent studies such as Eriksson, et al. (2010) and O’Fallon, et al. (2004), where the combination of carrot and sticks measures are suggested as the most applicable method to employ in order to stimulate a reduction in SOV use
- Policy appraisal is examined by utilising behavioural elicitations from SP (i.e. regression coefficients, elasticities, what if simulations etc.) to guide parameter modifications to a FSM in order to produce real life estimates of mode share
- The discovery of the inelasticity of cyclists to react in response to improvements made to cycling infrastructure, while implemented in conjunction with improvements made to pedestrian infrastructure was a key finding from this research which may contribute to our understanding of cyclist behaviour
- Incentivising carpooling and car-sharing was estimated to be more cost-effective to implement and led to a better return on investment than investing in PT or in active modes, which suggests that more attention should be devoted to enabling greater incentivisation of these modes

7.4 Discussion

The overarching research question of this thesis was to determine the effect of providing a range policy incentives on the commuting population of the GDA, and would such policy provision lead to a reduction in commuter car trips (i.e. car-shedding)? This question was tested by means of discrete choice modelling and four-stage transport modelling to estimate the impact of introducing measures that could lead to time, cost, convenience and safety improvements for commuting trip purposes. One of the most notable findings produced from this work found that pedestrians, rather than cyclists or other alternative modes, were most elastic to the policy incentives tested in the four-stage model. These results were obtained from the ERM, correspond closely with findings produced in studies conducted by O'Fallon, et al. (2004), and Mackett (2001), whom determined that an increase in the incidence of cycle lanes did in fact not have an immediate effect in increasing cycling activity (i.e. an increase in cycling trips) and in encouraging a mode shift from SOV use to cycling. The results in O'Fallon et al. (2004) found that the walk option was the most popular alternative alongside PT given the incentives tested, while Mackett (2001) concluded that only 2% of car drivers would be willing to shift to cycling given infrastructural improvements made to the cycle network. This is comparable to the results produced in this thesis in the active modes scenario, where a reduction of only 1.08% private car commuting trips was recorded.

The four stage modelling also determined that, in the active modes and the optimal car-shedding model results, walking experienced the largest and, in some cases, the only increase in mode share. Hence, it is proposed that pedestrian infrastructure should arguably be prioritised over cycling infrastructure initially. It is assessed that this could also be seen as an equitable choice of investment as the SP study showed that both women and older people were more positive about walking than other users: indeed all commuters are pedestrians at some point of their journey and so investment in walking infrastructure will benefit most commuters. Much of the emphasis in the past in Dublin and other cities has been on increasing cycling infrastructure. However, the results of this study emphasise the importance of not neglecting walking infrastructure as it is in this mode that the most significant increases might be experienced with increased investment.

The findings produced from the SP experiment are similarly comparable to other work in this area. For example, the MNL results produced in the active modes model showed that respondents were more willing to choose cycling as mode given time savings made in their commute, which is in line with findings from Li, et al. (2017), Abraham, et al. (2012) and Stinson and Bhat (2003) who found that commuters would be more willing to cycle given short travel times and would prefer routes with continuous cycling infrastructure, less traffic and few traffic controls.

In accordance with Malodia and Singla (2016) and Ahern and Tapley (2008) the results produced in this thesis also found that the provision of incentives that lead to cost and time savings for the commuter would result greater mode shifting behaviour than the benefits associated with any other policies tested.

This is similarly supported by Weibin et al. (2017) who stipulated that 'both income and time constraints have significant effects on the utility of alternative modes of transport for commuters' (Carroll, et al., 2017). While in relation to the shared use of the private cars specifically, Shaheen et al. (2016) also assert that 'cost and convenience are frequently cited as popular reasons for shifting to a shared mode'.

7.5 Critical Assessment Recommendations for Further Research

This section highlights that while the overall methodology employed in this research (see Figure 1.1 in Chapter 1) was effective in evaluating the necessary behavioural and environmental impacts of a range of policy incentives, it is acknowledged that there were some limitations to the study and ways in which the experiments could be improved in future.

Stated Preference Experiment

The hypothetical context in which the SP experiment in Chapter 4 was framed and the design of the survey itself presented some issues for data collection. These included some respondents not making trade-offs between the attributes, known as lexicographic behaviour, whereby an individual only considers one attribute in their choice (Bräuning, et al., 2017; Ahern, Tapley, 2008). An example of this would be an individual selecting the private car alternative in all choice scenarios as it reflects their real-life selection, without consideration of the policy incentives offered. This behaviour could have also been compounded by the fatigue effect or survey fatigue (Hess, et al., 2012; Bradley and Daly 1994), which is synonymous with the repetitive nature of answering numerous choice scenarios in one survey. Similarly, there exists the argument that individual stated preferences in a hypothetical context do not always reflect real-life choices. However, to combat this, the observed mode choices and trip characteristics of the sample were combined with SP choices in the SP experiment.

A suggestion for further research which seeks to replicate a study of this nature would be to firstly, reduce the study area to just Dublin city and replace the study using a sample from this area. In this way, better model fit and performance could be achieved where there are viable alternative to the private readily accessible as opposed to rural areas of the GDA that are experiencing limited public transport accessibility. In this way, the production of low coefficients and rho^2 values could be avoided, which was noted as limitation of this study. A second suggestion would be to conduct travel diaries to examine the mode choice behaviour before and after the experiment. In this way the respondents' choices could be analysed for the effect of the objective environment and the influence of potential social norms on choice making behaviour as examined by Schultz, et al. (2007) and Kormos, et al. (2015). A final recommendation for further work would be to select attributes that are applicable to all of the modes tested in order to present all of the alternatives in one choice scenarios and model the choice behaviour, rather than separating the modes into mode-specific choice scenarios.

Four Stage Modelling of Policy Incentives on Mode Shares and Emissions

The representation of the policy scenarios tested in the SP experiment in the NTA’s Eastern Regional Model (ERM) similarly highlighted some issues or limitations. For instance, the use of 2012 as the Base Scenario of the study was not ideal as in 2012 the effects of the worst recession that the Irish state has experienced were still evident. Thus, the bearing that this had on mode shares and the other modelled findings were accordingly acknowledged. The rationale for using 2012 as the Base Scenario, was attributed to the fact that the 2016 Census results were not published at the time the modelling was conducted. This was a limitation also cited by McGoldrick and Caulfield (2011) in their study of changes in car ownership levels in the GDA. However, in 2018 the ERM Base Scenario will be calibrated with results from the 2016 Census results, thus, it is recognised that some variations in estimated mode shares will be recorded.

The use of vehicle occupancy as a proxy for representing carpooling in the ERM is quite a crude measure of accounting for an increasing in carpooling, as carpooling is not defined as a separate mode in the NTA model, this was seen as a limitation to the model. Other notable limitations of the ERM were: the structure of the time periods (i.e. AM, LT, SR, PM, OP), particularly the Off Peak period as it represents the time between 19:00 and 7:00, which, given that this is a large period of time, perhaps should be broken down into sub time periods, in order to more accurately predict demand during this time of the day; trip chaining is also not modelled in the ERM, which may impact on the fidelity of the origin and destinations of trips and is perhaps not a fair reflection of travel behaviour, in addition to explicit assumptions of rational mode choice.

This is one of the main criticisms of conventional four stage modelling (i.e. trip generation, distribution, model choice and trip assignment) is that it lacks a valid representation of underlying travel behaviour as it is based distinctly on the concept of utility maximisation (McNally and Rindt, 2007). In this way, it fails to consider other factors that influence and also account for decision making such as habit and intention formation (McNally and Recker, 1986). The FSM was developed initially as tool in the 1960s for predicting the future demand and performance of a transport network, and to examine the cause and effect of large scale infrastructure projects on the functioning of the network. However, McNally and Rindt (2007) stipulate that it has not been used effectively for policies ‘involving the management and control of existing infrastructure and explicitly not to the evaluation of restrictive policies involving demand management’. Other notable shortcomings of the FSM approach include: the ignorance of demand generated from activity related decisions; a focus on individual trips and neglect for the spatial and temporal interrelationship between trips and activities; and the iterative process of the feedback of generalised costs (from the trip assignment stage to the trip distribution and mode choice stages) not being computationally efficient as it requires several iterations to reach a point of convergence or equilibrium (Mladenović and Trifunović, 2014; McNally and Rindt, 2007).

However, as a means of overcoming these shortcomings, the activity-based modelling approach (ABA), established by Mitchell and Rapkin (1954), has been recognised as a notable solution to the limitations posed by the FSM. This approach considers that the way in which travel decisions are made is determined by a collection of activities in the form of an agenda or a trip chain and in this way, it is fundamentally differentiated from individual trips modelled in the FSM (McNally and Rindt, 2007). As a result of the need to combine multiple trips into a single agenda for participation, the demand for each activity is measured and an interdependence of destinations, modes and routes taken for each portion of the trip is required (Oppenhiem, 1995). Moreover, in the ABA, the socio-demographic and situational factors, and trip chain attributes included in the Bamberg, et al. (2011) conceptual framework, outlined in Chapter 2, Section 2.4, are reflected upon as motivational factors influencing travel decisions. Therefore, it is recommended that the ABA would offer a more robust modelling framework to represent travel behaviour and to estimate the behavioural response of policy incentives on mode choice, should a similar experiment be adopted in future studies.

7.6 Overall Conclusion

To conclude, it has been demonstrated in this thesis that strategically designed policy incentives alone act as an effective tactic to encourage and accelerate a reduction in car trips for commuting purposes in the GDA. The empirical evidence that supports this claim may offer valuable guidance and recommendations for policymakers that seek to devise strategies to induce sustainable behaviour change and to reduce the modal share of the private cars, ultimately leading to an abatement in emissions from transport in Ireland.

PUBLICATIONS

Journal Papers

Carroll, P., J., Caulfield, B., and Ahern, A. (2017a) Examining the potential for car-shedding in the Greater Dublin Area, *Transportation Research Part A: Policy and Practice,* Vol. 106, pp. 440-452.

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APPENDIX A: Copy of the Stated Preference Survey and Invitation Emails

1. Main Invitation Email

Dear Member,

Please take our new survey which should take 10 to 12 minutes to complete. After taking part you will have a chance to enter a draw for **3 cash prizes of €50 each**.

Please click here to take part in this survey.

Note that this survey does not carry the normal Ask Me... Pay Me! rewards for each participant – instead there will be **3 winners of prizes**.

You will have an opportunity to enter the draw at the end of the survey questionnaire. Your unique draw entry code is **n4561** (you will be asked to enter this at the end of the survey).

This is a very important academic survey concerning transport options in Ireland, your participation will be greatly appreciated.

The prize draw for this survey will take place when we have reached our target number of responses.

Thank you,

The Ask Me... Pay Me! team

If you experience problems opening the link, please copy and paste the following into your browser address bar: http://surveys.delve-surveys.com/s3/ampmMar17?refid=n4561

You are receiving this email because you are a registered member of the Ask Me... Pay Me! opinion panel. You can unsubscribe from this panel at any time by logging into your account and clicking "unsubscribe".

2. Main Reminder Email

Dear Member,

Thanks to everyone who has already taken part in our newest prize draw survey. If you haven't yet done so, you can still take part - we'd really appreciate your input on this important topic.

Please click here to take part in this survey.

Note that this survey does not carry the normal Ask Me... Pay Me! rewards for each participant – instead there will be **3 winners of prizes**.

It should take 10 to 12 minutes to complete. After taking part you will have a chance to enter a draw for a **3 cash prizes of €50 each**.

You will have an opportunity to enter the draw at the end of the survey questionnaire. Your unique draw entry code is **a2122** (you will be asked to enter this at the end of the survey).

This is a very important academic survey concerning transport options in Ireland, your participation will be greatly appreciated.

The prize draw for this survey will take place when we have reached our target number of responses.

Thank you,

The Ask Me... Pay Me! team

If you experience problems opening the link, please copy and paste the following into your browser address bar: http://surveys.delve-surveys.com/s3/ampmMar17?refid=a2122

You are receiving this email because you are a registered member of the Ask Me... Pay Me! opinion panel. You can unsubscribe from this panel at any time by logging into your account and clicking "unsubscribe".

GREENING TRANSPORT

1. How do you usually travel to work/ education?

- Not at work/ education
- On foot
- Bicycle
- Bus, minibus or coach
- Train, DART or Luas
- Motorcycle or scooter
- Driving a car
- Passenger in a car
- Alternatively fueled car (electric etc.)
- Van
- Other, including taxi or truck
- Work mainly from home (i.e. telecommuting)

** Please answer the following questions with reference to your current commute to work or education.

If you are not currently in work or education please answer based on how used to travel to work or education **

2. What distance is your journey from your home to work/ education and how long does it usually take?

	Distance	Time
Select one answer from each of the drop-down menus		

3. What is the approximate out-of-pocket cost of your daily commute (total = both to and from your place of work/ education)?

- It doesn't cost me anything
- €1 - €5 per day
- €5 - €10 per day
- €10 - €15 per day
- €15+ per day

4. Do you have a driving license?

- Yes
- No

5. How many cars are owned or are available for use by one or more members of your household?

- One
- Two
- Three
- Four or more
- None

6. Is free parking available at your workplace/ place of education?

- Yes
- No

GREENING
TRANSPORT

7. Which of the following measures would encourage you to cycle to work if you lived close enough and owned a bicycle? (Please select one)

- Improved cycle routes
- Bicycle facilities and security in work
- Less traffic on the roads
- Loans to buy a bicycle
- Financial incentives
- N/A
- Other (please specify)

8. Which of the following measures would encourage you to use public transport to travel to/ from work? (Please select one)

- More frequent services
- Nicer vehicles
- Reliable services
- More information
- Better stop locations
- Discounted tickets
- N/A
- Other (please specify)

9. Please state the importance of the following measures in encouraging you to carpool to and from work/ education.

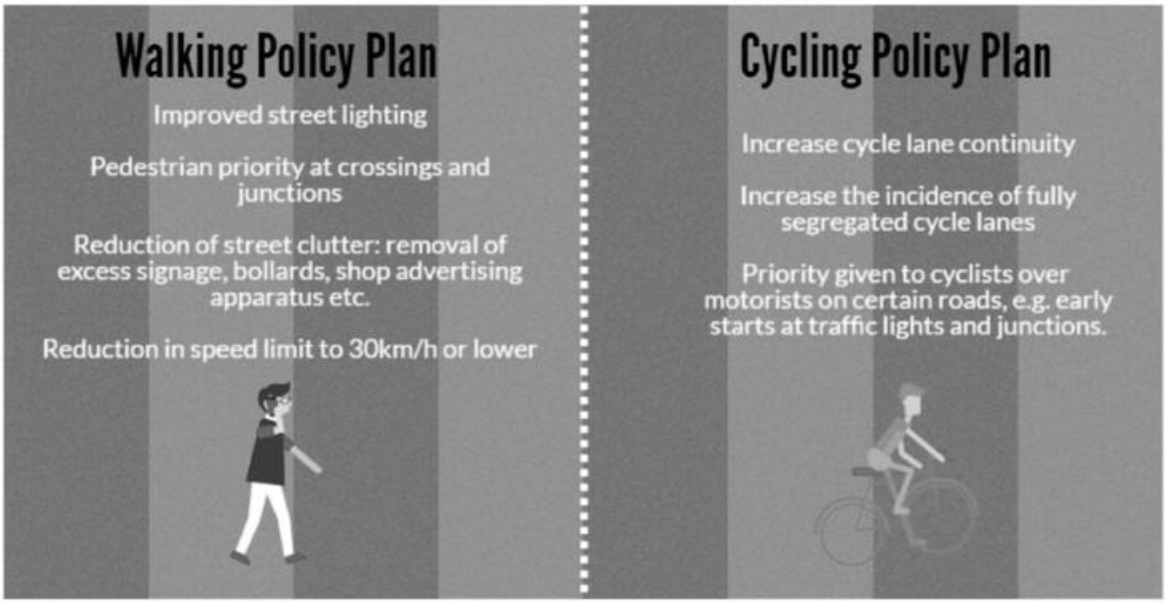
	Important	Undecided	Unimportant
Help finding a carpool/ car-share partner	☐	☐	☐
Free taxi home if let down by carpool partners/ guaranteed ride home	☐	☐	☐
Financial incentives/ rewards to carpool or car-sharing	☐	☐	☐
Free parking	☐	☐	☐
Free tolls	☐	☐	☐
Availability of carpool lanes/ high occupancy lanes	☐	☐	☐

Other (please specify)

GREENING TRANSPORT

Active Modes Scenario 1

This section asks you to imagine that you have been offered a job in anew location and you are deciding how to travel to work based on the introduction of new policies.



You will be presented with choice scenarios; in which you will be asked to rank your preferred modes of transport.

Imagine how you will travel to your new work location. Taking note of the above policy plans, please consider the following scenarios and rank the modes that you would take.

Option	Policy	Effect on your trip		
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Walk 	Walking Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		20% of trip with widened, even paths	2 mins off trip time	50% of trip with 30km/h speed limit
Cycle 	Cycling Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		20% of trip fully segregated from traffic	2 mins off trip time	50% of trip with 30km/h speed limit

10. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

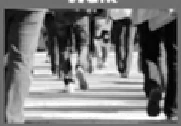
Private Car (drive alone)

Walk

Cycle

GREENING TRANSPORT

Active Modes Scenario 2

Option	Policy	Effect on your trip		
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Walk 	Walking Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		40% of trip with widened, even paths	6 mins off trip time	100% of trip with 30km/h speed limit
Cycle 	Cycling Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		60% of trip fully segregated from traffic	4 mins off trip time	75% of trip with 30km/h speed limit

11. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

Private Car (drive alone)

Walk

Cycle

GREENING
TRANSPORT

Active Modes Scenario 3

Option	Policy	Effect on your trip		
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		
Walk 	Walking Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		60% of trip with widened, even paths	4 mins off trip time	75% of trip with 30km/h speed limit
Cycle 	Cycling Policy Plan	Infrastructure	Time	Adj. Traffic Speed
		40% of trip fully segregated from traffic	6 mins off trip time	100% of trip with 30km/h speed limit

12. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Private Car (drive alone)
- Walk
- Cycle

Greening Transport

Public Transport Scenario 1

Imagine how you will travel to your new work location. Taking note of the above policy plan, please consider the following scenarios and rank the modes that you would take.

Option	Policy	Effect on your trip		
Bus		Frequency	Time	Cost
	Bus Policy Plan	25% more often	15% reduction in trip time	15% cheaper trip
Private Car (drive alone)		Cost		
	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		
Train/ Luas		Frequency	Time	Cost
 	Train Policy Plan	25% more often	15% reduction in trip time	15% cheaper trip

13. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Bus
- Private Car (drive alone)
- Train/ Luas

Option	Policy	Effect on your trip		
Bus 	Bus Policy Plan	Frequency: 25% more often	Time: 15% reduction in trip time	Cost: 15% cheaper trip
Private Car (drive alone) 	Current situation/ Status Quo	Cost: Gradual increase in the ownership costs of a car		
Train/ Luas  	Train Policy Plan	Frequency: 25% more often	Time: 15% reduction in trip time	Cost: 15% cheaper trip

13. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- [ ] Bus
- [ ] Private Car (drive alone)
- [ ] Train/ Luas

GREENING TRANSPORT

Public Transport Scenario 3

Option	Policy	Effect on your trip		
		Frequency	Time	Cost
Bus 	Bus Policy Plan	Twice as often	15% reduction in trip time	15% cheaper trip
		Cost		
Private Car (drive alone) 	Current situation/ Status Quo	Gradual increase in the ownership costs of a car		
		Frequency	Time	Cost
Train/ Luas  	Train Policy Plan	50% more often	25% reduction in trip time	25% cheaper trip

15. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- Bus
- Private Car (drive alone)
- Train/ Luas

GREENING TRANSPORT

Smart Modes Scenario 1

Imagine how you will travel to your new work location. Taking note of the above policy plan, please consider the following scenarios and rank the modes that you would take.

Option	Policy	Effect on your trip		
Carpooling 	Carpooling Policy Plan	Convenience	Time	Cost
		10% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Car-sharing (GoCar/ Toyota Yuko)  	Car-sharing Policy Plan	Convenience	Time	Cost
		10% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		

16. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

Carpooling

Car-sharing (GoCar/ Toyota Yuko)

Private Car (drive alone)

GREENING
TRANSPORT

Smart Modes Scenario 2

Option	Policy	Effect on your trip		
Carpooling 	Carpooling Policy Plan	Convenience: 30% reduction in access/ wait time	Time: 35% reduction in trip time	Cost: 35% reduction in trip cost
Car-sharing (GoCar/ Toyota Yuko)  	Car-sharing Policy Plan	Convenience: 50% reduction in access/ wait time	Time: 15% reduction in trip time	Cost: 15% reduction in trip cost
Private Car (drive alone) 	Current situation/ Status Quo	Cost: Gradual increase in the ownership costs of a car		

17. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- [ ] Carpooling
- [ ] Car-sharing (GoCar/ Toyota Yuko)
- [ ] Private Car (drive alone)

GREENING TRANSPORT

Smart Modes Scenario 3

Option	Policy	Effect on your trip		
Carpooling 	Carpooling Policy Plan	Convenience	Time	Cost
		50% reduction in access/ wait time	15% reduction in trip time	15% reduction in trip cost
Car-sharing (GoCar/ Toyota Yuko)  	Car-sharing Policy Plan	Convenience	Time	Cost
		30% reduction in access/ wait time	35% reduction in trip time	35% reduction in trip cost
Private Car (drive alone) 	Current situation/ Status Quo	Cost		
		Gradual increase in the ownership costs of a car		

18. Please rank the mode you would most likely choose in this scenario (1 = most likely, 3 = least likely)

- [ ] Carpooling
- [ ] Car-sharing (GoCar/ Toyota Yuko)
- [ ] Private Car (drive alone)

GREENING
TRANSPORT

19. Which of the following features influenced your choice the most in the scenarios?

- ◯ Time
- ◯ Cost
- ◯ Frequency
- ◯ Adjacent Traffic Speed.
- ◯ Convenience
- ◯ Infrastructure

20. How difficult would it be for you to take the following modes to work/ education?

	Very Easy	Easy	Neutral	Difficult	Very Difficult
Walk	◯	◯	◯	◯	◯
Cycle	◯	◯	◯	◯	◯
Bus	◯	◯	◯	◯	◯
Train	◯	◯	◯	◯	◯
Luas	◯	◯	◯	◯	◯

21. Why do you feel that these modes would be difficult to take to work/ education?

- ◯ N/A
- ◯ Please state your reason:

22. Which of the following aspects is most important to you when commuting to and from work/ education? (Please select one)

- ◯ That the schedule is flexible
- ◯ That it is convenient to use
- ◯ That it is quick
- ◯ That I feel comfortable
- ◯ That it is cheap
- ◯ That I am protected from the weather
- ◯ That I can have control over my time
- ◯ Other (please specify)

GREENING
TRANSPORT

23. Gender?

- ◯ Male
- ◯ Female

24. What is your age range?

- ◯ 18-24 years old
- ◯ 25-34 years old
- ◯ 35-44 years old
- ◯ 45-54 years old
- ◯ 55-64 years old
- ◯ 65+ years old

25. What is your highest level of education which you have completed to date?

- ◯ No former education/ training
- ◯ Primary education
- ◯ Secondary education
- ◯ Technical or vocational
- ◯ Advanced Certificate/ Completed Apprenticeship
- ◯ Higher Certificate
- ◯ Ordinary Bachelor Degree/ Diploma
- ◯ Honours Bachelor Degree
- ◯ Postgraduate Diploma/ Degree
- ◯ Doctorate (Ph.D) or Higher

26. What is your current marital status?

- Single
- Married
- Separated
- Divorced
- Widowed

27. How many children/ dependents do you have?

- None
- 1
- 2
- 3
- More than 3

28. Please answer the following:

	Dublin City Centre (i.e. within the canals)	Inner Suburbs (i.e. within canals & M50 motorway)	Outer suburbs (i.e. outside M50 motorway)	Commuter town	Rural Area
Where do you live?					
Where do you work/ study?					

29. What is your average annual household income range?

- €24,999 or less
- €25,000 - 49,999
- €50,000 - 74,999
- €75,000 - 99,999
- €100,000 or more
- I'd rather not say

30. How would you describe your present principal status?

- Working for payment or profit
- Looking for first regular job
- Unemployed
- Student
- Looking after home/ family
- Retired from employment
- Unable to work due to permanent sickness or disability
- Other (please specify)

31. To enter the prize draw for 3 chances to win €50 please enter your unique code here (this code is in your invitation email)

APPENDIX B: Evidence of ERM coding modifications

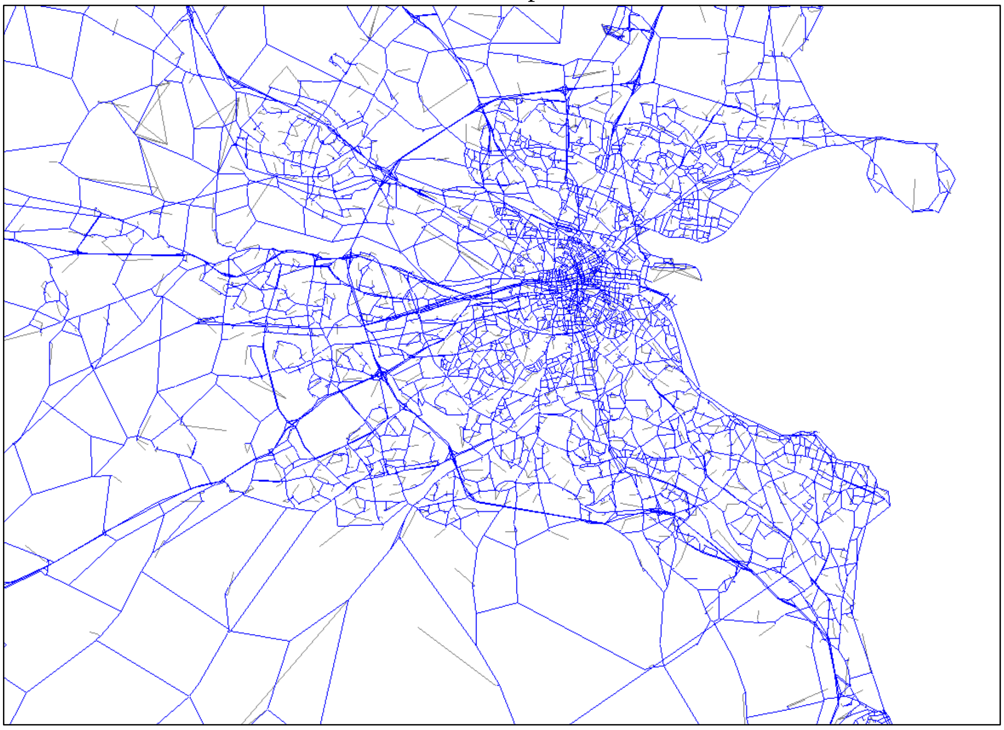
CUBE Voyager coding for walk and cycle speeds

```
RUN PGM=NETWORK PRNFILE="{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Procedural\Demand\ActAss\ACT_AM_2.PRN" MSG='Add Cycle and Ped Characteristics to
Network'
FILEI LINKI[1] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\PT\AM\PRIOR.NET"
FILEI LINKI[2] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Input\Networks\AMM\CYCLE_DATA.DBF"
FILEI LINKI[3] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Input\Networks\AMM\PED_ONLY.DBF"
FILEI LINKI[4] = "{CATALOG_DIR}\Temp\AM_ActTemp_1.DBF"
FILEO NETO = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Active\AM\Act_Pre_Assign.NET",
 INCLUDE=A B DISTANCE CI LINK_TYPE CYC_SPEED PED_ONLY REVERSED LEFTDRIVE=T


MERGE RECORD=TRUE FIRST=REVERSED

PROCESS  PHASE=LINKMERGE

  IF (Li.1.LINK_TYPE=27) DELETE

  Cyc_Speed = Li.2.CYC_SPEED

  IF (Cyc_Speed=0) Cyc_Speed = 12.0   ;Source NHTS (20 to 60 years)

  Wlk_Speed = 5.1                     ;Source NHTS (20 to 60 years)

  IF (LINK_TYPE=0)
    PED_ONLY=1
    LINK_TYPE=99
  ENDIF

  IF(Li.4.CI=7,8,71-73,81-83,121-122 && PED_ONLY=1) DELETE  ; delete reversed motorways

ENDPROCESS

ENDRUN
```

CUBE Voyager coding for walk and cycle speeds

```
      ;Create link times for each user class and mode
      LW.Wlk_UC1_Time=LI.DISTANCE*60/LI.Wlk_Speed
      LW.Wlk_UC2_Time=LI.DISTANCE*60/LI.Wlk_Speed
      LW.Wlk_UC3_Time=LI.DISTANCE*60/LI.Wlk_Speed
      LW.Wlk_UC4_Time=LI.DISTANCE*60/(LI.Wlk_Speed*_WlkFac_Edu)
      LW.Wlk_UC5_Time=LI.DISTANCE*60/(LI.Wlk_Speed*_WlkFac_Ret)
      LW.Cyc_UC1_Time=LI.DISTANCE*60/LI.Cyc_Speed
      LW.Cyc_UC2_Time=LI.DISTANCE*60/LI.Cyc_Speed
      LW.Cyc_UC3_Time=LI.DISTANCE*60/LI.Cyc_Speed
      LW.Cyc_UC4_Time=LI.DISTANCE*60/(LI.Cyc_Speed*_CycFac_Edu)
      LW.Cyc_UC5_Time=LI.DISTANCE*60/(LI.Cyc_Speed*_CycFac_Ret)

ENDPROCESS

PROCESS PHASE=ILOOP

;Walk UC1
  PATHLOAD PATH=LW.Wlk_UC1_Time EXCLUDEGROUP=1 VOL[1]=MI.1.1 CONSOLIDATE=T,
  MW[11]=PATHCOST, NOACCESS=0,
  MW[21]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Walk UC2
  PATHLOAD PATH=LW.Wlk_UC2_Time EXCLUDEGROUP=1 VOL[2]=MI.1.2 CONSOLIDATE=T,
  MW[12]=PATHCOST, NOACCESS=0,
  MW[22]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Walk UC3
  PATHLOAD PATH=LW.Wlk_UC3_Time EXCLUDEGROUP=1 VOL[3]=MI.1.3 CONSOLIDATE=T,
  MW[13]=PATHCOST, NOACCESS=0,
  MW[23]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Walk UC4
  PATHLOAD PATH=LW.Wlk_UC4_Time EXCLUDEGROUP=1 VOL[4]=MI.1.4 CONSOLIDATE=T,
  MW[14]=PATHCOST, NOACCESS=0,
  MW[24]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Walk UC5
  PATHLOAD PATH=LW.Wlk_UC5_Time EXCLUDEGROUP=1 VOL[5]=MI.1.5 CONSOLIDATE=T,
  MW[15]=PATHCOST, NOACCESS=0,
  MW[25]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Cycle UC1
  PATHLOAD PATH=LW.CYC_UC1_Time EXCLUDEGROUP=1,2 VOL[6]=MI.1.6 CONSOLIDATE=T,
  MW[16]=PATHCOST, NOACCESS=0,
  MW[26]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Cycle UC2
  PATHLOAD PATH=LW.CYC_UC2_Time EXCLUDEGROUP=1,2 VOL[7]=MI.1.7 CONSOLIDATE=T,
  MW[17]=PATHCOST, NOACCESS=0,
  MW[27]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Cycle UC3
  PATHLOAD PATH=LW.CYC_UC3_Time EXCLUDEGROUP=1,2 VOL[8]=MI.1.8 CONSOLIDATE=T,
  MW[18]=PATHCOST, NOACCESS=0,
  MW[28]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Cycle UC4
  PATHLOAD PATH=LW.CYC_UC4_Time EXCLUDEGROUP=1,2 VOL[9]=MI.1.9 CONSOLIDATE=T,
  MW[19]=PATHCOST, NOACCESS=0,
  MW[29]=PATHTRACE(LI.DISTANCE), NOACCESS=0
;Cycle UC5
  PATHLOAD PATH=LW.CYC_UC5_Time EXCLUDEGROUP=1,2 VOL[10]=MI.1.10 CONSOLIDATE=T,
  MW[20]=PATHCOST, NOACCESS=0
```

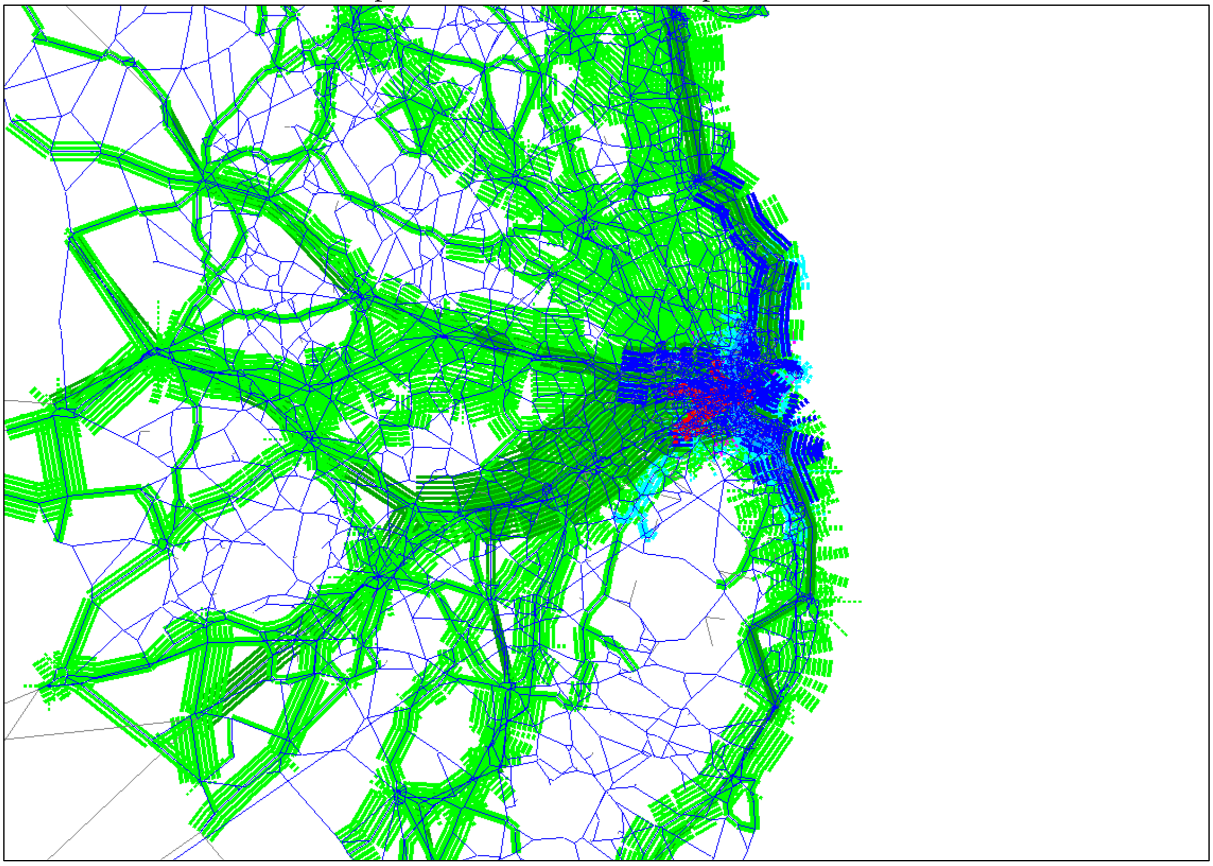
GDA active modes network represented the ERM model



CUBE Voyager coding of public transport modes

```
RUN PGM=PUBLIC TRANSPORT PRNFILE="{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Procedural\Demand\PTAss\AM_PT_ASS_8.PRN" MSG='Set Up Non-Transit Links'
FILEI LINEI[1] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Input\Lines\Bus_{Run ID}_{Model Year}.LIN"
FILEI LINEI[2] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Input\Lines\Rail_{Run ID}_{Model Year}.LIN"
FILEI FACTORI[6] = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\Factor_Files\{MODEL YEAR}_ZOD_AM.FAC"
FILEI FACTORI[5] = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\Factor_Files\{MODEL YEAR}_RET_AM.FAC"
FILEO NETO = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\AM\PT_PREP.NET"
FILEI FACTORI[4] = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\Factor_Files\{MODEL YEAR}_EDU_AM.FAC"
FILEI FACTORI[3] = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\Factor_Files\{MODEL YEAR}_OTH_AM.FAC"
FILEI FACTORI[2] = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\Factor_Files\{MODEL YEAR}_COM_AM.FAC"
FILEI FACTORI[1] = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\Factor_Files\{MODEL YEAR}_EMP_AM.FAC"
FILEI SYSTEMI = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\INPUT\Additional_PT\SYSTEM_FILE.PTS"
FILEI LINEI[3] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Input\Lines\New_Mode_{Run ID}_{Model Year}.LIN"
FILEI NETI = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\AM\PRIOR.NET"
FILEO NTLEGO = "{CATALOG_DIR}\RUNS\{MODEL YEAR}\{RUN ID}\OUTPUT\{GROWTH}\PT\AM\PT_PREP.NTL"
FILEO LINKO[1] = "{CATALOG_DIR}\RUNS\{Model Year}\{Run ID}\OUTPUT\{Growth}\PT\AM\AM_LINK_RECS_PREP.DBF",
      ONELINKREC=Y NTBYLINK=N BYCLASS=N NTLEGS=N
FILEO LINKO[2] = "{CATALOG_DIR}\RUNS\{Model Year}\{Run ID}\OUTPUT\{Growth}\PT\AM\AM_ON_OFFS_PREP.DBF",
      ONOFFS=Y NTLEGS=N


PROCESS PHASE=linkread

; Drive access (mode 96)
IF (A<={Zones} || B<={Zones})
  LW.MOT_NTL_COST=30+Li.AM_PT_TIME  ; Assumed 2*(30 minute wait time on connector + drive time)
ELSE
  LW.MOT_NTL_COST=Li.AM_PT_TIME   ; motorised walk cost on all links except zone connectors
ENDIF

; Walk - Zone-to-zone (mode 98)
IF (A<={Zones} & B>{Zones})
  LW.WLK_NTL_COST=15+Li.WALK_TIME  ; Assumed 2*walk time + 30 min [2*15] for wait+brd+fare+penalty
ELSE
  LW.WLK_NTL_COST=Li.WALK_TIME   ; walk cost on all links except zone connectors
ENDIF

ENDPROCESS
```

Public transport routes in the GDA represented in the ERM



CUBE Voyager coding of car occupancy level values

```
RUN PGM=MATRIX PRNFILE="{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Procedural\Demand\Choice_Model\AssPrep\AssPrep_2.PRN" MSG='Period To Hou
Factoring & Vehicle Conversion'
FILEI MATI[1] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\UC1_EMP_AllTravel.ATM"
FILEI MATI[2] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\UC2_COM_AllTravel.ATM"
FILEI MATI[3] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\UC3_OTH_AllTravel.ATM"
FILEI MATI[4] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\UC4_EDU_AllTravel.ATM"
FILEI MATI[5] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\UC5_CON_AllTravel.ATM"
FILEI MATI[6] = "{CATALOG_DIR}\Params\AssPrep\PeriodToHour.PRM"
FILEI MATI[7] = "{CATALOG_DIR}\Params\AssPrep\CarUserToCarDriver.PRM"
FILEO MATO[1] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\AM_CorrectedUnits.CUM",
      MO =  101,121,141,161,181,106,126,146,166,186,
            111,131,151,171,191,116,136,156,176,196, DEC = 20 * D,
      NAME =  M1_UC1, M1_UC2, M1_UC3, M1_UC4, M1_UC5,
              M2_UC1, M2_UC2, M2_UC3, M2_UC4, M2_UC5,
              M3_UC1, M3_UC2, M3_UC3, M3_UC4, M3_UC5,
              M4_UC1, M4_UC2, M4_UC3, M4_UC4, M4_UC5
FILEO MATO[2] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\LT_CorrectedUnits.CUM",
      MO =  102,122,142,162,182,107,127,147,167,187,
            112,132,152,172,192,117,137,157,177,197, DEC = 20 * D,
      NAME =  M1_UC1, M1_UC2, M1_UC3, M1_UC4, M1_UC5,
              M2_UC1, M2_UC2, M2_UC3, M2_UC4, M2_UC5,
              M3_UC1, M3_UC2, M3_UC3, M3_UC4, M3_UC5,
              M4_UC1, M4_UC2, M4_UC3, M4_UC4, M4_UC5
FILEO MATO[3] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\SR_CorrectedUnits.CUM",
      MO =  103,123,143,163,183,108,128,148,168,188,
            113,133,153,173,193,118,138,158,178,198, DEC = 20 * D,
      NAME =  M1_UC1, M1_UC2, M1_UC3, M1_UC4, M1_UC5,
              M2_UC1, M2_UC2, M2_UC3, M2_UC4, M2_UC5,
              M3_UC1, M3_UC2, M3_UC3, M3_UC4, M3_UC5,
              M4_UC1, M4_UC2, M4_UC3, M4_UC4, M4_UC5
FILEO MATO[4] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\PM_CorrectedUnits.CUM",
      MO =  104,124,144,164,184,109,129,149,169,189,
            114,134,154,174,194,119,139,159,179,199, DEC = 20 * D,
      NAME =  M1_UC1, M1_UC2, M1_UC3, M1_UC4, M1_UC5,
              M2_UC1, M2_UC2, M2_UC3, M2_UC4, M2_UC5,
              M3_UC1, M3_UC2, M3_UC3, M3_UC4, M3_UC5,
              M4_UC1, M4_UC2, M4_UC3, M4_UC4, M4_UC5
FILEO MATO[5] = "{CATALOG_DIR}\Runs\{Model Year}\{Run ID}\Output\{Growth}\Demand\OP_CorrectedUnits.CUM",
      MO =  105,125,145,165,185,110,130,150,170,190,
            115,135,155,175,195,120,140,160,180,200, DEC = 20 * D,
      NAME =  M1_UC1, M1_UC2, M1_UC3, M1_UC4, M1_UC5,
              M2_UC1, M2_UC2, M2_UC3, M2_UC4, M2_UC5,
              M3_UC1, M3_UC2, M3_UC3, M3_UC4, M3_UC5,
              M4_UC1, M4_UC2, M4_UC3, M4_UC4, M4_UC5
```

Car occupancy level values per user class by time period

*1 UC1_TP1 | 2 UC2_TP1 | 3 UC3_TP1 | 4 UC4_TP1 | 5 UC5_TP1 | 6 UC1_TP2 | 7 UC2_TP2 | 8 UC3_TP2 | 9 UC4_TP2 | 10 UC5_TP2

	Sum	1	2	3	4	5	6	7	8	9	10	11	12
	670619.52	851.04	851.04	851.04	851.04	851.04	851.04	851.04	851.04	851.04	851.04	851.04	851.04
1	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
2	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
3	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
4	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
5	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
6	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
7	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
8	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
9	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
10	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
11	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
12	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
13	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
14	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
15	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
16	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
17	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
18	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
19	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08
20	851.04	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08

An example of the cycle speeds network database file with the 40% modified cycle speeds is outlined in the table below. Columns A and B are the node ID numbers that connect the links for which the cycle speeds and link distances correspond to.

A	B	CYC_SPEED	DISTANCE
13496	13497	16.8	1.380
13497	13496	18.4	1.380
13276	13497	16.8	0.510
13497	13276	18.4	0.510
13496	13531	16.8	0.960
13531	13496	18.4	0.960
13530	13531	15.2	0.130
13531	13530	15.2	0.130
13529	13530	15.2	0.263
13530	13529	15.2	0.263
13102	13529	15.2	0.214
13529	13102	15.2	0.214
13102	13150	15.2	0.101
13150	13102	15.2	0.101
13146	13150	15.2	0.084
13150	13146	15.2	0.084
13123	13146	15.2	0.214
13146	13123	15.2	0.214
13123	13147	16.8	0.520
13147	13123	18.4	0.520
13147	13549	16.8	0.281
13549	13147	18.4	0.281
13114	13175	17.2	0.100
13175	13114	17.2	0.100
13114	13533	17.2	0.154
13533	13114	15.2	0.150
13533	13534	17.2	0.101

An example of the fare file coding in the ERM, which outlines the fare system coding for DART, Luas, Dublin Bus and Bus Eireann services is shown in the table below

```
FARESYSTEM NUMBER=1,
           NAME="Rail_DART",
           LONGNAME="DART - Distance Based",
           STRUCTURE=DISTANCE,
           SAME=CUMULATIVE,
           IBOARDFARE=0,
           FAREFROMFS=0,-0.44,-0.44,-0.44,0,0,-0.44,-0.44,0,0,0,0,0,0,-0.44,-0.44,-0.44,982*0,
           FARETABLE=0-1.04, 1-1.04, 5-1.46, 10-1.76, 15-1.95, 20-2.03, 25-2.48, 30-2.63, 35-3.08, 40-3.19, 50-3.30,

FARESYSTEM NUMBER=2,
           NAME="Luas",
           LONGNAME="Luas Zone Based Fare System",
           STRUCTURE=COUNT,
           SAME=CUMULATIVE,
           IBOARDFARE=0,
           FAREFROMFS=-0.44,0,-0.44,-0.44,0,0,-0.44,-0.44,0,0,0,0,0,0,-0.44,-0.44,-0.44,982*0,
           FAREZONES=NI.LUAS_FAR_Z,
           FARETABLE=1-1.09, 2-1.22, 3-1.37, 4-1.46, 5-1.46, 6-1.46, 7-1.46, 8-1.46

FARESYSTEM NUMBER=3,
           NAME="DublinBus",
           LONGNAME="Dublin Bus - zone based fare system",
           STRUCTURE=COUNT,
           SAME=CUMULATIVE,
           IBOARDFARE=0.44,
           FAREFROMFS=0.38,0.38,0.56,0.38,0.56,0.56,0.38,0.38,0.56,0.56,0.56,0.56,0.56,0.56,0.38,0.38,0.38,982*0.56,
           FAREZONES=NI.DBUS_FAR_Z,
           FARETABLE=1-0, 2-0.62, 3-0.62, 4-0.97, 5-0.97,
           6-0.97, 7-0.97, 8-1.08, 9-1.08, 10-1.08,
           11-1.08, 12-1.08, 13-1.08, 14-1.28, 15-1.28,
           16-1.28, 17-1.28, 18-1.28, 19-1.28, 20-1.28,
           21-1.28, 22-1.28, 23-1.28, 24-1.28, 25-1.28,
           26-1.28, 27-1.28, 28-1.28, 29-1.28, 30-1.28,
           31-1.28, 32-1.28, 33-1.28, 34-1.28, 35-1.28,
           36-1.28, 37-1.28, 38-1.28, 39-1.28, 40-1.28

FARESYSTEM NUMBER=4,
           NAME="BusEireann",
           LONGNAME="Bus Eireann - Distance based",
           STRUCTURE=DISTANCE,
           SAME=CUMULATIVE,
           IBOARDFARE=0,
           FAREFROMFS=-0.88,-0.88,-0.88,0,0,0,-0.88,-0.88,0,0,0,0,0,0,-0.88,-0.88,-0.88,982*0,
           FARETABLE=0-2.08,20-2.08,40-3.47,60-4.85,80-5.90,120-6.24 INTERPOLATE = T
```

APPENDIX C: Full mode share outputs from the ERM

Active mode changes output for the inner metropolitan area of the GDA, 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	1,196,848	49.84	Car	1,153,893	48.00	-1.84	Car	1,134,015	47.15	-2.69
PT	313,886	13.07	PT	236,694	9.85	-3.22	PT	211,938	8.81	-4.26
Walk	731,163	30.45	Walk	888,248	36.95	6.50	Walk	943,378	39.23	8.78
Cycle	159,567	6.64	Cycle	124,885	5.20	-1.44	Cycle	115,551	4.80	-1.84
Total	2,401,464	100.00	Total	2,403,720	100.00		Total	2,404,883	100.00	
Commute Trip Purpose (Base Scenario 2012)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	689,787	63.21	Car	676,782	62.16	-1.05	Car	677,275	62.20	-1.01
PT	146,747	13.45	PT	130,522	11.99	-1.46	PT	120,574	11.07	-2.37
Walk	192,742	17.66	Walk	228,140	20.95	3.29	Walk	240,595	22.10	4.43
Cycle	61,944	5.68	Cycle	53,320	4.90	-0.78	Cycle	50,386	4.63	-1.05
Total	1,091,220	100.00	Total	1,088,763			Total	1,088,830	100.00	

Active mode changes output for the inner metropolitan area of the GDA, 2035 Strategy

All Trip Purposes (2035 Strategy)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Ca	1,226,278	45.75	Car	1,199,213	44.77	-0.98	Car	1,179,220	43.90	-1.85
PT	599,407	22.36	PT	477,762	17.84	-4.52	PT	432,085	16.08	-6.28
Walk	723,939	27.01	Walk	907,747	33.89	6.88	Walk	974,989	36.29	9.28
Cycle	130,649	4.87	Cycle	93,908	3.51	-1.36	Cycle	100,098	3.73	-1.14
Total	2,680,273		Total	2,678,628			Total	2,686,393		
Commute Trip Purpose (2035 Strategy)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	717,454	58.38	Car	693,263	57.05	-1.34	Car	703,879	57.29	-1.09
PT	293,918	23.92	PT	273,916	22.54	-1.38	PT	256,156	20.85	-3.07
Walk	177,381	14.43	Walk	216,824	17.84	3.41	Walk	234,015	10.05	4.61
Cycle	40,105	3.26	Cycle	31,222	2.57	-0.69	Cycle	34,558	2.81	-0.45
Total	1,228,858		Total	1,215,225	100.00		Total	1,228,608	100.00	

Cycle speeds only changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)			**Do Something Scenario** 40% increase in cycle speeds				**Do Maximum Scenario** 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Ca	3,141,710	62.23	Car	3,140,507	62.21	-0.02	Car	3,141,033	62.21	-0.02
PT	489,307	9.69	PT	475,544	9.42	-0.27	PT	470,570	9.32	-0.37
Wal	1,206,692	23.90	Walk	1,195,460	23.68	-0.22	Walk	1,189,533	23.56	-0.34
Cycle	210,814	4.18	Cycle	237,006	4.69	0.51	Cycle	248,282	4.92	0.74
Total	5,048,523	100.00	Total	5,048,517	100.00		Total	5,049,418	100.00	
Commute Trip Purpose (Base Scenario 2012)			**Do Something Scenario** 40% increase in cycle speeds				**Do Maximum Scenario** 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Ca	763,007	72.89	Car	763,943	72.97	0.08	Car	751,863	71.81	-1.08
PT	110,731	10.58	PT	106,209	10.15	-0.43	PT	113,085	10.80	0.22
Walk	133,777	12.78	Walk	131,743	12.58	-0.20	Walk	131,764	12.58	-0.20
Cycle	39,282	3.75	Cycle	44,974	4.30	0.54	Cycle	50,331	4.81	1.05
Total	1,046,797	100.00	Total	1,046,869	100.00		Total	1,047,043	100.00	

Cycle speeds only changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)			**Do Something Scenario** 40% increase in cycle speeds				**Do Maximum Scenario** 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,495,087	58.40	Car	3,518,683	58.78	0.38	Car	3,516,575	58.74	0.34
PT	968,176	16.18	PT	944,954	15.78	-0.40	PT	940,213	15.71	-0.47
Walk	1,327,328	22.18	Walk	1,312,057	21.92	-0.26	Walk	1,309,521	21.87	-0.30
Cycle	194,189	3.24	Cycle	210,842	3.52	0.28	Cycle	220,220	3.68	0.43
Total	5,984,781		Total	5,986,537	100		Total	5,986,529	100.00	
Commute Trip Purpose (2035 Strategy)			**Do Something Scenario** 40% increase in cycle speeds				**Do Maximum Scenario** 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	872,227	68.76	Car	861,644	68.07	-0.69	Car	861,337	68.05	-0.71
PT	237,856	18.75	PT	242,058	19.12	0.37	PT	240,928	19.03	0.28
Walk	131,266	10.35	Walk	130,416	10.30	-0.05	Walk	129,972	10.27	-0.08
Cycle	27,163	2.14	Cycle	31,690	2.50	0.36	Cycle	33,556	2.65	0.51
Total	1,268,512		Total	1,265,809			Total	1,265,793	100.00	

Active Modes (Walking and Cycling) changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,141,710	62.23	Car	3,075,717	60.90	-1.33	Car	3,046,485	60.32	-1.91
PT	489,307	9.69	PT	382,308	7.57	-2.12	PT	347,444	6.88	-2.81
Walk	1,206,692	23.90	Walk	1,430,299	28.32	+4.42	Walk	1,507,846	29.85	5.95
Cycle	210,814	4.18	Cycle	162,146	3.21	-0.97	Cycle	148,916	2.95	-1.23
Total	5,048,523	100.00	Total	5,050,470	100.00		Total	5,050,691	100.00	

Commute Trip Purpose (Base Scenario 2012)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	763,007	72.89	Car	754,971	72.08	-0.81	Car	755,662	72.14	-0.75
PT	110,731	10.58	PT	100,319	9.58	-1.00	PT	93,351	8.91	-1.67
Walk	133,777	12.78	Walk	158,748	15.16	2.38	Walk	167,107	15.95	3.17
Cycle	39,282	3.75	Cycle	3,3381	3.19	-0.57	Cycle	31,395	3.00	-0.76
Total	1,046,797	100.00	Total	1,047,419	100.00		Total	1,047,515	100.00	

Active Modes changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,495,087	58.40	Car	3,453,837	57.68	-0.72	Car	3,418,993	57.07	-1.33
PT	968,176	16.18	PT	790,666	13.20	-2.98	PT	725,408	12.11	-4.07
Walk	1,327,328	22.18	Walk	1,606,653	26.83	4.65	Walk	1,706,142	28.48	6.30
Cycle	194,189	3.24	Cycle	136,628	2.29	-0.96	Cycle	140,758	2.35	-0.89
Total	5,984,781	100.00	Total	5,987,783	100.00		Total	5,991,301	100.00	

Commute Trip Purpose (2035 Strategy)			**Do Something Scenario** 25% increase in Ped. speeds and 40% increase in cycle speeds				**Do Maximum Scenario** 35% increase in Ped. speeds and 60% increase in cycle speeds			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	872,227	68.76	Car	863,739	68.20	-0.56	Car	864,797	68.26	-0.50
PT	237,856	18.75	PT	222,683	17.58	-1.17	PT	210,763	16.64	-2.12
Walk	131,266	10.35	Walk	159,509	12.59	2.25	Walk	169,081	13.35	3.00
Cycle	27,163	2.14	Cycle	20,618	1.63	-0.51	Cycle	22,307	1.76	-0.38
Total	1,268,512		Total	1,266,550	100.00		Total	1,266,948	100.00	

PT (Bus and Rail) changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)			**Do Something Scenario** 25% decrease in headways and fares				**Do Maximum Scenario** 35% decrease in headways and fares			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,141,710	62.23	Car	3,126,738	61.95	-0.28	Car	3,125,756	61.71	-0.52
PT	489,307	9.69	PT	556,819	11.03	1.34	PT	596,193	11.77	2.08
Walk	1,206,692	23.90	Walk	1,171,901	23.22	-0.68	Walk	1,158,232	22.87	-1.03
Cycle	210,814	4.18	Cycle	191,964	3.80	-0.38	Cycle	184,668	3.65	-0.53
Total	5,048,523	100.00	Total	5,047,423	100.00		Total	5,064,850	100.00	
Commute Trip Purpose (Base Scenario 2012)			**Do Something Scenario** 25% decrease in headways and fares				**Do Maximum Scenario** 35% decrease in headways and fares			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	763,007	72.89	Car	747,506	71.41	-1.48	Car	744,580	71.13	-1.76
PT	110,731	10.58	PT	133,658	12.77	2.19	PT	140,753	13.45	2.87
Walk	133,777	12.78	Walk	130,183	12.44	-0.34	Walk	128,152	12.24	-0.54
Cycle	39,282	3.75	Cycle	35,502	3.39	-0.36	Cycle	33,280	3.18	-0.57
Total	1,046,797	100.00	Total	1,046,850	100.00		Total	1,046,765	100.00	

PT changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)			**Do Something Scenario** 25% decrease in headways and fares				**Do Maximum Scenario** 35% decrease in headways and fares			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,495,087	58.40	Car	3,504,611	58.53	0.13	Car	3,491,842	58.33	-0.07
PT	968,176	16.18	PT	1,007,074	16.82	0.64	PT	1,039,911	17.37	1.19
Walk	1,327,329	22.18	Walk	1,294,491	21.62	-0.56	Walk	1,278,396	21.36	-0.82
Cycle	194,189	3.24	Cycle	181,434	3.03	-0.21	Cycle	175,987	2.94	-0.30
Total	5,984,781	100.00	Total	5,987,610	100.00		Total	5,986,137	100.00	
Commute Trip Purpose (2035 Strategy)			**Do Something Scenario** 25% decrease in headways and fares				**Do Maximum Scenario** 35% decrease in headways and fares			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	872,227	68.76	Car	859,724	67.90	-0.86	Car	858,175	67.77	-0.99
PT	237,856	18.75	PT	250,891	19.82	1.06	PT	255,368	20.17	1.42
Walk	131,266	10.35	Walk	129,736	10.25	-0.10	Walk	128,060	10.11	-0.24
Cycle	27,163	2.14	Cycle	25,808	2.04	-0.10	Cycle	24,710	1.95	-0.19
Total	1,268,512	100.00	Total	1,266,159	100.00		Total	1,266,313	100.00	

Carpooling changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)			**<u>Do Something Scenario</u> 25% increase in car occupancy values**				**<u>Do Maximum Scenario</u> 35% increase in car occupancy values**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,141,710	62.23	Ca	3,172,694	62.84	0.61	Car	3,181,254	63.01	0.78
PT	489,307	9.69	PT	474,860	9.41	-0.28	PT	470,106	9.31	-0.38
Walk	1,206,692	23.90	Walk	1,195,139	23.67	-0.23	Walk	1,192,981	23.63	-0.27
Cycle	210,814	4.18	Cycle	205,896	4.08	-0.10	Cycle	204,689	4.05	-0.13
Total	5,048,523	100.00	Total	5,048,587	100.00		Total	5,049,031	100.00	
Commute Trip Purpose (Base Scenario 2012)			**<u>Do Something Scenario</u> 25% increase in car occupancy values**				**<u>Do Maximum Scenario</u> 35% increase in car occupancy values**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	763,007	72.89	Car	765,678	73.10	0.21	Car	769,459	73.47	0.58
PT	110,731	10.58	PT	108,786	10.39	-0.19	PT	105,819	10.10	-0.47
Walk	133,777	12.78	Walk	133,584	12.75	-0.03	Walk	133,306	12.73	-0.05
Cycle	39,282	3.75	Cycle	39,358	3.76	0.01	Cycle	38,704	3.70	-0.06
Total	1,046,797	100.00	Total	1,047,407	100.00		Total	1,047,289	100.00	

Carpooling changes output for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)			**<u>Do Something Scenario</u> 25% increase in car occupancy values**				**<u>Do Maximum Scenario</u> 35% increase in car occupancy values**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,495,087	58.40	Car	3,566,160	59.59	1.19	Car	3,605,725	60.23	1.83
PT	968,176	16.18	PT	965,288	16.13	-0.05	PT	901,285	15.06	-1.12
Walk	1,327,329	22.18	Walk	1,277,129	21.34	-0.84	Walk	1,295,827	21.65	-0.53
Cycle	194,189	3.24	Cycle	176,028	2.94	-0.30	Cycle	183,415	3.06	-0.18
Total	5,984,781	100.00	Total	5,984,605	100.00		Total	5,986,252	100.00	
Commute Trip Purpose (2035 Strategy)			**<u>Do Something Scenario</u> 25% increase in car occupancy values**				**<u>Do Maximum Scenario</u> 35% increase in car occupancy values**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	872,227	68.76	Car	883,886	69.79	1.03	Car	893,759	70.57	1.81
PT	237,856	18.75	PT	228,433	18.04	-0.71	PT	215,297	17.00	-1.75
Walk	131,266	10.35	Walk	129,029	10.19	-0.16	Walk	130,569	10.31	-0.04
Cycle	27,163	2.14	Cycle	25,120	1.98	-0.16	Cycle	26,890	2.12	-0.02
Total	1,268,512	100.00	Total	1,266,467	100.00		Total	1,266,514	100.00	

Optimal Car-shedding Model changes output for the 2012 Base Scenario

All Trip Purposes (Base Scenario 2012)			**Do Something Scenario All changes**				**Do Maximum Scenario All changes**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,141,710	62.23	Car	3,088,584	61.17	-1.06	Car	3,061,181	60.63	-1.60
PT	489,307	9.69	PT	423,225	8.38	-1.31	PT	403,933	8.00	-1.69
Walk	1,206,692	23.90	Walk	1,389,524	27.52	3.62	Walk	1,452,053	28.76	4.86
Cycle	210,814	4.18	Cycle	147,651	2.92	-1.26	Cycle	131,397	2.61	-1.57
Total	5,048,523	100.00	Total	5,048,984	100.00		Total	5,048,563	100.00	
Commute Trip Purpose (Base Scenario 2012)			**Do Something Scenario All changes**				**Do Maximum Scenario All changes**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	763,007	72.89	Car	763,552	72.87	-0.02	Car	766,075	73.11	0.22
PT	110,731	10.58	PT	102,954	9.83	-0.75	PT	97,866	9.34	-1.24
Walk	133,777	12.78	Walk	153,125	14.61	1.83	Walk	159,058	15.18	2.40
Cycle	39,282	3.75	Cycle	28,142	2.69	-1.07	Cycle	24,855	2.37	-1.38
Total	1,046,797	100.00	Total	1,047,772	100.00		Total	1,047,855	100.00	

Optimal Car-shedding Model changes for the 2035 GDA Strategy

All Trip Purposes (2035 Strategy)			**Do Something Scenario All changes**				**Do Maximum Scenario All changes**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	3,495,087	58.40	Car	3,498,783	58.45	0.06	Car	3,477,329	58.07	-0.33
PT	968,176	16.18	PT	800,201	13.37	-2.81	PT	749,579	12.52	-3.66
Walk	1,327,329	22.18	Walk	1,558,373	26.04	3.86	Walk	1,633,315	27.28	5.10
Cycle	194,189	3.24	Cycle	127,913	2.14	-1.10	Cycle	127,815	2.13	-1.11
Total	5,984,781	100.00	Total	5,985,290	100.00		Total	5,988,037	100.00	
Commute Trip Purpose (2035 Strategy)			**Do Something Scenario All changes**				**Do Maximum Scenario All changes**			
Base	**Trips**	**Mode Share %**		**Trips**	**Mode Share %**	**% diff. from Base**		**Trips**	**Mode Share %**	**% diff. from Base**
Car	872,227	68.76	Car	886,461	69.95	1.20	Car	892,712	70.43	1.67
PT	237,856	18.75	PT	206584	16.30	-2.45	PT	192,658	15.20	-3.55
Walk	131,266	10.35	Walk	155,425	12.27	1.92	Walk	162,971	12.86	2.51
Cycle	27,163	2.14	Cycle	18,718	1.48	-0.66	Cycle	19,251	1.52	-0.62
Total	1,268,512	100.00	Total	1,267,187	100.00		Total	1,267,591	100.00	

APPENDIX D: Full emissions estimation outputs

Active mode changes emissions output for the 2012 Base Scenario

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	844,342	152,896.80	730,923	140,552.07	293,448.86			571.62	70.90	642.52			29.64	1.29	30.93	
Car Commute	3,652,487	661,407.03	3,161,855	608,005.70	1,269,412.73			2,472.73	306.70	2,779.43			128.24	5.56	133.80	
Car Education	55,114	9,980.21	47,710	9174.42	19,154.63			37.31	4.63	41.94			1.94	0.08	2.02	
Car Other	5,241,784	949,203.28	4,537,664	872,565.57	1,821,768.85			3,548.69	440.15	3,988.84			184.04	7.99	192.03	
Bus	174,753	199,100.07			199,100.07			1,609.48		1,609.48			14.2		14.16	
DART	185,605	2,041.65			2,041.65											
Luas	184,464	13,023.19			13,023.19											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	835,305	151,260.41	723,100	139,047.80	290,308.21	-3,140.65		565.50	70.14	635.64	-6.88		29.33	1.27	30.60	-0.33
Car Commute	3,685,029	667,299.79	3,190,025	613,422.68	1,280,722.47	11,309.74		2,494.76	309.43	2,804.20	24.77		129.38	5.61	135.00	1.20
Car Education	49,993	9,052.99	43,278	83,22.06	17,375.06	-1,779.57		33.85	4.20	38.04	-3.90		1.76	0.08	1.83	-0.19
Car Other	5,228,593	946,814.53	4,526,245	870,369.69	1,817,184.22	-4,584.63		3,539.76	439.05	3,978.80	-10.04		183.58	7.97	191.54	-0.49
Bus	162,548	185,194.51			185,194.51	-13,905.56		149.07		149.07	-112.41		13.173		13.173	-0.99
DART	168,928	1,858.21			1,858.21	-183.44										
Luas	158,382	11,181.74			11,181.74	-1,841.45										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	830,120	150,321.38	718,611	138,184.59	288,505.97	-4,942.89		561.99	69.71	631.70	-10.82		29.15	1.26	30.41	-0.52
Car Commute	3,695,511	669,197.83	3,199,099	615,167.48	1,284,365.32	14,952.59		2,501.86	310.31	2,812.17	32.74		129.75	5.63	135.38	1.58
Car Education	48,176	8,723.88	41,704	8,019.52	16,743.40	-2,411.23		32.62	4.05	36.66	-5.28		1.69	0.07	1.76	-0.26
Car Other	5,210,331	943,507.65	4,510,436	867,329.81	1,810,837.46	-10,931.39		3,527.39	437.51	3,964.91	-23.93		182.93	7.94	190.87	-1.16
Bus	160,327	182,664.08			182,664.08	-16,435.99		1,476.61		1,476.61	-132.87		12.99		12.99	-1.17
DART	162,916	1,792.07			1,792.07	-249.58										
Luas	149,836	10,578.42			10,578.42	-2,444.77										

Active mode changes emissions output for the 2035 GDA Strategy

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	900,494	163,065.09	779,532	149,899.38	312,964.47			609.63	75.61	685.25			31.62	1.37	32.99	
Car Commute	4,760,750	862,095.61	4,121,246	792,490.89	1,654,586.5			3,223.03	399.76	3,622.79			167.15	7.25	174.40	
Car Education	50,774	9,194.44	43,954	8,452.09	17,646.52			34.37	4.26	38.64			1.78	0.08	1.86	
Car Other	5,549,993	1,005,014.99	4,804,472	923,871.11	1,928,886.1			3,757.35	466.03	4,223.38			194.86	8.46	203.32	
Bus	1,361,613	1,551,315.41			1,551,315.4			12,540.5		12,540.5			110.35		110.35	
DART	1,009,375	11,103.13			11,103.13											
Luas	311,162	21,968.02			21,968.02											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	914,600	165,619.49	791,744	152,247.54	317,867.03	4,902.56		619.18	76.80	695.98	10.73		32.11	1.39	33.51	0.52
Car Commute	4,802,545	869,664.11	4,157,427	799,448.31	1,669,112.4	14,525.91		3,251.32	403.27	3654.59	31.81		168.62	7.32	175.93	1.53
Car Education	46,951	8,502.00	40,644	7,815.56	16,317.56	-1,328.96		31.79	3.94	35.73	-2.91		1.65	0.07	1.72	-0.14
Car Other	5,618,409	1,017,404.03	4,863,698	935,259.87	1,952,663.9	23,777.81		3,803.66	471.78	4,275.44	52.06		197.26	8.56	205.82	2.51
Bus	1,236,113	1,408,330.48			1,408,330.5	-142,984.93		11,384.6		11,384.6	-1,155.9		100.17		100.17	-10.17
DART	884,469	9,729.16			9,729.16	-1,373.97										
Luas	249,485	17,613.61			17,613.61	-4,354.41										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	909,705	164,733.05	7,87506	151,432.67	316,165.72	3,201.25		615.87	76.39	692.26	7.01		31.94	1.39	33.33	0.34
Car Commute	4,801,258	869,431.09	4,156,313	799,234.11	1,668,665.2	14,078.70		3,250.45	403.16	3,653.61	30.83		168.57	7.32	175.89	1.48
Car Education	45,002	8,149.05	38,957	7,491.11	15,640.16	-2,006.36		30.47	3.78	34.24	-4.39		1.58	0.07	1.65	-0.21
Car Other	5,600,896	1,014,232.67	4,848,537	932,344.56	1,946,577.2	17,691.14		3,791.81	470.31	4,262.11	38.74		196.65	8.53	205.18	1.86
Bus	1,181,309	1,345,891.50			1,345,891.5	-205,423.91		10,879.9		10,879.9	-1,660.6		95.73		95.73	-14.61
DART	850,441	93,54.86			9,354.86	-1,748.27										
Luas	231,674	16,356.18			16,356.18	-5,611.83										

PT changes emissions output for the 2012 Base Scenario

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	844,342	152896.80	730,923	140,552.1	293448.86			571.62	70.90	642.52			29.64	1.29	30.93	
Car Commute	3,652,487	661407.03	3,161,855	608,005.7	1269412.73			2,472.73	306.70	2,779.43			128.24	5.56	133.80	
Car Education	55,114	9980.21	47,710	9,174.42	19154.63			37.31	4.63	41.94			1.94	0.08	2.02	
Car Other	5,241,784	949203.28	4,537,664	872,565.6	1821768.85			3,548.69	440.15	3,988.84			184.04	7.99	192.03	
Bus	174,753	199100.07			199100.07			1,609.48		1,609.48			14.2		14.16	
DART	185,605	2041.65			2041.65											
Luas	184,464	13023.19			13023.19											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	737,834	133609.86	638,722	122,822.3	2564,32.20	-37,016.67		499.51	61.96	561.47	-81.05		25.91	1.12	27.03	-3.90
Car Commute	2,410,700	436539.12	2,086,874	401,293.4	837,832.52	-431,580.21		1,632.04	202.43	1,834.47	-944.96		84.64	3.67	88.31	-45.49
Car Education	1,459,620	264313.75	1,263,551	242,973.3	507,287.09	488,132.45		988.16	122.56	1,110.73	1,068.8		51.25	2.22	53.47	51.45
Car Other	5,212,172	943840.98	4,512,030	867,636.2	1,811,477.20	-10,291.65		3,528.64	437.67	3,966.31	-22.53		183.00	7.94	190.94	-1.08
Bus	207,460	236363.37			236,363.37	37,263.29		1,910.70		1,910.70	301.23		16.81		16.81	2.65
DART	216,712	2383.83			2,383.83	342.18										
Luas	206,292	14564.22			14,564.22	154.03										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	835,971	151380.98	723,676	139,158.6	290,539.61	-2,909.26		565.95	70.20	636.15	-6.37		29.35	1.27	30.62	-0.31
Car Commute	3,620,687	655648.50	3,134,326	602,712.1	1,258,360.60	-11,052.13		2,451.21	304.03	2,755.23	-24.20		127.12	5.52	132.64	-1.16
Car Education	52,462	9499.95	45,414	8,732.93	18,232.88	-921.76		35.52	4.41	39.92	-2.02		1.84	0.08	1.92	-0.10
Car Other	5,196,351	940976.05	4,498,334	865,002.6	1805,978.66	-15,790.19		3,517.93	436.34	3,954.27	-34.57		182.44	7.92	190.36	-1.66
Bus	284,919	324614.27			324,614.27	125,514.20		2,624.10		2,624.10	1,014.6		23.09		23.09	8.93
DART	231,492	2546.41			2,546.41	504.76										
Luas	218,936	15456.90			15,456.90	2,433.71										

PT changes emissions output for the 2035 GDA Strategy

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	900,494	163,065.09	779,532	149,899.38	312,964.47			609.63	75.61	685.25			31.62	1.37	32.99	
Car Commute	4,760,750	862,095.61	4,121,246	792,490.89	1,654,586.51			3,223.03	399.76	3,622.79			167.15	7.25	174.40	
Car Education	50,774	9,194.44	43,954	8,452.09	17,646.52			34.37	4.26	38.64			1.78	0.08	1.86	
Car Other	5,549,993	1,005,014.99	4,804,472	923,871.11	1928886.10			3,757.35	466.03	4,223.38			194.86	8.46	203.32	
Bus	1,361,613	1,551,315.41			1551315.41			125,40.45		12,540.45			110.35		110.35	
DART	1,009,375	11,103.13			11103.13											
Luas	311,162	21,968.02			21968.02											
Do Something	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	900,380	163,044.43	779,433	149,880.39	312,924.81	-39.66		609.56	75.61	685.16	-0.09		31.61	1.37	32.98	0.01
Car Commute	4,778,471	865,304.61	4,136,589	795,440.80	1,660,745.41	6,158.90		3,235.02	401.25	3,636.27	13.49		167.77	7.28	175.05	0.65
Car Education	51,135.33	9,259.80	44,266	8,512.16	17,771.96	125.43		34.62	4.29	38.91	0.27		1.80	0.08	1.87	0.01
Car Other	5,595,495	1,013,254.57	4,843,861	931,445.43	1,944,700.00	15,813.90		3,788.15	469.85	4,258.00	34.63		196.46	8.53	204.98	1.67
Bus	1,735,241	1,976,998.39			1,976,998.39	425,682.98		15,981.57		15,981.57	3,441.12		140.62		140.62	30.28
DART	1,060,527	11,665.80			11,665.80	562.67										
Luas	293,611.1	20,728.95			20,728.95	-1239.07										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	897,070	162,444.96	776,568	149,329.32	311,774.28	-1,190.19		607.32	75.33	682.64	-2.61		31.50	1.37	32.86	-0.13
Car Commute	4,768,668	863,529.52	4,128,101	793,809.03	1,657,338.54	2,752.04		3,228.39	400.43	3,628.81	6.03		167.43	7.27	174.69	0.29
Car Education	50,477	9,140.58	43,696	8,402.57	17,543.15	-103.37		34.17	4.24	38.41	-0.23		1.77	0.08	1.85	-0.01
Car Other	5,575,934	1,009,712.36	4,826,928	928,189.21	1,937,901.57	9,015.47		3,774.91	468.21	4,243.12	19.74		195.77	8.50	204.27	0.95
Bus	1,735,241	1,976,998.39			1,976,998.39	425,682.98		1,5981.57		15,981.57	3,441.12		140.62		140.62	30.28
DART	1,070,322	11,773.54			11,773.54	670.42										
Luas	312,961	22,095.05			22,095.05	127.03										

Carpooling changes emissions output for the 2012 Base Scenario

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	844,342	152896.80	730,923	140,552.07	293,448.86			571.62	70.90	642.52			29.64	1.29	30.93	
Car Commute	3,652,487	661407.03	3,161,855	608,005.70	1,269,412.73			2472.73	306.70	2779.43			128.24	5.56	133.80	
Car Education	55,114	9980.21	47,710	9,174.42	19,154.63			37.31	4.63	41.94			1.94	0.08	2.02	
Car Other	5,241,784	949203.28	4,537,664	872,565.57	1,821,768.85			3548.69	440.15	3988.84			184.04	7.99	192.03	
Bus	174,753	199100.07			199,100.07			1609.48		1609.48			14.16		14.16	
DART	185,605	2041.65			2,041.65											
Luas	184,464	13023.19			13,023.19											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	857,080	155203.47	741,950	142,672.50	297,875.98	4,427.11		580.24	71.97	652	9.69		30.09	1.31	31.4	0.47
Car Commute	3,126,229	566110.13	2,706,288	520,402.98	1,086,513.11	-182,899.62		2116.46	262.51	2379	-400.47		109.76	4.76	115	-19.28
Car Education	48,171	8722.99	41,700	8,018.70	16,741.69	-2,412.94		32.61	4.04	37	-5.28		1.69	0.07	1.8	-0.25
Car Other	5,320,334	963427.31	4605,662	885,641.17	1,849,068.47	27,299.62		3601.87	446.75	4049	59.77		186.80	8.11	195	2.88
Bus	174,748	199093.80			199,093.80	-6.27		1609.4		1609.4	-0.05		14.16		14	0.00
DART	179,056	1969.62			1,969.62	-72.03										
Luas	176,661	12472.25			12,472.25	-550.94										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	859,971	155,726.94	744,452	143,153.71	298,880.65	5,431.79		582.20	72.21	654	11.89		30.19	1.31	32	0.57
Car Commute	2,974,973	538,720.01	2,575,350	495,224.30	1,033,944.31	-235,468.42		2014.06	249.81	2264	-515.57		104.45	4.53	109	-24.82
Car Education	45,849	8,302.50	39,690	7,632.17	15,934.67	-3,219.96		31.04	3.85	35	-7.05		1.61	0.07	1.7	-0.34
Car Other	5,340,100	967,006.70	4622,773	888,931.57	185,5938.27	34,169.42		3615.25	448.41	4064	74.82		187.49	8.14	196	3.60
Bus	170,436	194,181.65			194,181.65	-4,918.42		1569.72		1570	-39.76		13.81		13.8	-0.35
DART	175,921	1,935.13			1,935.13	-106.52										
Luas	175,464	12,387.77			12,387.77	-635.42										

Carpooling changes emissions output for the 2035 GDA Strategy

Base	CO_2 Emissions (kg)							NO_x Emissions (kg)					$PM_{2.5}$ Emissions (kg)			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	900,494	163,065.09	779,532	149,899.38	312,964.47			609.63	75.61	685.25			31.62	1.37	32.99	
Car Commute	4,760,750	862,095.61	4,121,246	792,490.89	1,654,586.51			3,223.03	399.76	3,622.79			167.15	7.25	174.40	
Car Education	50,774	9,194.44	43,954	8,452.09	17,646.52			34.37	4.26	38.64			1.78	0.08	1.86	
Car Other	5,549,993	1005,014.99	4,804,472	92,387.11	1,928,886.10			3,,757.35	466.03	4,223.38			194.86	8.46	203.32	
Bus	1,361,613	1551,315.41			1,551,315.41			12540.45		12,540.45			110.35		110.35	
DART	1,009,375	11,103.13			11,103.13											
Luas	311,162	21,968.02			21,968.02											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	951,375	172,278.76	823,578	158,369.15	330,647.91	17,683.44		644.08	79.89	723.97	38.72		33.40	1.45	34.85	1.86
Car Commute	4,125,015	746,974.25	3,570,909	686,664.31	1,433,638.56	-220,947.95		2,792.64	346.38	3,139.01	-483.78		144.83	6.28	151.11	-23.29
Car Education	46,797	8,474.26	40,511	7,790.06	16,264.31	-1,382.21		31.68	3.93	35.61	-3.03		1.64	0.07	1.71	-0.15
Car Other	5,772,568	1,045,319.62	4,997,148	960,921.58	2,006,241.21	77,355.11		3,908.03	484.72	4,392.75	169.37		202.67	8.79	211.47	8.15
Bus	1,345,425	1,532,872.62			1,532,872.62	-18,442.79		12,391.37		12,391.37	-149.09		109.03		109.03	-1.31
DART	905,688	9,962.57			9,962.57	-1,140.56										
Luas	277,210	19,571.02			19,571.02	-2,397.00										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	1,010,890	183,055.94	875,098	168,276.19	351,332.13	38,367.66		684.37	84.88	769.26	84.01		35.49	1.54	37.03	4.04
Car Commute	5,481,508	992,613.34	4,745,186	912,470.75	1,905,084.09	250,497.58		3,710.98	460.28	4,171.26	548.48		192.46	8.35	200.81	26.40
Car Education	6,4936	11,758.93	56,214	10,809.53	22,568.45	4,921.93		43.96	5.45	49.41	10.78		2.28	0.10	2.38	0.52
Car Other	5,812,147	1,052,486.77	5,031,411	967,510.06	2,019,996.83	91,110.73		3,934.82	488.05	4,422.87	199.49		204.06	8.86	212.92	9.60
Bus	1,321,503	1,505,617.03			1,505,617.03	-45,698.38		12,171.04		12,171.04	-369.41		107.09		107.09	-3.25
DART	888,793	9,776.72			9,776.72	-1,326.40										
Luas	271,691	19,181.36			19,181.36	-2,786.66										

Optimal Car-shedding emissions output for the 2012 Base Scenario

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	844,342	152,896.80	730,923	140,552.07	293,448.86			571.62	70.90	642.52			29.64	1.29	30.93	
Car Commute	3,652,487	661,407.03	3,161,855	608,005.70	1,269,412.73			2472.73	306.70	2779.43			128.24	5.56	133.80	
Car Education	55,114	9,980.21	47,710	9,174.42	19,154.63			37.31	4.63	41.94			1.94	0.08	2.02	
Car Other	5,241,784	949,203.28	4,537,664	872,565.57	1,821,768.85			3548.69	440.15	3988.84			184.04	7.99	192.03	
Bus	174,753	199,100.07			199,100.07			1609.48		1609.48			14.16		14.16	
DART	185,605	2,041.65			2,041.65											
Luas	184,464	13,023.19			13,023.19											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	841,414	152,366.54	728,388	140,064.62	292,431.16	-1,017.70		569.64	70.65	640.29	-2.23		29.54	1.28	30.82	-0.11
Car Commute	3,121,821	565,311.82	2,702,472	519,669.12	1,084,980.94	-184,431.79		2,113.47	262.14	2,375.61	-403.82		109.61	4.76	114.36	-19.44
Car Education	42,636	7,720.72	36,909	7,097.36	14,818.09	-4,336.55		28.86	3.58	32.44	-9.50		1.50	0.06	1.56	-0.46
Car Other	5,253,733	951,366.91	4,548,007	874,554.51	1,825,921.42	4,152.57		3,556.78	441.16	3,997.93	9.09		184.46	8.00	192.46	0.44
Bus	207,460	236,363.37			236,363.37	37,263.29		1,910.70		1,910.70	301.23		16.81		16.81	2.65
DART	180,392	1,984.31			1,984.31	-57.34										
Luas	163,929	11,573.41			11,573.41	-1,449.78										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	837,420	151,643.28	724,930	139,399.75	291,043.03	-2,405.83		566.93	70.32	637.25	-5.27		29.40	1.28	30.68	-0.25
Car Commute	2,965,755	537,050.77	2,567,370	493,689.84	1,030,740.62	-238,672.11		363.58	249.03	612.62	-522.58		104.13	4.52	108.65	-25.16
Car Education	38,741	7,015.40	33,537	6,448.98	13,464.38	-5,690.25		26.23	3.25	29.48	-12.46		1.36	0.06	1.42	-0.60
Car Other	5,246,235	950,009.29	4,541,517	873,306.51	1,823,315.79	1,546.94		3,551.70	440.53	3,992.23	3.39		184.20	0.06	184.25	-7.77
Bus	284,919	324,614.28			324,614.28	125,514.21		2,624.10		2,624.10	1014.63		23.09		23.09	8.93
DART	179,437	1,973.81			1,973.81	-67.84										
Luas	160,982	11,365.34			11,365.34	-1,657.86										

Optimal Car-shedding Model emissions output for the 2035 GDA Strategy

Base	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**			**Diesel Emiss.**	**Petrol Emiss.**	**Total**	
Car Emp. Business	900,494	163,065.09	779,532	149,899.38	312,964.47			609.63	75.61	685.25			31.62	1.37	32.99	
Car Commute	4,760,750	862,095.61	4,121,246	792,490.89	1,654,586.51			3,223.03	399.76	3,622.79			167.15	7.25	174.40	
Car Education	50,774	9,194.44	43,954	8,452.09	17,646.52			34.37	4.26	38.64			1.78	0.08	1.86	
Car Other	5,549,993	1,005,014.99	4,804,472	92,387.11	1,928,886.10			3,757.35	466.03	4,223.38			194.86	8.46	203.32	
Bus	1,361,613	1,551,315.41			1,551,315.41			12,540.45		12,540.45			110.35		110.35	
DART	1,009,375	11,103.13			11,103.13											
Luas	311,162	21,968.02			21,968.02											
Do Some	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	938,190	169,891.15	812,164	156,174.31	326,065.46	13,100.99		635.15	78.78	713.93	28.69		32.94	1.43	34.37	1.38
Car Commute	4,112,377	744,685.68	3,559,968	684,560.52	1,429,246.19	-225,340.31		2,784.08	345.32	3,129.40	-493.39		144.39	6.27	150.65	-23.75
Car Education	41,701	7,551.40	36,099	6,941.70	14,493.10	-3,153.42		28.23	3.50	31.73	-6.90		1.46	0.06	1.53	-0.33
Car Other	5,720,333	1,035,860.76	4,951,930	952,226.42	1,988,087.18	59,201.08		3,872.67	480.34	4,353.00	129.62		200.84	8.72	209.56	6.24
Bus	1,438,686	1,639,127.15			1,639,127.15	87,811.74		13,250.30		13,250.30	709.85		116.59		116.59	6.25
DART	897,481	9,872.30			9,872.30	-1,230.83										
Luas	234,351	16,545.17			16,545.17	-5,422.85										
Do Max	**CO_2 Emissions (kg)**							**NO_x Emissions (kg)**					**$PM_{2.5}$ Emissions (kg)**			
	Diesel kms	**Diesel Emiss.**	**Petrol kms**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**		**Diesel Emiss.**	**Petrol Emiss.**	**Total**	**Diff. from base**
Car Emp. Business	94,0856	170,374.05	814,473	156,618.22	326,992.26	14,027.79		636.96	79.00	715.96	30.71		33.03	1.43	34.47	1.48
Car Commute	3,901,182	706,441.59	3,377,142	649,404.22	1,355,845.81	-298,740.70		2,641.10	327.58	2,968.68	-654.11		136.97	5.94	142.91	-31.49
Car Education	38,457	6,963.89	33,291	6,401.64	13,365.53	-4,280.99		26.04	3.23	29.26	-9.37		1.35	0.06	1.41	-0.45
Car Other	5,745,684	1,040,451.38	4,973,875	956,446.40	1,996,897.78	68,011.68		3,889.83	482.47	4,372.29	148.91		201.73	8.75	210.48	7.17
Bus	1,494,676	1,702,917.77			1,702,917.77	151,602.36		13,765.97		1,3765.97	1225.52		121.13		121.13	10.78
DART	847,564	9,323.20			9,323.20	-1,779.93										
Luas	226,373	15,981.93			15,981.93	-5,986.09										