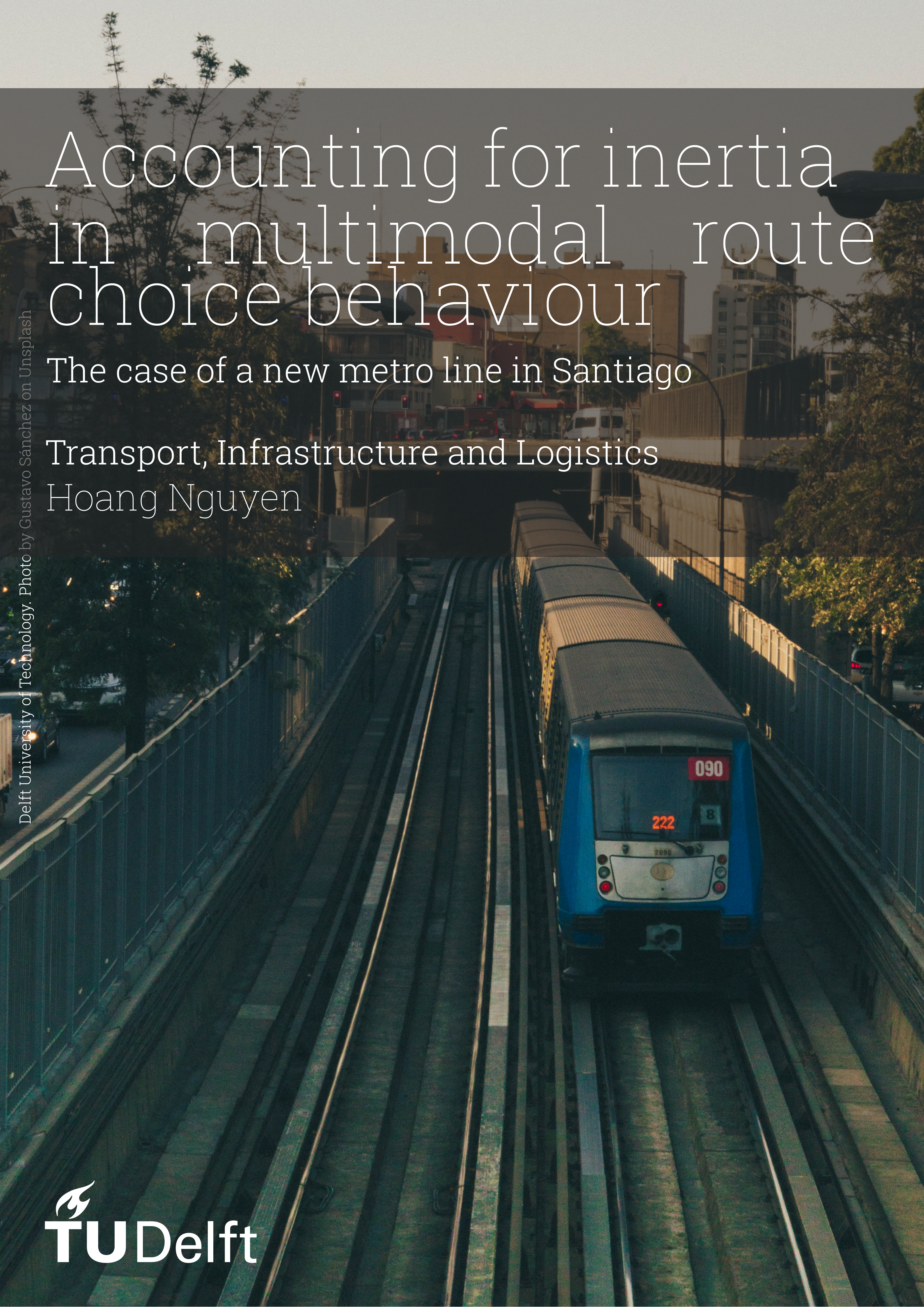


Accounting for inertia in multimodal route choice behaviour

The case of a new metro line in Santiago

Transport, Infrastructure and Logistics

Hoang Nguyen

Accounting for inertia in multimodal route choice behaviour

The case of a new metro line in Santiago

by

Hoang Nguyen

to obtain the degree of Master of Science
in Transport, Infrastructure and Logistics
at the Delft University of Technology,
to be defended on April 20^{th}, 2023.

Student number:	4303091	
Project duration:	May 18, 2022 – April 20, 2023	
Thesis committee:	Prof. dr. O. Cats,	TU Delft, chair
	Dr. B. Pudãne,	TU Delft, daily supervisor
	Dr. J. Soza-Parra,	TU Delft, daily supervisor

This thesis is confidential and cannot be made public until April 15^{th}, 2023.

TU Delft

Preface

This report concludes the end of my master thesis project which started nearly a year ago. It combines both my interest in public transport and the travel behaviour of people. Although I had little idea how this thesis would shape when I started, the more time passed, the more the research became concrete and the more I enjoyed the process. The process and completion of this thesis would not have been possible without my thesis committee Baiba, Jaime and Oded for whom I'd like to express my gratitude.

I want to thank Oded for guiding me in the very beginning in searching for a suitable thesis topic and ultimately introducing this interesting topic together with Jaime to me. I want to thank you for your time and your constructive criticism during the few meetings we had that helped improve this research. I want to thank Baiba and Jaime for your time during the bi-weekly supervision meetings. To Jaime, thank you for your guidance and support during this research. Also for your encouraging words during the last stage of completing my research when I wasn't always confident in my work. To Baiba, thank you for the enthusiasm you showed from the very beginning. You always pushed me in improving my work and helped me guide my thoughts and ideas during the process of this research. I enjoyed every meeting we had together and wish you two the very best in your academic careers. My gratitude for you all is boundless.

I want to thank my family and friends for the past year. Special thanks to Mike for your advice on life as a TIL graduate and for always being a listening ear. And to Wouter, for always taking the time and patience in sharing your knowledge on coding during this research. In addition, the many coffee breaks helped distract me from my thesis. Lastly, thank you Eleni for always showing interest and loving support during my graduation process.

Hoang Nguyen
Delft, April 2023

Executive Summary

The daily travel patterns that for instance, involve choosing a route to work or preferred mode of transportation, tend to repeat themselves over time. If the choices people make while performing these activities repeat over time, under stable conditions their behaviour eventually may become habitual. Modelling the travel behaviour associated with choosing a route or mode has often been done using Discrete Choice Models based on the notion of Random-Utility-Maximization. This paradigm assumes that travellers have perfect knowledge of their choice situation and have the cognitive ability to evaluate each alternative in the choice set in order to make a deliberate choice. However, due to habitual behaviour people tend to automatize certain decisions under stable conditions in order to minimize their cognitive load by repeating past choices that are associated with the goal and context of a choice.
But what if the conditions are not stable and people are faced with changing travel environments such as new transport services. Do people who are habitual still make deliberate evaluation of their choices when facing new transport alternatives? If not, how should Discrete Choice Models based on utility maximization be modified in order to account for habitual behaviour. Additionally, habitual behaviour may lead to people resisting to change, which is also known as the inertia effect. While choice models remain a powerful tool for travel demand forecasting, not accounting for the inertia effect can have several implications for travel demand estimation. When facing new transport alternatives, the inertia effect may lead to travellers resisting to use these new transport services leading to sub-optimal utilization of the new alternative. For policy makers, if travel demand strategies focus on rational arguments such as lowering costs, people who are habitual may not be susceptible to these arguments which in turn attenuates these travel demand strategies.

This research aims to include habit in the Discete Choice Modelling framework and investigate how the inertia effect plays a role in route choice within a multimodal public transport network when travellers face a new transport alternative. This leads to the following main research question of this research:

To what extent (if any) does inertia have an effect on the route choice behaviour of travellers when faced with a new metro line in a multimodal public transport network?

To answer this research question we use the city of Santiago, Chile as a case study. We draw on two weeks of processed smart card data, which was gathered prior to and after the opening of Santiago Metro Line 6 (L6). These characteristics make this data set suitable for investigating habitual behaviour and inertia effects. The new L6 is part of the large multimodal public transport network of Santiago consisting of a metro network that serves as a backbone and an extensive bus network. Every week more than 20 million journeys are made within the public transport system with nearly half of the trips made by the metro, which underscores the importance of the metro for the Santiago transport system.

Methodology
Since we are only interested in how L6 affects the route choice of travellers, we select origin-destination (OD) pairs where L6 is at least part of one of the alternatives. Selection is performed by filtering the data set *after* L6 by selecting only journeys where L6 is used in any part of the journey. To identify the choice set for each observation, OD pair zones were created which are the area within a radius of 100 Euclidean meters around the selected OD pair stops. The choice set is identified using the Historical/Cohort approach which identifies the choice set for each traveller based on the observations of the smart card data.

The first step in answering the main research question is to quantify to what extent route choice is habitual given our data. We use the work by Kim et al. (2017) who quantify habitual route choice behaviour based on smart card data in a public transport system by developing the method of *Stickiness Index* (SI). This method quantifies the tendency an individual has to stick to a particular route within a given OD pair. A high stickiness indicates that a person tends to repeat a single route over others,

while a low stickiness indicates that a person is variety-seeking and uses different routes more evenly. In this research, we assume someone is habitual if their SI is 1 and non-habitual if their SI is lower than 1. We acknowledge that this assumption is rather conservative, as a person who has a SI lower than 1 might still exhibit habitual behaviour. A person may be habitual from week to week or be forced to choose a different route due to disruptions within the week of analysis. However, the data size of a single week makes it difficult to capture variability, hence this binary classification of habitual behaviour was made. A SI of 1 means that a person repeats every journey within a given OD pair with the same route. While if a person has a SI lower than 1, this means that a person uses at least two different routes to travel within a given OD pair.
For estimating the *Stickiness Index*, two requirements are imposed on the sample prior-L6. For the first requirement, only OD pairs that have ten or more individuals travelling between them are included to ensure an OD pair is valid. For the second requirement, we only include travellers that make two journeys or more to ensure we are able to quantify habitual behaviour. Based on the last requirement, we hypothesize that the higher the minimum number of journeys, the more likely a person is habitual and thus the larger the inertia effect with respect to L6. After estimating the SI for each traveller for a given OD pair, the traveller SI is aggregated to determine the average SI for a given OD pair. This gives insight into the average stickiness tendency for an OD pair and allows the comparison of different OD pairs to find whether there are any spatial differences associated with the OD-level SI.

The next step is to specify the Discrete Choice Modelling framework for this research. A novel approach is adopted by including a simplified SI in the DCM specifications as a binary classification for habitual behaviour. We want to emphasize that we do not include the SI as proposed by Kim et al. (2017) in its full account in the choice modelling framework. Within the context of this research, the SI was reduced to a simple binary indicator.
We understand from the literature review that habitual behaviour may lead to inertia, therefore in the DCM framework, the SI indicator reflects the inertia effect of an individual. We hypothesize that travellers who are classified as habitual prior to L6 are less willing to use L6 as opposed to others. Three route discrete choice models are specified. A Multinomial Logit (MNL) model (model 1), a MNL model with L6 (model 2) and a MNL model with inertia effects (model 3). The MNL model is often used in route discrete choice models for its simplicity (Anderson et al., 2017; Jánošíková et al., 2014). To account for overlapping routes, a Path-Size Factor is included in the deterministic part of the utility. The PSF reduces the utilities of overlapping route alternatives. The parameter for the PSF is therefore expected to be positive. Various model specifications were tested in order to find a model that best explains the travel behaviour. The final utility function for the base MNL model includes: bus in-vehicle time, metro in-vehicle time, waiting time, transfer bus to bus, transfers bus to metro, transfer metro to bus, Path-Size Factor and mode-specific constants for bus and metro. Model 2 is an extension of the base MNL model and includes a dummy variable for L6 that reflects the perception of both segments (habitual and non-habitual) within the sample. The L6 indicator is 1 for alternatives that have L6 and 0 otherwise. Model 3 is an extension of model 2 and includes an interaction effect for L6 with SI. The interaction effect is an additional effect for L6 only if travellers are habitual.

By aggregating individual route choice preferences, the outcomes of the DCMs estimations were used to predict market shares for L6. The aim of predicting the shares for the new alternative is to assess whether including inertia effects affects the accuracy of travel demand predictions and assess the validity of the models. To validate the prediction power of the models on unseen data and test whether the models are generic, a hold-out validation approach is performed. This validation approach splits the sample into two non-overlapping parts. The models are trained on 80% of the sample and estimations from the estimation sample will be tested on the remaining 20% of the sample. This process is repeated five times to eliminate the role of randomness when splitting the sample. Furthermore, the hold-out validation is assessed using the average final log-likelihood and a False Positive Rate analysis. The latter is performed to differentiate the predictions of L6 between the model and journeys that do not use L6.

Results
SI Estimation
A sample of 13.618 traveller-OD (i,k) pairs was used as input for the *Stickiness Index* estimation. Re-

sults showed that 27% have a SI smaller than 1 which translates to 3661 travellers-OD. Within the set of non-habitual travellers, the majority make 3 journeys while choosing two different routes within a given OD pair. We should be cautious with these empirical findings, since only a single week of data is used. If a person repeats the non-habitual behaviour pattern over a longer period, can this person then also be classified as habitual? To make any hard conclusions, a period of analysis of months, for example, would be able to better capture variability in the travel behaviour of individuals.
For the analysis of the OD-level SI, we focus on four OD pairs where the largest number of people travelled between them. For the origins, variations in OD-level SI between OD pairs were minimal. While for the destinations more variation in OD-level SI was observed. The variation between different OD pairs can be explained by either the type of travel behaviour such as home-work commuting or network service. From a network service point of view, if people tend to choose the service with the highest frequency, a network service that has a large difference in service frequency across alternatives may lead to higher average SI for a given OD pair as people would repeatedly choose the service with the highest frequency. This is especially the case where the combination bus-metro is often made. A person may be habitual in choosing the same metro route but more variety-seeking in the bus trip of the journey. If there is less variety in service frequency of alternatives, a person may opt for any alternative for the bus trip as long the same metro trip is made. This leads to a lower average SI for a given OD pair.

Discrete Choice Models Estimations
Due to alternatives with overlapping modes, the decision was made to continue with the models where mode-specific constant metro was fixed to zero. It resulted in a slightly higher final log-likelihood and higher model fit as opposed to setting mode-specific constant for bus to zero. For all three models, all parameters were significant at $p < 0.05$ level. A considerable improvement in final log-likelihood was observed from the MNL model (-9400 LL) to MNL model with inertia (-8900 LL). All estimated parameters had expected signs except for the parameter of PSF.
Since the PSF reduces the utility of overlapping route alternatives, it was expected the estimation to be positive. However, it is not unexpected to find negative estimates which indicate that travellers actually prefer overlapping route alternatives. These results have been found in earlier research on multimodal public transport route choice models (Anderson et al., 2017. As public transport systems are subject to delays and disruptions, preference towards overlapping route alternatives means that travellers prefer to have the availability of en-route alternatives which also reflects the robustness of the transport network. Transfer type metro to bus was found to be valued more negatively than transfer type bus to metro. As the metro is considered more reliable and frequent, the transfer type to metro is preferred by travellers (Arriagada et al., 2022). Transfer type bus to bus is the transfer type disliked the most by travellers which might be explained due to the large uncertainty with using the bus which is characterised by high travel time variability (Durán-Hormazábal and Tirachini, 2016). The parameter for in-vehicle time metro was found less negative than in-vehicle time bus. When comparing this with earlier research on multimodal route choice in Santiago, the opposite was actually the case. The argument was made that crowding levels are high within the Santiago metro network which explains in the findings of earlier research. However, the main difference is that our analysis focuses on the period right after the opening of L6 and the entire day as opposed to the morning peak. We speculate that the crowding levels might not be as high right after L6 opened which results in the in-vehicle time for metro being perceived more positively than in-vehicle time for bus in our case.
Comparing model 2 with model 3, a marginal improvement in model fit and final log-likelihood was observed (-8975 to -8900). For the MNL model with inertia, the parameter for L6 was negative and significant. This reflects that within the entire sample, there is a dislike towards L6. The additional interaction effect in model 3 is negative and significant. This reveals that the marginal utility for L6 is comparatively larger for travellers who are habitual than others. This confirms our belief that habitual travellers are less willing to use L6. When comparing the rates of substitution of the inertia effect with respect to in-vehicle times to other studies which use a joint revealed preference/stated preference data set, this study found higher values for the inertia effect. This study found that the inertia effect represents roughly 10 minutes of in-vehicle time bus, while earlier studies using stated preference data, found values of roughly 2 to 5 minutes. This can be explained due to the underestimation of the inertia effect in stated preference studies as people do not experience the real outcomes of SP experiments. Regarding the magnitude of the inertia effect, further empirical research is needed in other cities or networks.

As previously stated, we only included travellers who make a minimum of 3 journeys to be included within the sample. To test how this threshold affects the model estimations, a sensitivity analysis was performed on the minimum number of journeys. The main model with inertia effect was tested on a threshold of 2, 3 and 4 journeys. The results from the marginal rate of substitution revealed that for 2 and 3 journeys, habitual travellers perceive the usage of L6 as 3.5 min and 10 min with respect to bus in-vehicle time, respectively. This is interesting which might indicate that the higher the threshold, the more likely a person is habitual and thus leading to a larger inertia effect. By including travellers who make a minimum of 2 journeys, we might have classified them as habitual while their repeated behaviour may be due to sporadic choices.

Implications Demand Estimation

To validate the prediction power of the models, the estimations from the estimation sample were used on the validation sample. If habitual behaviour exists and thus inertia, the inertia effect should be accounted for in DCMs. Not doing so, results in an overestimation of shares for new transport services due to travellers being less willing to change. Table 5.6 shows the predicted average shares for L6 for all three models and the observed values. It can be seen that the share for L6, comprises largely non-habitual travellers. For the MNL model with inertia effects, within the share for L6, 34% are habitual travellers. Furthermore, the observed shares for L6 are 119 journeys. The MNL model predicts 179 journeys which is an overestimation of roughly 50%. The MNL model with L6 and MNL model with inertia effects predict 144 and 140 journeys for L6, respectively. The aggregated shares for L6 revealed that the base MNL model overestimates the shares for L6 substantially, while the MNL model with inertia still overestimates but remains relatively close to the observed.

Table 1: Average predictions for journeys with L6 and journeys without L6: MNL, MNL with L6 and MNL with Inertia (20% entire sample). Also distinction between whether traveller is habitual or non-habitual

Description	Observed	MNL	MNL with L6	MNL with Inertia
L6 = 0 | SI = 0	734.2	669.2298	697.2	706.7
L6 = 0 | SI = 1	1395.8	1370.152	1407.448	1402.5
L6 = 1 | SI = 0	69	107.522	78.1	93.15
L6 = 1 | SI = 1	50	72.1	66.353	46.83

The False Positive Rate analysis revealed that the base MNL model and MNL model with inertia have a sensitivity of 0.49 and 0.83, respectively (Table 2. The sensitivity (between 0 and 1, the higher the better) tells us when the journey is actually with L6, how often the model predicts that it is L6. The False Positive Rate of the base MNL model is 0.057 which is higher than the MNL model with inertia. This means that if 1000 journeys are observed, the base MNL model predicts 57 journeys with L6 while they are actually not with L6.

Table 2: Accuracy prediction power of models using FPR analysis on validation sample

Model	TP	TN	FP	FN	ACC	SENS	SPEC	FPR	Average LL
MNL	58.38	2008.7	121.3	60.6	0.91	0.49	0.94	0.057	-1868
MNL with L6	93.6	2079.3	50.72	25.36	0.966	0.78	0.976	0.0238	-1781.9
MNL with Inertia	98.01	2088.03	41.97	20.98	0.97	0.83	0.98	0.019	-1764.5

Note: number of observations is 2249. TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives, ACC = Accuracy, SENS = Sensitivity, SPEC = Specificity, FPR = False Positive Rate, Average LL = Average log-likelihood

Conclusions and Recommendations

In this research, we investigated the inertia effects in route choice within a multimodal public transport network. If travellers exhibit habitual behaviour in the sense of repeating route choices in the past, not taking this into account may have implications for travel demand estimation and policy making. The outcome of including the inertia effect in the Discrete Choice Modelling framework revealed that inertia exists and should be accounted for. The empirical results confirm earlier research that accounts for habit and inertia in choice models. By comparing the model with inertia with a traditional route choice model based on 'hard information' (e.g. time and costs) only, it revealed that not including inertia effects when habitual behaviour exists, overestimates travel demand for new services by roughly 50% due to habitual travellers being less willing to change.

It is important when planning and designing urban space to take into account travel behaviour dynamics which makes investigating inertia effects and its implications on new transport services an interesting topic for further research. As it is likely that travel behaviour dynamics vary across individuals, future work could include estimating a random parameter model. It would also be interesting to capture time dynamics and investigate how the inertia effect with respect to new transport alternatives changes over time. Lastly, reducing mental effort is a reason for the inertia effect as previously stated. Additionally, earlier research also finds that risk aversion in combination with the costs of learning is another reason for the emergence of the inertia effect. Future research could focus on combining both the cognitive process and risk aversion with revealed preference data to fully account for the inertia effect.

When transport planners and policy makers design transport systems, neglecting the inertia effects, which arise from habitual behaviour, can have implications for travel demand estimations. Moreover, policies that focus solely on rational arguments such as travel cost reduction, might see their strategies be attenuated and become less effective as habitual travellers may not be led by such measures.
The next step is to explore how habits may be broken in order to shift people's travel behaviour and improve the overall quality of the public transport system. With the implementation of new transport alternatives aimed at relieving the pressure of other parts of the transport system, how should policies be designed to effectively target habitual travellers. Verplanken et al. (1997) found that habit may be accompanied by less motivation to search out for information, regardless of whether the information is important or unknown. Therefore making people aware of the new transport alternative may not be sufficient in getting individuals to change their routes. To induce a change in travel behavior, awareness-raising measures must be accompanied by stable travel conditions in which new transport services operate. This fosters the formation of new behaviour and eventually may lead to maintenance of desired behaviours as intended by policy makers.

This research was carried out using the city of Santiago as a case study. The temporary outcome of this research and recommendations are useful for Santiago only. As the city continues to expand the metro network, the results of this thesis may be helpful in developing route choice models and evaluation of the policies for new transport services in the urban network. For the new Santiago Metro Line 7 (L7) in 2027, including the inertia effect will help predict more accurately travel demand estimations for L7 and improve the quality of the transport network flow. Secondly, policies should aim at making individuals aware of L7 and make it accessible. For instance, giving individuals a one-week free public transport pass for those travellers using L7. Secondly, it is paramount to create stable conditions when operating L7 in its initial phase. A stable environment is crucial for attaining and maintaining new habits. If the new L7 is accompanied with delays and disruptions, travellers may show aversion from L7 and return people back into their usual travel habits, thereby rendering the implementation of the new line as ineffective. Consequences of people returning to their old routines, include for instance, continual high crowding levels on those other lines which were intended to be alleviated from their high crowding levels and poor quality of the public transport network. This underscores that transport planners and policy makers should be aware of the role of travel behaviour when designing new urban systems.

Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

Abbreviation	Definition
DCM	Discrete Choice Modelling
FPR	False Positive Rate
L6	Metro Line 6
LRS	Likelihood Ratio Test
ML	Mixed Logit
MNL	Multinomial Logit
OD	Origin Destination
PSL	Path-Size Logit
PSF	Path-Size Factor
RUM	Random Utility Maximisation
RP	Revealed Preference
SC	Smart Card
SI	Stickiness-Index
SP	Stated Preference
TPR	True Positive Rate

1 Introduction

People's daily travel patterns tend to repeat themselves over a longer period of time, assuming a stable environment. As the choices people make while performing these travel activities repeat, a person may become habitual in their travel behaviour (Thøgersen, 2006). Travel behaviour choices for example, include selection of mode, timing and route choice. In the context of route choice, people's travel behaviour has often been modelled using Discrete Choice Models (DCM) based on the notion of Random-Utility-Maximization (RUM) (Manski, 1977). This assumption tells us that travellers have perfect knowledge of their choice situation and have the cognitive ability to evaluate their entire choice set in order to make a deliberate choice. Under a stable travel environment, evaluating each alternative within a travellers choice set would require high cognitive resources. Therefore, people tend to automatize certain decisions in order to minimize their cognitive load by making repeated choices (Kahneman, 2017). Are these automatized choices that form habitual behaviour based purely on deliberation? If not, how should DCMs based on utility maximisation be modified in order to account for such habitual behaviour?

But when the travel environment changes, how does habit play a role in people's travel behaviour? While traditional DCMs remain a powerful tool for transport planners and policy makers to predict travel demand and market shares for services (Chorus, 2012), not accounting for habit in route discrete choice models can have implications with its bearing on travel demand strategies. When people are faced with new transport alternatives, habit can play a role in people's decision-making process and prevent people to pursue these new alternatives. This resistance to change is also known as the inertia effect (Cherchi and Manca, 2011). Inertia is usually framed as the tendency to minimize mental effort in a given context and its associated goals that trigger the repetitive behaviour (Gärling and Axhausen, 2003). Chorus and Dellaert (2012) argues that complementary to minimizing mental effort as reason for inertia, the effect of inertia may also arise from a combination of risk aversion and the costs of learning new alternatives that are associated with uncertainty. If people due to inertia do not make deliberate choices, travel demand strategies that focus on rational arguments such as costs may not be as effective. Or in the case of a new transport alternative may lead to sub-optimal usage of the new alternative as travellers who exhibit habitual behaviour may have the tendency to stick to their usual choices.

Although the RUM paradigm is often used for route choice modelling and is considered superior to other route choice models that for example, assume that travellers only minimize travel costs. When considering behavioural realism, traditional route choice models that explain travel behaviour by 'hard information' (e.g. time, costs and well-measured socio-economic characteristics) do not account for latent psychological factors (e.g. habits, attitude) and therefore do not explain behaviour that deviates from the random utility theory (M. Ben-Akiva et al., 2002; Di and Liu, 2016; Jánošíková et al., 2014). For this reason, there are trends in the past decades to develop models that expand on the RUM paradigm such as the Hybrid Choice Model (HCM). The HCM is an expansion of the RUM framework that includes for example dependence on history, attitudes, perception and preferences of individuals (M. Ben-Akiva et al., 2002). Bounded Rationality (BR) takes a different stance and opposes the aforementioned notion. It assumes people are actually limited in their knowledge and cognitive abilities. This paradigm tries to explain deviations from the RUM assumptions. There is evidence why perfect rationality is not able to capture people's cognitive processes and why a more realistic assumption such as BR is needed in travel behaviour modelling. Di and Liu (2016) mentions evidence such as heuristics in decision-making leading to systematic errors, cognitive limit in route choice and violation of taking shortest paths.

It becomes clear that micro-economic theories where people evaluate available alternatives and choose the one with the highest subjective utility are not able to capture the full account of human behaviour. Especially in transport context such as route choice, where people repeat behaviour and become habitual, their route choice behaviour may not only be expressed in 'hard information' such as travel time and costs (Gao et al., 2021). Nevertheless, in situations where travel behaviour is repetitive, attempts have been made to account for habit and successfully incorporated into various DCMs such as mode choice based on RP/SP data (Gao et al., 2021; Verplanken et al., 1997) or pseudo-RP data (Yáñez et al., 2009) and car route choice based on SP data (Bogers et al., 2007). Gao et al. (2021) found that inertia is mode specific and that ignoring inertia effects leads to implications for demand estimations. The majority of literature on travel behaviour modelling supports the significance of inertia in repetitive travel behaviour and therefore should be accounted for in travel behaviour modelling.

To investigate whether inertia plays a role in route choice, our aim is to include habit in the route choice-making process. To the author's knowledge, no studies have been conducted yet that investigate habitual multimodal route choice under the condition of changing public transport supply side using a fully Revealed Preference (RP) data set. In the context of inertia effects under changing travel conditions, earlier studies focus on mode choice and use panel data with either SP data (Chatterjee, 2011) or mixed revealed preference/stated preference (SP) data (Cherchi and Manca, 2011; González et al., 2017). This research tries to fill in this gap by conducting a multimodal route choice study of a newly implemented metro line by using a fully RP data set based on a large number of smart card observations.

The remainder of this chapter starts with the problem statement. After establishing the problem, we present the research objective and research questions in section 1.2. Following, the societal and scientific relevance of this study is discussed in section 1.3. This chapter concludes with the research approach and report outline in sections 1.4 and 1.5, respectively.

1.1. Problem Statement

In practice, modelling route choice in a multimodal network has often been done based RUM theory, with utility of alternatives expressed as observable factors such as travel time and costs (Anderson et al., 2017; Jánošíková et al., 2014). But the choice of taking a route from origin to destination within a given origin-destination (OD) pair usually tends to repeat itself from day to day or week to week, which potentially involves the inertia effect (Yáñez et al., 2009). Ignoring the inertia effect can have a negative impact on travel demand predictions. In traditional route choice models we assume travellers who travel from origin to destination choose the alternative with the highest utility. If inertia exists, this may lead to an overestimation of particular alternatives due to travellers being less willing to change. Policy makers who rely on model estimates that do not account for habitual behaviour, may see their travel demand strategies be attenuated. Since these models assume people making rational decision while in reality people might opt for the usual alternative due to habitual behaviour. For instance, in a public transport system with a newly introduced transport service, it is important for transport planners to accurately predict travel demand by taking this habitual behaviour into account if it exists. With respect to multimodal public transport route choice, little research can be found where the effect of changing services or infrastructure on habitual route choice has been studied using large number of observations.

1.2. Research Objective, Scope and Research Questions

The purpose of this study is to include habit in route discrete choice models and study its effect in case of changing transport supply based on revealed preference data. If travellers exhibit habitual behaviour due to repeating choices, inertia should be accounted for in the route choice model process. The objectives are:

- to account for inertia in route choice models in the context of a public transport network with a new metro line.
- to compare traditional route DCM with models that include inertia and their effect on travel demand estimation

To the authors knowledge this has not been done before, mainly due to the complexity of having revealed preference data around the implementation of a new public transport alternative. To identify habitual behaviour, panel data is also required which makes it more difficult to obtain such specific data.

The main research question follows from the research objective and problem statement. Research sub-questions are derived from the main research question in order to propose a structured research strategy. The main research question (RQ) is as follows:

To what extent (if any) does inertia have an effect on the route choice behaviour of travellers when faced with a new metro line in a multimodal public transport network?

With the sub-questions:

1. To what extent is travellers' route choice habitual in a non-changing public transport network?

2. How can inertia be quantified and be included within a route discrete choice model?

3. After the opening of a new metro line, to what extent does inertia play a role in people's route choice decision-making

4. To what extent does accounting for inertia improve the accuracy of route travel demand prediction?

The first sub-question tries to give an answer on whether route choice is habitual given our data set. The second sub-question then aims at understanding how inertia effect can be quantified in the DCM framework by studying previous work on habit and inertia in the field of DCMs. The third question tries to answer that if travellers are habitual in their route choice, do traveller exhibit inertia effects when faced with a new transport alternative. The last sub-question continues on question 3 that if inertia exists in route choice behaviour, if so to what extent does it improve the accuracy of route travel demand prediction? Does accounting for inertia effect in route choice behaviour actually improve model estimations and does it contribute to capturing more behaviour realism when understanding route choice behaviour in changing travel environments.

Regarding the scope of this research, discrete choice models will be specified with different underlying assumptions. We do not consider it within the scope of this study to investigate which models give the best outcomes. We also do not consider it within the scope of this study to test which inertia definition best describes travel behaviour. We simply want to reveal whether the inertia effect exists in the research context.

1.3. Societal and Scientific relevance

This section elaborates on the relevance of this study, both societal and scientific.

1.3.1. Societal relevance

As cities continue to grow in size, it is important for public transport systems and public transport services to meet the growing demand. This is important for the transport system to be efficient but also for travellers to have a pleasant journey without too much discomfort. In order to predict this growing demand, choice models have been widely used as they capture behavioural realism and reveal underlying preferences in people's choices. Growing demand puts authorities under pressure to design more efficient public transport systems. Measures can be taken such as travel demand specific policies or new public transport infrastructure investments. But if travellers who make repeated daily trips, exhibit habitual behaviour (and thus inertia) (Cherchi and Manca, 2011), it can be likely that travel demand management strategies will be attenuated. Assuming habitual behaviour is non-deliberate (Verplanken et al., 1997), if these travel demand strategies try to affect habitual behaviour with rational arguments such as costs, policy makers will see their strategies be less effective than intended as individuals who exhibit habitual behaviour might use their usual alternative as they are guided by their past experiences rather than the fastest or cheapest alternative. This has implications for the public transport system as a whole. For instance, if policy makers and transport planners aim to design new services in order to relieve the pressure of other segments with the transport networks, habitual travellers may be less willing to use these new services due to inertia which then leads to continual high crowding levels on these aforementioned segments of the network. Ultimately, leading to poor quality of the transport system and unsatisfied travellers.

As people tend to stick to their habits, by gaining insight into what extent inertia has an effect on route choice when faced with a new public transport alternative, transport planners are able to use travel demand strategies more effectively. By understanding that people maybe indeed have inertia effect when choosing a route, policy makers for instance would be able to develop strategies aiming to break these habits in order to attract these travellers to new transport alternatives. For both the quality of the public transport system and the people using it, it is imperative that travel demand models take dynamic travel behaviour into account and accurately predict travel flow. Accurately predicting travel demand flow can help policy makers in developing effective policies at for instance alleviating overcrowding on specific transport lines, thereby enhancing the quality of the transport system. If not, overcrowding may lead to longer transfer times and overall reduction in quality of the public transport system. This opens the door for policy makers to then ask themselves how these habits can be broken, as in how to make choices rational again or how travellers to get out of their travel habit. As this research only tries to account for inertia effect in route choice, it opens the door for more future research opportunities that can extend this research and for example investigate whether the inertia effect maybe differ between different groups of individuals or areas in a city, as it is likely that habitual behaviour differs among individuals.

1.3.2. Scientific relevance

Researchers strive to improve choice models by including more behavioural realism in models in order to more accurately predict future demand for public transport systems in order to develop more effective transport policies. This research tries to contribute to the above by empirically investigate inertia effects of past behaviour in a multimodal route choice model under changing transport supply. The majority of research that accounts for inertia effects in transport choice modelling under changing conditions, mainly focuses on mode choice (González et al., 2017; Yáñez et al., 2009) as literature study shows. Another aspect that this study differs from previous research that empirically investigate inertia in choice modelling, is the use of a fully revealed preference (RP) data set based on a large number of smart card observations. Contrary to earlier studies that a combined RP/SP data set, this allows studying inertia in choice modelling using real observations of people's travel behaviour, eliminating bias in people's choices when using a stated preference (SP) data set. Additionally, using observed smart card data eliminates the problem that in SP data sets people do not experience the real transport alternative and therefore their choice preferences might be altered when compared to observations of their real behaviour. Using RP data, this research tries to complement existing research on their empirical findings on inertia in travel behaviour.

1.4. Research Approach

To give an answer to the main research question and sub-questions, a suitable research strategy that consists of a literature study, data preparation and choice modelling was conducted. Literature research has been carried out to understand how habitual behaviour and inertia are understood in the field of transportation and psychology. Understanding these behavioural traits and early defining these terms for our own research helped shape this research and provide a foundation in order to understand how inertia may be quantified in the DCM framework.
To account for inertia effects in the DCM framework, we investigated to what extent route choice is habitual and quantified to what degree a traveller is habitual in a stable travel environment. The degree of habitual behaviour has consequences on the willingness of travellers for using new transport alter-

natives. To carry out this research, revealed preference data based on smart card observations from the city of Santiago, Chile was used. The data has the unique feature that it contains large number of observations prior to and after the opening of a metro line which makes it suitable to investigate inertia effects.
The results from quantifying habitual behaviour of travellers within the urban transport network, were integrated into the route discrete choice model. Two models were estimated, a base model and a model that accounts for the interaction effect of inertia with L6. Results from the DCM estimations were tested with statistical diagnostics and compared with earlier research on inertia and transport context. Since RP data is used, results of the estimation process were used to predict market shares for L6. Evaluating the different models in their predictive power for new transport alternatives, we were able to provide recommendations for transport policy in Santiago and future research.

1.5. Report Outline

This thesis report is structured as follows. Chapter 2 presents the literature review on how habit and inertia is understood in the field of psychology and transportation, more importantly how habitual behaviour has been included in the discrete choice modelling framework. Chapter 3 presents the case study of Santiago and the descriptive analysis of the data set. The descriptive analysis gives an initial insight into the patterns of the data set. The methodology of this research will be presented in chapter 4. The methodology provide a structured approach in answering the main research question. The findings resulting from the methodology are found in chapter 5. This research concludes with the discussion of the results and conclusion in chapter 6 and 7, respectively. The conclusion highlights the main findings, limitations of the study, policy recommendations and future research directions.

2

Literature review

The main purpose of this literature review is to get a understanding of habitual travel behaviour and how this has been investigated in previous transport studies. From the literature review, it becomes clear that the term habit and inertia is used interchangeably in literature. Therefore, this chapter starts with a theoretical framework on habitual behaviour and inertia and how it is defined within the context of this research. This chapter also aims to synthesize previous studies on modelling and empirical findings that include inertia effect in travel behaviour. An overview of studies that empirically reveal and model inertia effects are shown in Table 2.1. The outcome of this overview is to give an answer to the first sub-question:

How can inertia be quantified and be concluded within a route discrete choice model?

2.1. Theoretical Framework

2.1.1. Habitual Behaviour

It has been fairly agreed upon by psychologists that the concept of habit is narrowly described as a sequence of learned acts that can eventually lead to automatic choices when a person is faced with certain situations (Verplanken et al., 1997). These situations are characterised by specific goals that initialize automaticity in people's behaviour under a stable environment (Ouellette and Wood, 1998; Verplanken et al., 1997; Wood and Rünger, 2016). Habits are then tendencies grounded in memory that react automatically to cues associated with these goals that led to similar behaviour in the past and therefore reduce the mental effort associated with repeated decision-making (Verplanken and Orbell, 2022). Chorus and Dellaert (2012) also states that complementary to individuals economising on cognitive resources as a reason for inertia, it can be assumed that habitual behaviour is induced simply because the cost of searching for new alternatives and the expected gains corresponding with these alternatives are too uncertain. Therefore, people reuse past solutions that are more certain, to make their current choices easier and less risky. If people are risk averse, inertia emerges from a combination of risk aversion and the costs of learning new uncertain alternatives (Chorus, 2012). Insensitivity to new information or alternative choice options is a quality of habitual behaviour, together with resistance to change (Verplanken and Orbell, 2022).

Formation of habit occurs in everyday life and is closely intertwined with pursuing goals (Wood and Rünger, 2016). These goals in everyday life can be as simple as making coffee or commuting to work. We associate these goals with certain actions or means to attain these goals (Verplanken et al., 1997). As we repeatedly attain these goals, habits develop by repeatedly performing actions and choosing a specific mode or route to commute to work. As people repeat these actions, they learn and over time form habits. This is built on the fundamental principle that responses with a positive reward are repeated (Wood and Rünger, 2016). Ouellette and Wood (1998) also distinguishes between long-term and short-term positive rewards. People are more likely to change their behaviour if their new actions show positive rewards on short-term rather than long-term. Conversely, a negative reward or experience will weaken the connection between goal and behaviour and therefore decrease the probability that a person will continue with the behaviour (Aarts et al., 1998). Aarts et al. (1998) further define these goal-directed automatic responses as mental representations that can be activated by environmental stimuli. After some time performing a choice with a positive reward, the choice becomes script-based, allowing a person to go through less information and processing. In essence, the information associated with the decision is stored as a script, which can be retrieved in a specific context(Gärling and Axhausen, 2003; Verplanken et al., 1997).

For policy makers and transport planners, it is interesting to understand how habits are broken in order to accomplish mode shifts or attract travellers to new transport routes. Fujii and Kitamura (2003) offered free bus tickets for a month to habitual car drivers. Their goal was to attract habitual car users to public transport by making public transport accessible in terms of costs, hoping that car users would break their car habit and develop a new habit for public transport usage. Their results showed promising results and saw an increase in public transport usage and diminishing car habits. Overall attitude towards public transport became positive even after just one month after conducting the experiment. Contrary to this research, Bamberg et al. (2003) conducted an experiment where free public transport was offered to car drivers. Irrespective of whether these drivers were habitual or not, the increase in public transport usage rose to an equivalent extent. Therefore Bamberg et al. (2003) question the role of habit, it is the act of travelling that requires a sense of awareness which might play a role in the choice process (Gärling and Axhausen, 2003). These studies highlight it is not always evident to what extent habit plays a role in travel behaviour and its implications for policy makers to design effect measures to change behaviour.

The frequency in which behaviour has been performed in the past has been the standard to measure habit (Ouellette and Wood, 1998). However, repeated choices in the past do not simply imply that behaviour is habitual (Gärling and Axhausen, 2003). Frequency as an indicator of habitual behaviour has a weakness in that frequent behaviour is a necessary and not the only sufficient condition for forming a habit (Verplanken and Orbell, 2003). Besides the repetitive nature of habitual behaviour, also personal motives and external constraints are important factors for habitual behaviour (Thøgersen, 2006).
Research on how to measure habit or habit strength has been limited. Verplanken and Orbell (2003) developed a Self-Report Index on habit strength (SRHI) and investigated habits of students with respect to mode choice. They argue that repetition of past behaviour alone is only a proxy of true habitual behaviour. The advantages of the SRHI are that it adds value to the residual effect of past behaviour. However, disadvantages were that people had the tendency to report in a desirable way or provide answers to only appear consistent.
Kim et al. (2017) quantitatively measured habitual behaviour of bus users by introducing a simple metric, called the *Stickiness Index* (SI). Rather than using self-reports as a measure to qualitatively express habit, the authors measured habit as a repetition of previous choices in a stable context. The metric aims to measure the 'stickiness' of a route within a given OD pair. In their route choice analysis of bus users, stickiness is defined as how persistent a traveller is in staying on the same route when other alternatives are available.

2.1.2. Inertia in decision-making

In Newton's *Philosophiæ Naturalis Principia Mathematica*, inertia is described as a body resistant to change in its velocity (Newton, 1833). In many other fields, such as psychology or transportation, inertia has strongly been related to describing certain traits of human behaviour. One of those traits is habitual behaviour, where people respond automatically in stable conditions. Although habit and inertia are used interchangeably in literature, inertia is defined as resistance to change and encompasses habit. Habit can manifest itself as inertia, but not necessarily the other way around (Thorhauge et al., 2020). For example, a person can exhibit inertia but this does not mean the person is habitual, but over time inertia can lead to habitual behaviour.

2.1.3. Definitions

Due to the nature of our data (passive observations), we adopt a similar definition of habitual behaviour as Kim et al. (2017) which is based on frequency of behaviour under stable conditions. Because

our research will investigate the effect of a new metro line on travel behaviour, we are confronted with two situations. The first situation is prior to the opening and the second situation is after the opening. For this research, habit or habitual behaviour is referred to the situation where the travel environment is stable. It is defined by the repetition of past choices.
When habitual behaviour is established during the period prior to the opening of a new transport service, this can lead to inertia when the travel environment changes for travellers. For example, a new bus service or a new metro line. Inertia is then defined as the resistance to change (Alós-Ferrer et al., 2016; Cherchi and Manca, 2011). To remain consistent with terminology throughout this research, we refer to *habit* or *habitual* behaviour during a stable travel environment (e.g. no significant changes). Habitual behaviour can then lead to *inertia* if a new service or infrastructure is introduced, hence we will refer to *inertia* during the situation after the introduction of a new transport service.

2.2. Modelling Inertia Effects in Travel Behaviour

Transport researchers always strive to develop models that capture behavioural realism in order to more accurately predict future travel demand. As such, many studies have accounted for inertia, each with different approaches and empirical findings in a different transport context. These studies tried to quantitatively investigate past behaviour on current choices. In the case of repeated choices, the current choice depends on previous choices and thus serial correlation and state-dependency play an important role in choice modelling which we will discuss in this section.

Morikawa (1994) addresses state-dependency by introducing a dummy variable in a joint RP/SP model estimation. The dummy variable is expressed as one if the choice was chosen frequently in previous time periods. Adamowicz (1994) expressed habit as a state-dependence dummy variable as the frequency an alternative has been chosen in previous time periods. His work was later extended by other studies in the context of mode shift behaviour (Gao et al., 2021). Gao et al. (2021) modelled habit as state-dependence dummy variable and allowed interaction effects with LOS variables. The authors showed that ignoring habit interaction effects leads to a considerable impact on demand estimations. Although, the expression by Morikawa (1994) is rather simple, Cherchi and Manca (2011) tested various expressions of habit using RP/SP data set, among those the state-dependence dummy variable. They show that simple forms of habit also show significant model fits. Relative complex forms are not necessarily superior when estimating choice models.

Cantillo et al. (2007) used a more complex expression of habit and formulated it as a function of travellers valuation of previous choice systematic utilities in time period prior to the current one. They applied their model using a RP/SP data set and showed the effect of habit (leading to inertia) and serial correlation on travel demand estimations. Ignoring serial correlation and inertia effects leads to biased model estimates. The work by Cantillo et al. (2007) was later extended by González et al. (2017) and Yáñez et al. (2009). González et al. (2017) also tested for the inertia effect using Cantillo et al. (2007) expression of habit in the context of a new public transport alternative. The difference is that González et al. (2017) tested the inertia effect for both RP/SP and RP/RP and showed that no significant effect was found between the RP/SP wave. Their study is limited by only using students as respondents. Yáñez et al. (2009) showed empirically the effect of inertia in mode choice behaviour when travellers suddenly are confronted with a new public transport system. This sudden change, was also captured by adding a shock effect within their choice model. Another difference with Cantillo et al. (2007) and González et al. (2017) is that they used multiple waves to study inertia rather than a long panel data.

Swait et al. (2004) used another expression for inertia when accounting for temporal effects and past behaviour in Discrete Choice Models. They express habitual behaviour as a weighted average of past attribute perceptions to test for inertia effect between RP and SP choices. Differing from earlier mentioned research by adopting a different behavioural assumption that includes a memory decay parameter.

This literature review shows that different expressions of habit have been adopted in choice modelling. The majority of studies focus on the effect of inertia on mode choice, little research be found on what the inertia effects are on travellers' route choice when there is a change in transport supply. Studies that investigate the impact of a new transport alternative on travel behaviour, focus on aggregated spatial-temporal analysis (Brands et al., 2020; Fu and Gu, 2018). This includes investigating travel times and passenger flows. Another finding is that majority of literature uses a mixed RP/SP data set to empirically find the effect of inertia on travel behaviour (Cantillo et al., 2007; González et al., 2017; Yáñez et al., 2009). Our study tries to empirically investigate the inertia effect on route choice based on a fully RP data set. This allows the elimination of bias that is inherent in SP studies. Cantillo et al. (2007) mention the underestimation of their inertia parameters by conducting a RP/SP study as people do not experience the real outcome in a SP study.

Based on the conducted literature study where we found various expressions of habit in a different research context, we now briefly mention the different methods that correspond with the different expressions of the habit or inertia effect.

Method 1: Morikawa (1994)
The method is aimed at combined RP/SP estimation where the habit dummy corrects for state-dependency and where error terms of RP and SP are serial correlated. The method by Morikawa (1994) is considered to be relatively simple. The authors define inertia as a state-dependency dummy variable in the SP model which reflects the actual choice. The dummy variable is 1 if the chosen alternative *j* has been chosen in previous time period and 0 otherwise.

Method 2: Adamowicz (1994)
The second method is also defined as a state-dependence variable but differs from the first method by being expressed as the number of times an alternative *j* has been chosen in previous time periods. This method has later also been adopted by Vacca et al. (2019) in route choice behaviour of car users. The formulation is as follows:

$$I = \sum_{k=1}^{t-1} i \tag{2.1}$$

Where *i* is defined as:

$$i = \begin{cases} 1, & \text{if chosen alternative } j \text{ is equal to the alternative in the previous time period (t-1)} \\ 0, & \text{otherwise} \end{cases}$$

Method 3: Cantillo et al. (2007)
Cantillo et al. (2007) proposed a method to model inertia and serial correlation. One of their hypothesis was that habit is a function of a valuation of previous alternatives, hence they formulated habit in discrete choice modelling framework as the difference in systematic utilities. When a traveller evaluates an alternative, the person compares this alternative in the previous time period with the chosen alternative. Changes only occur if the inertia effect is positive, meaning disposition to change. This definition of the inertia effect has later been adopted in the study by Cherchi and Manca (2011) and González et al. (2017):

$$U = V - I + \epsilon \tag{2.2}$$

Where *I* is inertia effect, *V* systematic utility with vector of explanatory variables and ϵ the unobserved random part of utility.

$$I_j^t = (V_{iq}^{t-1} - V_{jq}^{t-1}) \tag{2.3}$$

Here *I* is the inertia effect in time period *t*, defined as the valuation of alternative *j* with chosen alternative *i* in time period *t-1*.

Method 4: Swait et al. (2004) Swait et al. (2004) linked the current time period attributes with previous time period systematic utilities. Each utility in the previous time period is then weighted by a parameter that indicates the dependence level of the past utility on the current one.

$$\tilde{V}_{jt} = \sum_{s=0} \alpha_{js} * exp(V_{jt-s}) \tag{2.4}$$

Here α is the dependence parameter, *j* the alternative and *t* the time period.

An overview of literature that accounts for inertia effects in travel behaviour can be seen in Figure 2.1. The overview allows the reader to understand how inertia has been quantified in DCMs in previous studies and under which research objectives.

Since habitual behaviour can lead to inertia, we consider the method of *Stickiness-Index* (SI) by Kim et al. (2017). To our knowledge, this is the only research that quantifies habitual behaviour of public transport users based on RP data. This research takes a novel approach by including the SI metric in our DCM framework. As we discuss the further specification of the DCMs in the later stage of this research, we want to emphasize that we use a simplified version of the SI, where we only consider the binary classification of the SI, rather than using it to its full extent.
When comparing the method by Kim et al. (2017) with the aforementioned methods on inertia effects, the SI does not take into account time dependency but focuses merely on frequency. The method is relatively simple to use and easy to include within the DCM framework, contrary to the inertia effect defined as the weighted average of past experiences (Swait et al., 2004) or valuation of previous choice utilities with the current one (Cantillo et al., 2007).

2.3. This study

This chapter presents findings on how habit or inertia is understood in different fields of research. We then present findings on studies that reveal, model and empirically investigate the effect of inertia in travel behaviour. Different expressions of inertia have been used in various studies, such as the state-dependence dummy variable or more specified inertia expressions. Different models have been used in different context, such as a long panel RP/SP data set or panel data with multiple waves. However, the literature review makes it clear that little research has been carried out yet that tries to empirically investigate the effect of inertia on route choice behaviour in the case of a new metro line. Though some studies analyze the impact of a new metro line on travel behaviour, majority focus on the aggregated analysis of travel time and passenger flow (Brands et al., 2020; Fu and Gu, 2018). The key difference is that our study tries to investigate if inertia exists in the context of public transport route choice behaviour, and if so to what extent it has an effect on route choice behaviour.

Table 2.1: Studies on inertia effects in DCM framework and their approaches

Reference	**Method**	**Data type**	**Objective**
Cantillo et al. (2007)	Discrete choice modeling with both MNL and ML models using inertia as defined as: $(V_{jq} - V_{kq})$	Simulated and mixed RP/SP data	Study serial correlation and inertia effects in mode choice context
Cherchi and Manca (2011)	ML with various definitions for inertia	Mixed RP/SP data set	Study different expressions for inertia in modal choices
Gao et al. (2021)	A joint ML model. Inertia defined here as state-dependence dummy variable and as $(V_{jq} - V_{kq})$	RP/SP surveys	Empirically investigate inertia effects of past behaviour on commuting modal shift behaviour.
González et al. (2017)	Discrete choice modeling on both RP/RP and RP/SP surveys. Using inertia as defined as: $(V_{jq} - V_{kq})$	RP/RP and RP/SP panel surveys data	Testing for inertia effects on mode choice in context of new public transport alternative
Kim et al. (2017)	Quantifying habitual behaviour using the method of *Stickiness-Index*	RP data	Investigate the tendency of travellers to stick to a particular route
Morikawa (1994)	Joint RP/SP estimation with inertia dummy variable for state-dependency and serial correlation of RP/SP error terms	RP/SP surveys	Control biased responses to SP questions influenced by real behaviour in mode choice context
Swait et al. (2004)	Discrete choice modeling. Inertia is defined as weighted average of past attribute perceptions	RP and SP panel data	Test for temporal dependence in context of location/site choice
Yáñez et al. (2009)	Discrete choice modeling with inertia and shock effects defined as $(V_{jq} - V_{kq})$	Four wave pseudo RP panel data	Mode choice process where habitual choice is interrupted by sudden change in public transport context

3
Data

For the purpose of our research, we use the city of Santiago, Chile as a case study. Revealed preference (RP) data based on a large number of smart card (SC) observations from the multimodal network of Santiago is used. The data contains observations of people travelling within Santiago's large multimodal public transport network. The content of the data is particularly interesting because it has been gathered around the opening of 'Santiago Metro Line 6', which is referred to as 'L6' in this thesis. The data provides the opportunity to investigate travel behaviour in the case of a changing transport network.

The aim of this chapter is to present the case for our study and to gain initial insight into the characteristics and possible patterns in the data set. Section 3.1 presents the case study of Santiago, data sources and the data processing workflow. Then section 3.3 presents the descriptive analysis of our data, where we focus on the impact of L6 on the urban public transport of Santiago.

3.1. Case Study and Data Sources

3.1.1. Case Study

The period of analysis is from 31 July till 16 November 2017. During that period, Santiago has a multimodal public transport system that consists of a metro network, urban bus network and a railway system. A population of 6.8 million people generate roughly 18 millions trips on a normal working day. The shares of these trips are 28% for car and 25% for public transport (Pineda and Lira, 2019a). The metro plays an important role in the public transport system as half of the public transport share comprises of a metro trip. The metro system consisted of 5 metro lines and serves as a backbone for the public transport system of Santiago due to the large number of shares for metro trips. The importance of the metro in Santiago has been made clear and expanding the metro network continues to be a priority. for the government. One of those expansions is Metro Line 6 (L6) which was announced in 2009 and realised in 2017, see Figure 3.1.

Our study focuses on the effect of a new metro line on travel behaviour, therefore we focus on the opening of L6. It added 10 new stations to the metro network with a total line length of 15.3 km. On a normal week, 3.5 million passengers use the multimodal public transport network resulting in 25 million public transport trips per week. Travellers who make use of the system, pay by using the smart card Bip!. Upon check-in, travellers are allowed to transfer up to two times within a travel period of 120 minutes. Although there are different tariffs for the metro depending on time of day, the difference is only a couple of cents. For the bus, there is a flat fare to pay upon usage. Our study focuses on observations by travellers within the urban area only, therefore we limit our study to the metro system and urban buses. Currently, the metro system has 7 metro lines, but the data for this research is from 2017 when only 5 metro lines existed within the metro network. L6 was opened on 2^{nd} of November 2017.

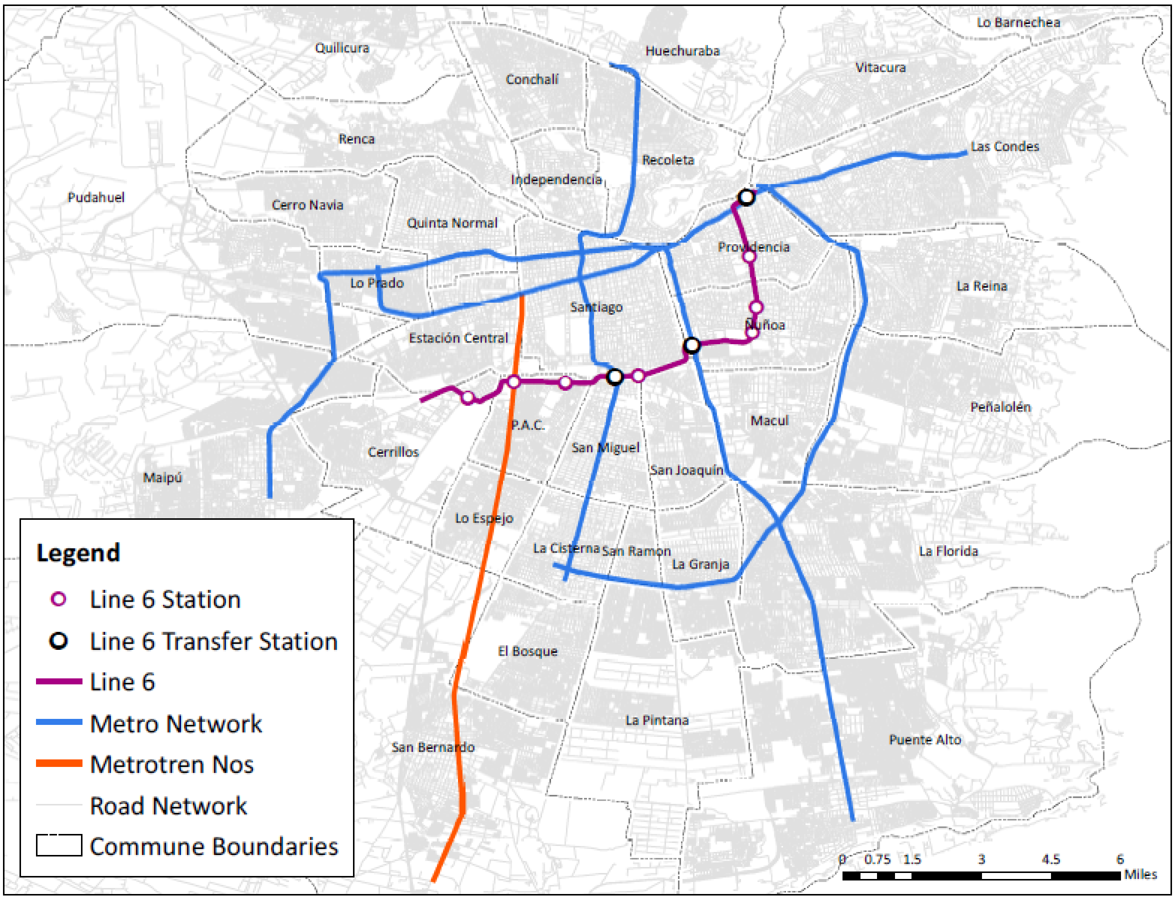


Figure 3.1: Metro network Santiago, Chile (source: Pineda and Lira, 2019b)

3.1.2. Data Sources

We draw upon two weeks of processed smart card (SC) data and geographic data on the bus and metro stops of the Santiago public transport network. The first week is prior to the opening of L6 (July 31^{st} till August 6^{th} 2017) and the second week is after the opening of L6 (November 10^{th} till November 16^{th} 2017), both comprising 7 subsequent days. The first week contains 22,7 million journey observations and the second week contains 24 million journey observations. Data is anonymized meaning each observation is only identified by a traveller's identification (id) number. An important note is that the data is not raw data (e.g. only containing time and location of check in) but has been pre-processed. From the raw data, it has been turned into data that contains the entire journey from starting origin till final destination. This includes alighting time and location, but also mode and line used. The second data type source is the geographical coordinations of the bus stops and metro stations. This data contains the *xy* UTM coordinates of each bus stop and metro station in Santiago. This data is important to construct the clusters of bus stops and metro stations which is used later on for choice set construction of travellers, which is an important step in route choice analysis.

3.2. Data

3.2.1. Definitions

To clarify some terminology in this research, we define some terms. A person travels between a given OD pair and we refer to this as a *journey*. While doing so, the person uses a *route* that can consist of multiple single trips. Each trip has a board and alight stop and uses a single mode, either bus or metro.

3.2.2. Data Preparation

The initial step is preparing both the smart card data and geographic data by removing invalid observations in order to make both data sets compatible with one another. This includes removing observations that miss boarding/alighting stops or invalid numeric values.
The geographic data of the urban public transport network must be converted from x-y coordinates to longitude and latitude coordinates in order to calculate distances between pairwise stops. The geographic data is then compared with the SC data in order to find missing stops or stations. Names also have to be changed in order for both data sets to match one another. For example, a couple of metro stations were missing and therefore had to be added afterward to the geographic data. It is a time consuming task where missing stops in either of the data sets have to be removed or renamed in order to match both data sets.

3.2.3. Data Processing Workflow

To investigate the effect of L6 on people's travel behaviour, we focus only on a subset of OD pairs where L6 is at least part of one of the alternatives for a given OD pair. To select these OD pairs, we selected only those journeys where L6 is part of any trip of the journey. To identify the choice sets for these OD pairs, we used the work by Arriagada et al. (2022) who estimated route choice models with Santiago as case study. The zones around these stops have a radius of 100 Euclidean meters. After identifying the relevant OD pairs, we analysed the trips between these OD pairs during the study period of two weeks, one week prior and one week after opening of L6.
A graphical workflow representation of processing the data is presented in Figure 3.2. Between the brackets are the number of journeys obtained after each process. We start with selecting journeys with L6 in any part of the journey. From the geographic data, we create a distance matrix that determines the Euclidean distance between each pairwise stop and/or station. By combining the distance matrix with the selected journeys, we are able to create the relevant OD pair zones. For each origin or destination stop that is selected, we put it through our distance matrix in order to find other stops that are within a range of 100 Euclidean meters of the selected stop. Once these OD pair zones are created, we then filter the data prior and after opening of L6 with these OD pair zones. The final result is a data set that contains only those journeys that are within the subset of OD pairs in which the new metro L6 has an effect.

3.2.4. Data Processing Results

Processing SC Data After Opening

The first step as Figure 3.2 shows is by selecting the relevant OD pairs by using the data set after the opening of the metro line. Table 3.1 gives an overview of the data sizes after filtering for prior and after L6. The relevant OD pairs are selected by only selecting those journeys that use L6 in any part of their journey. As a result, 574.618 journeys were selected for further investigation. This subset of L6 journeys comprises of 67.443 OD pairs. To construct the choice set for a traveller for each journey that has been made, we find the OD pair zones for each OD pair. Based on the relevant subset of OD pairs, the number of total available routes based on this clustering method is 580.404 routes. The average number of routes is 8.6 per OD pair. Based on this subset of OD pairs, the week after the opening which had an original size of 24 million observations has been reduced to 1.026.984 journeys that are observed within the subset OD pairs. Lastly, we removed journeys with ambiguous metro lines which resulted in 987,044 journeys.

Processing SC Data Prior Opening

We use the relevant subset of OD pairs as determined in the previous section to filter the data prior to the opening of L6. The total of 22.7 million observations was reduced to roughly 565.998 journeys after filtering on relevant OD pair routes and removing ambiguous metro lines. Number of travellers is 302.653 which is less than the number of travellers after the opening. This is as expected as due to the opening of the new metro line, it possibly attracted many new travellers who simply want to explore the new metro line.

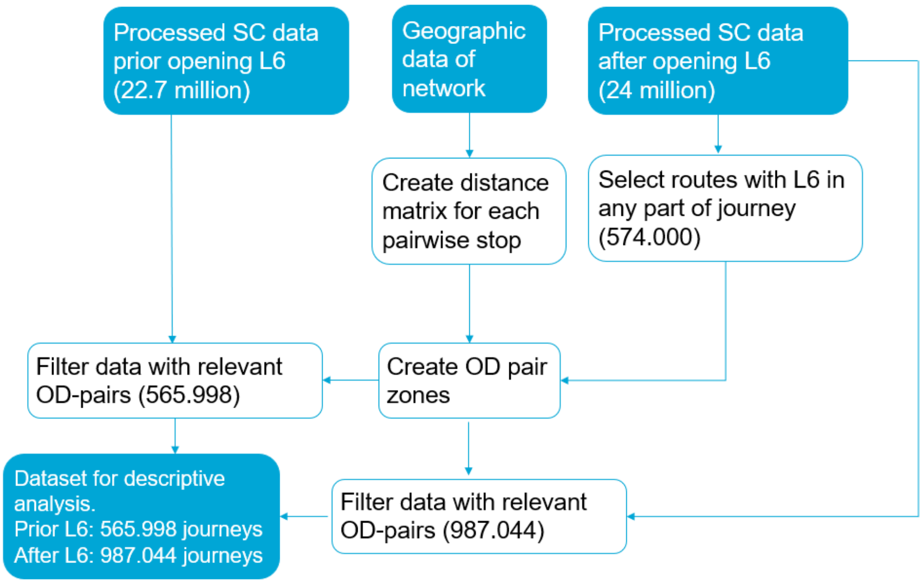


Figure 3.2: Data preparation workflow: initial data set filtered with relevant OD pairs

Table 3.1: The initial data size and the number of journeys, OD pairs and travellers after the filtering process

	Data size	Journeys	OD pairs	Origin	Destinations	Travellers
31/07 - 06/08 (Prior L6)	22,7 million	565.998	32.660	4163	3212	302,653
10/11 - 16/11 (After L6)	24 million	987.044	67.443	6074	4897	429,229

3.3. Impact New Metro Line in Santiago

We conduct a descriptive analysis to find patterns and features of processed SC data. Because we are only interested in the effect of the new metro line, we base the descriptive analysis on the selected OD pairs where L6 is part of an alternative as mentioned in section 3.2.3. For the descriptive analysis, we focus on all observed trips within the subset of OD pairs and we will compare the week prior with the week after L6 in order to gain insight into how the new metro line changed travel attributes.

3.3.1. Change in Number of Trips

The week after L6 has 987.044 journeys travelled between the subset of OD pairs. The number of unique travellers is 429.229. When we look at the number of trips per journey, the average number of trips taken is 1.44 trips per journey. Majority of travellers only have 1 trip in their journey, see Figures 3.3 and 3.4. Figure 3.3 also shows that the number of people who take 2 trips or more is less than people who only take 1 trip, indicating that people prefer avoiding transfers if possible.

Before L6, we observe 565.998 journeys travelled between the subset of OD pairs. The number of people travelling between these OD pairs is 302.653. The average number of trips is 1.50 per journey. The effect of the new metro line shows that within these OD pairs, people take fewer transfers as the average number of trips has decreased from 1.5 to 1.44 due to the implementation of L6. This empirical finding was also found by Pineda and Lira (2019b), who investigated travel time savings perception due to L6 in Santiago. They found that the total trips per journey reduced by 5% indeed confirming our analysis that travellers choose more direct journeys over journeys with transfers.

3.3.2. Travellers Using Line 6

When analyzing the week prior and after L6, we can observe the people who travelled prior the opening and continued to travel after the opening. By doing so, we can observe how many of those people actually start to use L6 as it becomes available as a travel option. Out of the 302.653 unique travellers that travel in the week before L6, 96.056 of those travellers continue to travel in the week after L6. Within the sample that travels longitudinally between the two weeks, 42.232 travellers use L6

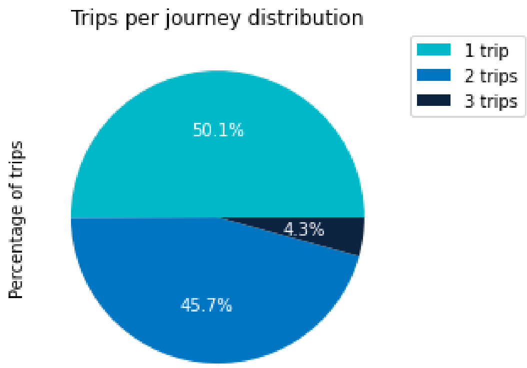


Figure 3.3: Percentage of number of trips in week prior L6 based on selection OD pairs

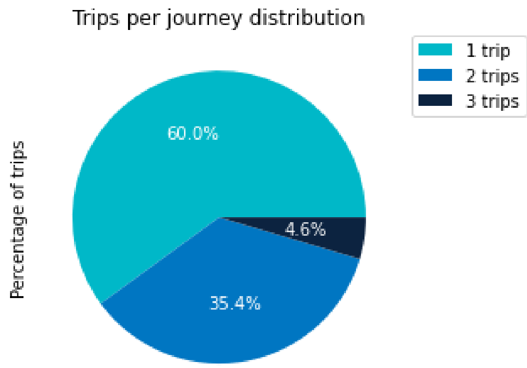


Figure 3.4: Percentage of number of trips in week after L6 based on selection OD pairs

at least once after L6 became available which is roughly 43.5 %.

When analyzing the total sample after L6 that use L6 in any part of the journey, not taking into account the fact that they have to travel before the opening, there are a total of 221.370 unique travellers that use L6. This shows an increase in travellers since there is a difference between people that travelled before the opening and use L6 and people who use L6 and did not travel before the opening. An interesting hypothesis is that due to the availability of L6, the transport system within these OD pairs attracted new travellers who did not use the public transport system before. However, we must be cautious with the increase in 'new' travellers, since people possibly might use new cards during the period of analysis. The number of people that use L6 twice or more is 129.281. The distribution of travellers using L6 twice or more is shown in Figure 3.5.

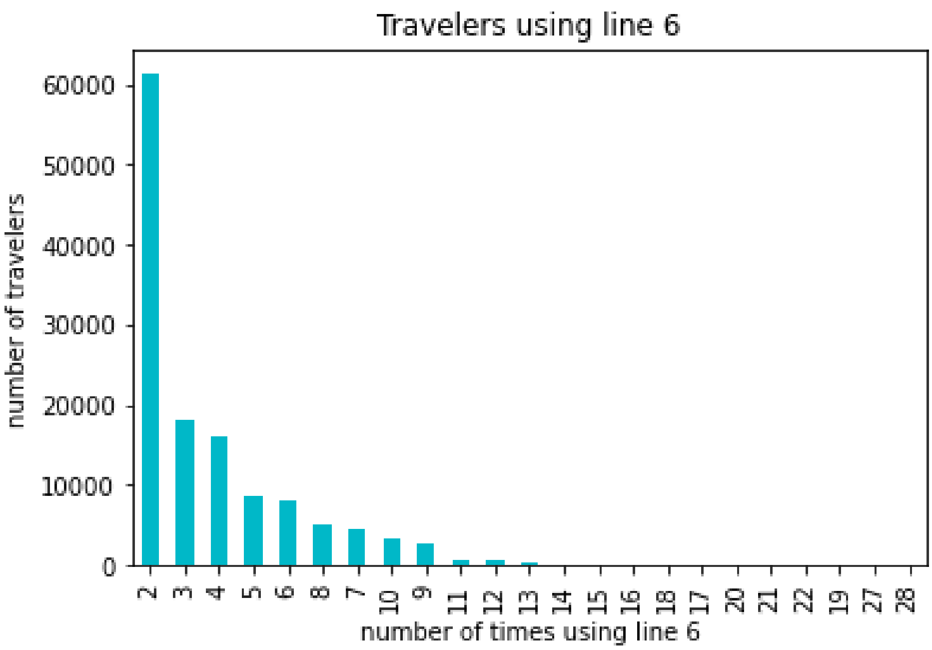


Figure 3.5: Number of travellers using L6 twice or more

3.3.3. Change in Travel Times and Distances

Travel time saving is one of the important travel attributes when it comes to cost-benefit analysis in transport context, hence why we highlight the impact of L6 on this travel attribute. We differentiate

between in-vehicle travel time and waiting time. Waiting time has the components walking, waiting and transfer time between trips. The number of travellers before and after the opening differs in numbers. The waiting time for the first leg has not been accounted for due to missing data. The average travel time in the week before L6 is 32.8 minutes, while the average travel time in the week after L6 is 29.46 minutes. Also, the waiting times have changed. Before L6, the average waiting time was 6 minutes, whereas the average waiting time after L6 is 5.18 minutes.
The average travel distances did also decrease. The total travel distance is defined as the sum of the distance travelled per mode per leg. The average travel distance of 12.5km before L6 decreased to an average of 11.76 km after L6.

3.3.4. Change in Mode Shares

When looking at the total share of ridership per mode, we see a clear difference in the before and after situation for the subset of OD pairs. There is a clear increase in metro usage by travellers in Santiago after opening of L6. Out of 565,998 journeys before the opening, the share of travellers using the metro only is 37%, bus only 18% and the share of journeys that have bus and metro combined is 45%. The week after the opening has an increase in total number of journeys, but it is clear that the share of only metro has increased significantly, see Figure 3.6. The week after the opening has 987,044 number of journeys, from which the share for metro only is 52%, bus only 10% and journeys with bus and metro combination is 38%. Overall, the bus share has decreased and a large increase in metro shares which was expected due to the opening of L6. The share with journeys that use a combination of bus and metro shows a relatively small increase. The large increase in metro shares shows the significant impact L6 has on the Santiago public transport system. It is noteworthy, that the figure represents the moment right after L6 opened, possibly indicating a high-point in the usage of L6. The large increase in the metro shares can be explained due to a large part of L6 covering an area in the west of Santiago which did not have the availability of the metro before as seen in Figure 3.1. Additionally, the opening of L6 possibly attracted many individuals who for the sake of exploration wanted to try out the new metro line.

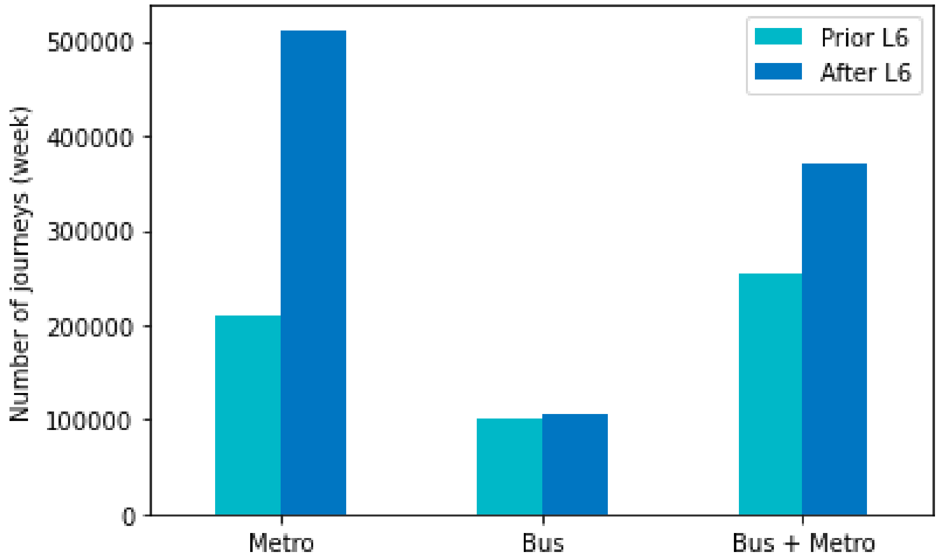


Figure 3.6: Change in mode share ridership within selected OD pairs

3.3.5. Geographical Distribution Origins L6 Travellers

Figure 3.7 shows the geographical distribution of origins where travellers who use L6 depart from. The bar on the right hand side shows the size of each origin in terms of number of journeys that use L6. We only included origins with 10 or more journeys departing from the origin. The figure shows clearly that the largest concentration of origins that use L6 are centered at the metro stations of L6. Other large origins with large number of routes departing are Manquehue and Tobalaba which are not stations on L6. Furthermore, other concentrations of origins that use L6 but in smaller numbers are located at the south and south-west of Santiago. It is no surprise that the largest concentrations are to be found at or near the stations that make up L6. From the analysis on mode shift, we see that there has been a large increase in metro only shares which most likely emerged from these newly available stations. People living near these stations now have direct access of using the metro which remains the backbone of the Santiago public transport system.

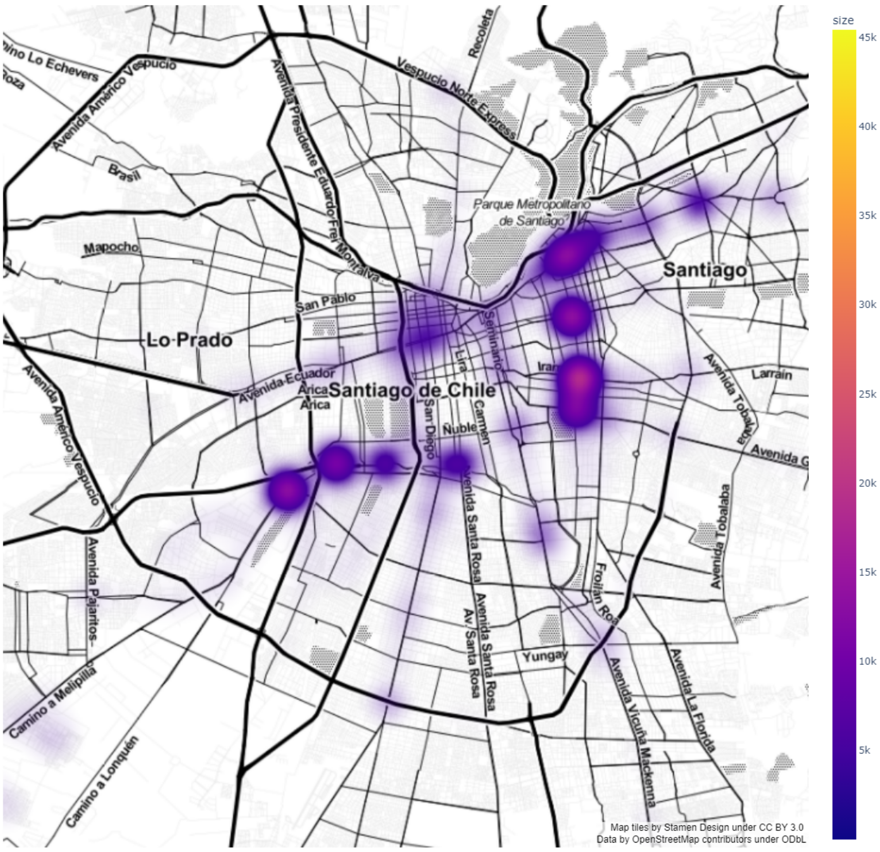


Figure 3.7: Geographical distribution origins of travellers using L6

3.4. Summary

In this chapter, we presented the case study of Santiago, Chile multimodal public transport network for our research. The data that we use is smart card data that includes two full weeks of observations, with one week prior to the opening of L6 and one week right after the opening. We then followed up on the data preparation and processing in order to convert the data into a workable format for route discrete choice modelling. Next, we conducted a descriptive analysis of the effect the new metro line has on travel behaviour in Santiago and expressed this by comparing travel attributes of the before and after situation.

The descriptive analysis showed us that L6 has a significant impact on the subset of OD pairs we selected. The selected OD pairs are those OD pairs that have L6 as travel alternative in the after situation. We see an overall decrease in waiting times and in-vehicle travel times. The average number of trips has also decreased, indicating that people take less transfers due to the new metro line. This can be explained by taking direct trips without for example having to use the bus first in order to reach the metro. Furthermore, when looking at travellers that travel before and continue to travel after the opening of L6, nearly one-third continue to travel after. This means that the new line also attracted new people within these OD pairs to use the Santiago public transport network due to a new transport alternative being available near their neighbourhood. This goes together with a large increase in metro only shares. These findings underscore the impact the new L6 has on the Santiago public transport system. The large increase in metro shares highlight the significant impact on travel behaviour.

However, we must be cautious with these findings, since we only use a single week of data right after L6 opened. The relative higher numbers of new travellers can also be possiblly explained due to people using new metro cards, since we assume a metro card 'id' is a traveller. Furthermore, the large increase in metro shares can also be partially explained due to the large number of people who for the sake of exploration wanted to try out the new L6.

4 Methodology

Travel demand prediction has largely been done using aggregated travel demand models up until the 1970's. They became more familiar in terms of modelling and required relatively little skills. Nevertheless, aggregate travel demand models have been criticized for their inaccuracy and inflexibility (de Dios Ortúzar and Willumsen, 2011). The beginning of the 1980's saw the rise of disaggregate travel demand models, including the widely used Discrete Choice Models (DCM). Due to its practical flexibility and a higher level of behavioural realism, DCMs have been widely used in travel research context ever since. DCMs have been reiterated and improved by adding increasing behavioural and practical realism. Examples are the Random Regret Minimization-based DCMs where anticipated regret is also a determinant for choices (Chorus, 2012) or the Path-Size Logit in the field of route discrete choice modelling (M. Ben-Akiva and Bierlaire, 1999) have contributed largely to the field of choice modelling.

The aim of this chapter is to provide a methodology that fits the problem definition and sub-questions. The first sub-question is answered by conducting a literature review in chapter 2. Because we are only interested in the effect of L6, we first do a selection of origin-destination (OD) pairs that are relevant to this study. For quantifying habitual route choice behaviour and the choice modelling part, we also have to create OD pair zones in order to identify the route choice set of travellers for a given OD pair.

This chapter methodology then continues with the method in order to answer the question: *To what extent is travellers' route choice habitual in a non-changing public transport network?* Following, we present the general framework for discrete choice modelling (DCM). This will be followed by the description of the choice set construction based on the Historical/Cohort approach. As this research involves route choices of travellers, we also discuss how the overlap of routes are accounted for using the path-size formulation. Then, based on the framework for DCM we provide the specification of the models. This includes specifying the basic utility function and the different model specifications. Finally, the chapter concludes with the model estimation and market share prediction for L6.

4.1. Selection OD pairs

We are interested in how L6 affects the route choice of travellers. As such, we restrict our analysis to those OD pairs where L6 is at least part of one of the alternatives. The first step is filtering the processed smart card (SC) data after L6 on those journeys that have L6 in any part of their journey. This results in a data set with a subset of origin and destination stops. The subset of origin and destination stops is used to create the origin and destination zones as we explain in the following section.

The next step is to further reduce the subset of OD pairs by excluding journeys with ambiguous metro trips. Observations that include for instance 'L1-L4' for metro line used are excluded. For each observation the data contains which mode and corresponding line (e.g. name of bus line or metro line) are used by an individual. In the case an individual enters a metro station with multiple metro lines, the line used is ambiguous. The moment a traveller enters the metro station after check-in, we are not able to 'look' underground past the point of check-in. For this reason, we exclude observations with ambiguous metro lines and do not consider it within the scope of this study to reveal which line exactly has been taken by a traveller.

Finally, to investigate inertia effects, we focus on those OD pairs where travellers exhibit habitual behaviour before L6 and continue to travel after L6 within the same OD pair. The consistency of OD pairs prior and after L6 is important to understand whether a traveller changes his or her route due to L6 within a given OD pair. For instance, if a person changes their origin and/or destination due to circumstances, this would lead to a different OD pair where the role of inertia might not be significant. When considering the analysis of the sample after L6, it is paramount to select those OD pairs where individuals travel between them in the situation prior and after L6.

4.2. Clustering OD pairs

To identify the choice set of travellers, we must identify the OD pair zones. These zones include stops that are within a 100m Euclidean distance of the journey origin and destination stops. We base our clustering method on the work by Arriagada et al. (2022) who explored route choice heterogeneity in Santiago. Arriagada et al. (2022) performed a sensitivity analysis and found that the distance of 100m showed the most consistent results in DCMs estimation. They highlighted that a larger zone radius resulted in unexpected travel time coefficients.

To create these OD pair zones, a distance matrix is made based on the geographic data that is converted into longitude and latitude coordinates of each stop and station. Using *haversine* formula, the great circle distance between each pairwise stop was computed. As mentioned before, we obtained a subset of OD pairs that have L6 in any part of their journey. For each unique stop or station in this subset we find the zones by using the distance matrix. For each stop or station in the transportation network, if another stop or station is within a distance of 100 Euclidean meters of this stop or station, we assign these stops or stations to the zone. This process is iterated for every stop or station in the subset of OD pairs, resulting in a set of OD pair zones. These zones are then linked to the subset of OD pairs origin and destination stops, resulting in every possible observed origin-destination pair possible within a given OD pair zone. To clarify this, for example, if a person travels from origin A to destination B (as identified in the SC data), the OD pair A-B zones contains every possible route as identified in the distance matrix. This however does not mean that all these routes are included in the OD pair, since we only include the routes observed in the data set. To illustrate this, Figure 4.1 shows the OD pair zones. The dark blue dots represent the origin and destination stops corresponding to a journey that includes L6 in any part of the route. The distance matrix is used to find the stops that are within 100m Euclidean distance of the origin and destination stop, resulting in OD pair zones.

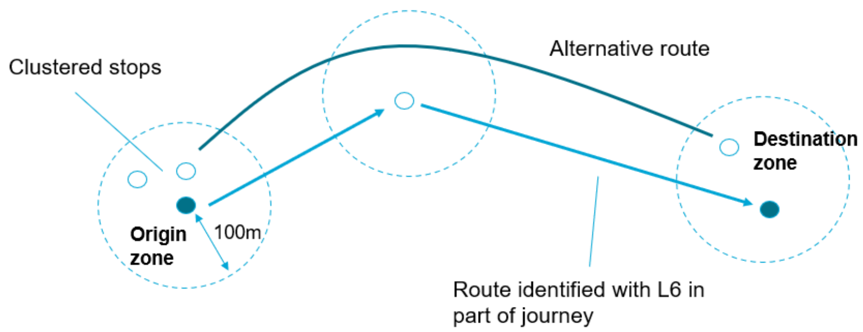


Figure 4.1: OD pairs and their zones. For each OD pair zone, the available route alternatives are identified using the distance matrix

4.3. Measuring Habitual Route Choice Behaviour

In daily routines such as commuting where people tend to choose the same route or mode, people exhibit habitual behaviour. Novel behaviour in the same context is rather the exception (Verplanken and Orbell, 2003). But what is habitual behaviour? Is it just repetition of certain choices? And in what sense is repetition of choices habitual? Could it every time be the outcome of rational decision-making where travellers maximize their utility? Distinguishing habit from rational decision-making remains a challenge due to the complexity of human behaviour. In the case of a new transport alternative, how does the nature of habitual behaviour affect people's willingness to pursue the travel option? To answer these questions, we first look at how to quantify habitual route choice behaviour in a stable travel condition. For this study, we therefore look at the period prior L6.

Measuring habitual behaviour in a multimodal public transport network has been done in limited studies as literature shows. Verplanken and Orbell (2003) developed a Self-Report Index, a qualitative measure where respondents were studied using surveys. Other studies adopted the method by Verplanken and Orbell (2003) such as Fujii and Kitamura (2003) who combined questionnaires with measuring frequency of behaviour. Unfortunately, this study does not acquire additional qualitative information on travel behaviour of the individuals that travelled during the period of analysis. Because our data contains large anonymized travel observations, we adopt the method by Kim et al. (2017) who developed the *Stickiness Index* to measure habitual route choice behaviour in the context of a public transport system using smart card (SC) data.

4.3.1. Stickiness Index Approach

In order to quantify to what extent route choice is habitual in a multimodal transport network, we first must determine when a traveller is classified as habitual, non-habitual or possibly something in between. The *Stickiness Index* (SI) tells us to what extent a person 'sticks' to a particular route within a given origin-destination (OD) pair. A high stickiness indicates that a person is often or always using the same route despite the availability of different routes to the user within the same OD pair and thus is considered habitual due to the repetitive nature of choices. Conversely, a low stickiness indicates that a traveller is using the available routes within an OD pair more evenly and thus considered variety seeking or non-habitual. The SI of a traveller is determined for a given OD pair. A traveller who is classified as habitual for a given OD pair where the activity is work might not exhibit the same type of behaviour for a different OD pair where the traveller visits a friend. The difference in transport network, goals and environment may lead to different type of behaviour. By aggregating the SI of all travellers within a given OD pair, we are able to determine the average OD-level SI. The average OD-level SI explains the average stickiness tendency for a given OD pair. Comparing different OD pairs and their average SI, allows us to gain insight into spatial patterns associated with travellers stickiness. The remainder of this section presents the formulation of *Stickiness Index* for traveller-level and OD-level. As the method captures repetition of route choice under stable conditions, we apply the method on the period prior L6.

4.3.2. Traveller-Level Stickiness Index

For each OD pair k, we construct a *Traveller-Route Matrix*, see Figure 4.3. The rows indicate the set of travellers I for a given OD pair k and the columns indicate the observed set of routes J for the same OD pair. An entry n corresponds with the frequency of a route for a particular traveller i using route j to travel within OD pair k.
To construct the *Traveller-Route Matrix*, we imposed three requirements to the filtered data set prior L6, see Figure 4.2. A total of 646.391 traveller-OD journeys was reduced further as we impose the requirements. The first requirement is imposing a minimum number of 3 journeys threshold for a traveller-OD to be considered valid. This resulted in 176.092 traveller-OD journeys. The second requirement makes sure that we only include OD pairs that have a minimum of 10 travellers or more travelling within to be valid. This resulted in 90.856 traveller-OD journeys. Finally, only those OD pairs were kept that had a minimum of two route alternatives observed. Resulting in the final data set of 51.898 traveller-OD journeys for SI estimation. An OD pair has on average 113 journeys made by travellers within the OD pair. Each traveller made on average 4.6 journeys.

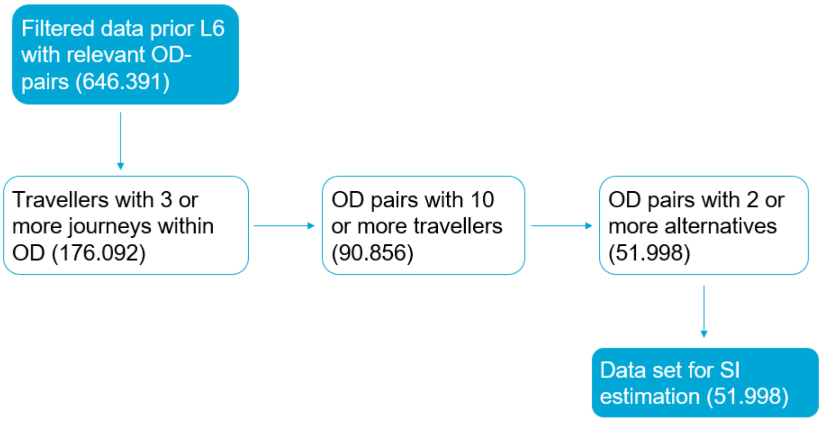


Figure 4.2: Data requirements for SI estimation

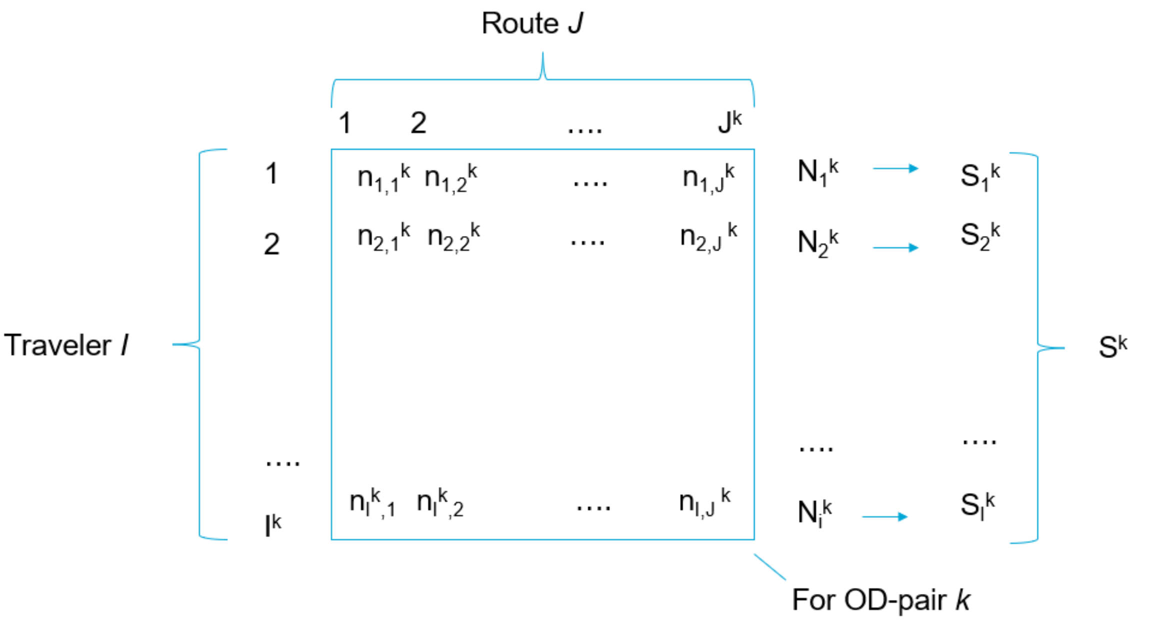


Figure 4.3: Traveller-Route Matrix (based on Kim et al. (2017))

Kim et al. (2017) base their *Stickiness Index* on a diversity index, an indicator well known in the field of ecology to measure biodiversity. The diversity index takes both into account richness (number of routes considered as alternatives by a traveller) and evenness (how is the distribution of each route among alternatives). The diversity formula is as follows (Kim et al., 2017):

$$D_i^k = \sum_{j=1}^{J^k} (p_{i,j}^k)^2 = \sum_{j=1}^{J^k} (\frac{n_{i,j}^k}{N_i^k})^2 \tag{4.1}$$

where $n_{i,j}^k$ represents the number of journeys made by a traveller *i* using route *j* to travel within OD pair *k*, N_i^k is the total set of journeys made by traveller *j* to travel with OD pair *k* and $p_{i,j}^k$ is the proportion of journeys made using route *j* so that $\sum_{j=1}^{J^k} p_{i,j}^k = 1$. $D_i^k = 1$ if only one route is and indicates no diversity. Maximum diversity occurs when all routes are equally used with $D_i^k = 1/J_i^k$.

As the diversity index takes into account both richness and evenness, in the context of habitual travel behaviour we are only interested in evenness. We want to know how the chosen routes are distributed *within* the number of routes used. The set of routes used (e.g. two routes or four routes) does not characterize the stickiness of traveller to a particular route. To only account for evenness of routes, equation 4.1 is normalized by the size of the routes used. This results in the *Stickiness Index* of a traveller *i*, travelling OD pair *k*. Which is as follows (Kim et al., 2017):

$$S_i^k = \frac{J_i^k * D_i^k - 1}{J_i^k - 1} \tag{4.2}$$

where J_i^k represents the number of routes us by a traveller *i* and D_i^k the diversity index as formulated in formula 4.1. The importance of transforming the diversity index to the SI, shows that we are only interested in the distribution of the routes used and not the size of the set of routes used. It is noteworthy, that we only consider OD pairs where the number of observed routes is two or more.

We explain the differences between the diversity index and stickiness index using three cases where for each case we discuss a different level of evenness (distribution of the routes). For case 1 (low evenness), 90% of journeys are allocated to one route and 10% of journeys are equally to the remaining routes. For instance, if a traveller makes 100 journeys for a given OD pair and uses three routes, 90 journeys are allocated to a single route, and the remaining 10 journeys are distributed for route 2 and 3 with each five journeys. For case 2 (medium evenness), 50% of journeys are allocated to a single route and 50% to the remaining routes. Lastly, for case 3 (high evenness) we discuss the case when all journeys made are distributed equally over all the routes used.

- Low evenness (case 1), where 90% of routes used is allocated to one route and 10% to the rest. Starting value for SI would be high due to the dominance of a single route. SI would increase with increasing routes used which indicates a high stickiness to one particular route (fractions journeys with other routes becomes smaller). The diversity index would also have a high starting value (very low evenness) and would slowly decrease with increasing number of routes used. Although richness increases for the diversity index (number of routes used), since 90% of journeys is allocated to a single route, the fraction for the other routes becomes smaller as richness increases. Fraction of other routes used becomes smaller (e.g decreasing evenness).
- Medium evenness (case 2), 50% of journeys is allocated to a single route and 50% to remaining other routes used. The values for SI would be smaller than for case 1 because of increasing evenness. With increasing routes used, the SI and diversity index would show similar patterns as for case 1.
- High evenness (case 3), all journeys made are distributed equally among all the routes used. Diversity index would decrease with number of routes used as both evenness and richness increase. SI would be zero indicating no stickiness to a particular route. Even if the number of routes increases, there is no tendency to stick to a particular route.

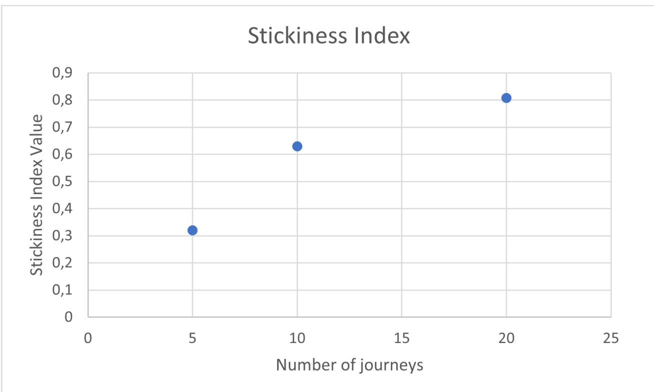


Figure 4.4: SI values at different number of journeys. The case of 2 routes, where only 1 journey has been used with a different route and remaining journeys assigned to the dominant route

To illustrate how the SI changes with different frequencies, Figure 4.4 shows how the values of SI with different number of journeys. We tested the case of 5, 10 and 20 journeys where only 2 routes are used by a traveller. More specifically, only 1 journey has been assigned to another route and the rest assigned to the dominant route. It can be seen that as the number of journeys increases, route 1 becomes increasingly more dominant relative to route 2 which only has one journey made by the traveller.

From the theoretical framework of the literature review, we found that the frequency of past choices has been the standard for measuring habit and thus repeating past choices results in a high stickiness. Based on this assumption, we only consider a traveller habitual if their SI equals 1 (e.g. all journeys allocated to a single route, despite having other alternative routes available). A person is non-habitual if their SI is lower than 1 (e.g. at least two different routes used).

4.3.3. OD-Level Stickiness Index

As we determine the SI for an individual traveller for a given OD pair, the next step is to aggregate the travellers' stickiness and obtain the average SI for each OD pair S^k. This gives insight into the stickiness tendency on OD-level and analyse if there are any spatial differences between different OD pairs. The OD-level SI is determined by a weighted average of each users SI (Kim et al., 2017):

$$S^k = \sum_{i=1}^{I^k} w_i^k * S_i^k \tag{4.3}$$

where S_i^k denotes the individual traveller SI for a given OD pair *k* and w_i is the proportion of a travellers total set of journeys within the entire set of journeys for a given OD pair and I^k is the set of all travellers for OD pair *k*. The proportion is defined as follows (Kim et al., 2017):

$$w_i^k = \frac{N_i^k}{\sum_{i=1}^{I^k} N_i^k} \tag{4.4}$$

Where N_i^k is the total number of journeys made by traveller *i* travelling OD pair *k* and I^k is the set of all travellers for OD pair *k*

4.4. Discrete Choice Modelling Framework

The Discrete Choice Model (DCM) is a powerful tool to analyze the choice behaviour of individual people and has been used in various research fields such as transportation and consumer product choice for example (Chorus, 2012). These individual choices lie down at the center of quantitative models that aim to predict aggregated market shares (M. E. Ben-Akiva et al., 1985). By observing choices people make, DCMs allows the modeller to understand the underlying preferences of people when also the characteristics of these choice options are known. Since our case involves route choice decision-making by travellers, these characteristics can be for example travel time, travel costs or waiting time. DCMs are then able to estimate weights decision-makers attach to these characteristics, so called taste parameters. To gain a better understanding of analysing travellers route choice behaviour, the aim of this section is to present the general framework of DCMs as described in the following paragraphs.

When a person faces a choice problem, for example choosing a route to work, the underlying fundamental procedures for DCMs that construct such a choice consist of the following elements the decision maker, the alternatives, the alternative attributes and the decision rule (M. E. Ben-Akiva et al., 1985). The decision maker can be an individual or a group of people such as a household. In this study, decision makers are the travellers using the Santiago multimodal public transport system. Although DCMs are used for estimating aggregated demand, it is important to address the differences among individuals as everyone has different preferences that are bound to the individual when making choices (M. E. Ben-Akiva et al., 1985).

The choice problem consists of alternatives a traveller can choose from, together the alternatives form the choice set of the traveller. Which alternatives enter the choice set depends on the feasibility of the alternative for the decision maker and which alternatives are known during the choice modelling process (M. E. Ben-Akiva et al., 1985). This study uses the Historical/Cohort approach, therefore the known alternatives during the choice modelling process are those alternatives observed from the data set. The choice set exhibits three characteristics: mutually exclusive, exhaustive and finite (Train, 2009). Mutually exclusive refers to that alternatives must be distinctive and choosing for example one route means the other routes are not chosen. Additionally, all possible alternatives must be included in the choice set. Lastly, the set of alternatives must be finite. In our route choice model, the set of alternatives is made feasible to the decision maker by clustering those route alternatives that are within a feasible walking distance for a traveller.

Which alternative ends up as the choice depends on the attributes of the alternative and the decision rule. The attributes characterize the alternatives and in the case of choosing a route alternative, these attributes can be for example the travel costs or travel time. For each alternative, these attributes levels vary therefore making each alternative distinct in terms of these attribute level values.

Lastly, when all these elements are defined within the DCM framework, the decision rule determines which choice is made. When a person chooses between a set of alternatives, an internal mechanism is used by the person in order to come to a decision. Due to the complexity of human behaviour, a decision rule as chosen by the modeller helps reduce the complexity to some extent to be of practical use for DCMs. One of the decision rules that is widely used in the field of transportation is Random-Utility Maximization (RUM). This rule dictates that a person attaches a utility to each alternative and chooses the alternative with the highest utility (Chorus, 2012).

4.4.1. Multinomial Logit

The Multinomial Logit (MNL) is widely used by researchers in discrete choice modelling practice, as well as in the field of transportation research due to its elegant form and ease of use. For route choice modelling it is not suitable due to the independence from irrelevant alternatives (IIA) property (Prato, 2009). To address the problem of overlapping route alternatives in route choice modelling, the Path-Size Logit (PSL) is used which is a modification of the MNL model. Based on RUM, given a subjective choice set for each individual *n*, the probability *P* that the individual chooses alternative *i* from choice set C_n is given by:

$$P_n(i) = Pr(U_{in} \geq U_{jn} \forall j \in C_n) \tag{4.5}$$

Where *U* is the utility function which consists of a deterministic component and random error component (formula 4.6). From the perspective of the modeller, the deterministic component is non-random and contains the observed factors. The deterministic part is in the linear additive form based on attributes and taste parameter for each attribute (formula 4.7). The error component is random and contains those factors that are not possible to observe by the modeller (Chorus, 2012).

$$U_{in} = V_{in} + \epsilon_{in} \tag{4.6}$$

$$V_{in} = \sum \beta_{im} * x_{im} \tag{4.7}$$

In formula 4.7 the β is the taste parameter for attribute *m* and alternative *i* and *x* is the attribute level for attribute *m* and alternative *i*. Based on the observed factors, the modeller decides which enters the systematic part in order to describe the alternatives. The process of deciding which factors enter the utility function is an iterative procedure and there is no straightforward avenue. The specification of the error component leads to different formulations of the choice probabilities. The widely used specification is when the error term is independently and identically distributed (iid), this leads to a closed form and therefore leads to the simple MNL formula 4.8:

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \tag{4.8}$$

Where P_n is the probability that decision maker *n* chooses alternative *i*, V_{in} is the utility of alternative *i* and V_{jn} is the utility of alternative *j*. The denominator is the sum of utilities of alternatives in choice set C_n.

Even though the MNL model exhibits the IIA (Independent from Irrelevant Alternatives) property and does not account for correlation among choices of the same individual, it is widely used in multimodal route choice modelling due to its simplicity and elegant form (Anderson et al., 2017; Jánošíková et al., 2014; Prato, 2009). Since there is no straightforward avenue, the 'art' of choice modelling is to start from a simple model specification with relatively small number of parameters and work towards a more advanced model. As we discuss later in section 4.5, the IIA property is accounted for by using the Path-Size formulation of the MNL model.

4.5. Route Choice Modelling

Every day people have to choose a route to go to work, school or visit relatives, which makes modelling route choice behaviour essential for our society. We undergo these travel activities with different modes and therefore route choice behaviour research has been done on various travel modes such as cycling (Ton et al., 2017), public transport (Jánošíková et al., 2014; Kim et al., 2017) and cars (Arnott et al., 1990). Due to the complexity of human behaviour, modelling people's route choice behaviour accurately is a great challenge. For society, route choice modelling is also highly important in predicting future traffic flow on transport networks, assessing hypothetical transport investments and understanding people's travel behaviour and perception of route characteristics (Prato, 2009).

There are various route choice models varying in decision rule and knowledge assigned to travellers. There is the route choice paradigm where we assume travellers have perfect knowledge of their route choice set and choose the route that minimizes their travel costs. Another route choice paradigm, realistically assumes travellers have imperfect knowledge and choose the route that minimizes their perceived travel costs (Prato, 2009). Alternatively, route choice is based on the discrete choice modelling framework. Widely used by researchers in route choice modelling and is able to capture more realistic route choice behaviour than previously mentioned paradigms (Jánošíková et al., 2014).

Within the discrete choice modelling framework, various choice models have been proposed and are based on modifications on the simple Multinomial Logit (MNL) model. These modifications are justified in earlier research and account for overlap between route alternatives. Bliemer and Bovy (2008) showed how the route choice set affects the route choice probabilities. They found that including irrelevant route alternatives affects the choice probability of attractive routes, therefore this should be accounted for in the route choice model. These MNL model modifications that include a correction term that reduces the utility of competing route alternatives include the C-Logit and Path-Size Logit (PSL) (Duncan et al., 2020). The C-Logit does this by including a commonality factor in the utility function. It still remains the elegant form of the MNL model. The C-Logit has the advantage with regard to the choice set size that it has the desired robustness of utility parameter estimates. Its disadvantage is that it only captures part of the similarity of alternatives (Prato, 2009). Compared to the Path-Size Logit (PSL), the C-logit has been outperformed in terms of likelihood values estimations, hence recent research uses the PSL for its model performance (Dixit et al., 2021; Prato, 2009).

4.5.1. Path-Size Logit

The PSL is based on adding a correction term to the systematic part of utility in order to account for overlap between route alternatives. M. Ben-Akiva and Bierlaire (1999) introduced the PSL within the DCM because of the assumption that overlapping route alternatives may not be considered distinct alternatives. Their PSL model remains the Logit closed form structure:

$$P_k = \frac{exp(V_k + \beta_{PS} * ln(PS_k)}{\sum_{l \in C} exp(V_l + \beta_{PS} * ln(PS_l)} \tag{4.9}$$

Where PS_k and PS_l are the path sizes of routes *k* and *l*, respectively. Parameter β_{PS} is to be estimated. The Path-Size factor (PSF) is defined as the fraction of a link with its route length *k* and weighted by whether the link is shared with other routes *l* (formula 4.10).

$$PSF_k = \sum_{a \in \Gamma_k} \frac{L_a}{L_k} * \frac{1}{\sum_{l \in C} \delta_{al}} \quad (4.10)$$

Where Γ_k is the set of links for route *k*, L_a is length of link, L_k total length of route *k* and δ_{al} is 1 if link a is on route *l* and 0 otherwise. Within multimodal transport route choice modelling, Hoogendoorn-Lanser et al. (2005) studied the effect of path size on multimodal transport network. The authors analyzed different options for route overlap in public transport network. Overlap can be defined in different ways, such as leg based, expected or scheduled travel time or distance (Hoogendoorn-Lanser et al., 2005). While the latter is the most natural, in the case of this research this is challenging due to the lack of automatic vehicle location (AVL) data. Travel time is a viable option, but the problem with actual travel time and scheduled travel time is the variability in actual travel time due to for example congestion. Scheduled travel time information is unfortunately not available. Therefore, we adopt the stop based approach by Tomhave and Khani (2022), since our data contains routes consisting of legs and their associated board and alight stops.
Although the PSL due to its closed form is used often in route choice modelling, the model is limited by only capturing part of the correlation among route alternatives, nevertheless its interpretation and relative ease of use make it a preferable model to account for route overlap among alternatives.

4.5.2. Calculation of Path-Size Factors

As mentioned earlier, in multimodal transport networks there are various possibilities for overlapping elements, unlike a road network. These elements can be nodes, modes and services (Hoogendoorn-Lanser et al., 2005). For this research, overlap is accounted and corrected for on stop level. In practice, this means that routes that share the same stops for a given leg in the route share a commonality and thus are overlapping.

In the case of multimodal transport networks, stops or legs (defined as a pair of stops served by the same mode) yield substantially better results than travel time or link length (Dixit et al., 2021; Hoogendoorn-Lanser et al., 2005). For example, a bus service and metro service may overlap in terms of travel time within a corridor but from a traveller point of a view differ in terms of service attributes (e.g. seats, comfort, stop spacing) and therefore the traveller considers either of the two but not both. In case routes do not share stops, a traveller considers the choice of stop hence when considering route choice correlation, spatial overlap or time overlap is less of a significant role in the route choice process of a traveller (Tomhave and Khani, 2022). For this reason, we adopt the approach of stop level, rather than the more widely used link or travel time based.

For each choice set within an OD pair the PSF is estimated based on the above method. For instance, route A that has legs 1 and 2, for which leg 1 is a bus service and leg 2 is a metro line. Route B has also two legs, with leg 1 operating a bus service and leg 2 another bus service. Both leg 1 of route A and B share the same board and alight stop. This is regarded as overlapping section on the stop level. The PSF term takes the value of 0 when no overlap occurs between route alternatives and decreases as routes overlap increases. The Path-Size correction term as presented in formula 4.10 is used but adapted towards stop overlap rather than link overlap, which is as follows:

$$PSF_{i,n} = \sum_{s \in \Gamma_i} \frac{1}{N_i} ln(\sum_{j \in C_n} \delta_{s,j}) \quad (4.11)$$

Where $PSF_{i,n}$ is the Path-Size factor for route *i* and person *n*, Γ_i is the set of all stops for route *i*, N_i total number of stops served by path *i*, C_n is the choice set of person *n* and δ is 1 if stop *s* is on path *j*, 0 otherwise. To illustrate this, Figure 4.5 shows for a given OD pair three routes where the dark blue dots represent stops and lines represent the trip link. Route A and B share overlapping stops, and route C shares no stops with any other alternative. To account and correct for overlapping alternatives, the utility for both route A and B is reduced by a PSF of -0.46[1]. Whereas the PSF for route C is 0 since it shares no overlapping stops with routes A and B.

[1] First stop is used on route A and B thus $\delta_{s,j}$ = 2, similar for the second stop. Results in (ln(2) + ln(2) + ln(1))/3 = 0.46

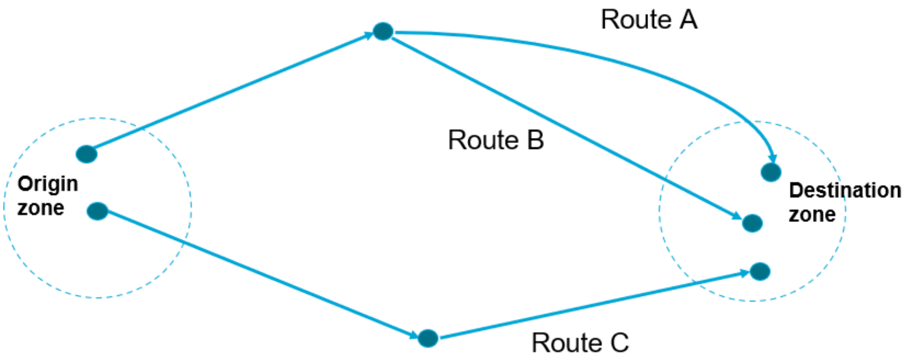


Figure 4.5: Overlapping routes on stop level: Route A and B share the same stops for the first leg.

4.6. Choice Set Construction

An important step for estimating DCMs is constructing the choice set for each traveller. The choice set within a given OD pair is the same for all travellers travelling between the given OD pair and we assume the choice set remains the same throughout the day. As we are only interested in the effect of L6, we focus on a subset of OD pairs where L6 is part of at least an alternative. Therefore the first step is selecting a subset of OD pairs as done in section 4.1. The criteria for the first selection is based on selecting routes after the opening that use L6 in any part of their journey. To identify the choice sets, we create the OD pair zones as described in section 4.2.

Generating the choice set will be based on the Historical/Cohort approach. This approach generates the choice set based on the revealed observations from the smart card data. Its limitation is that possible viable alternatives are not included within the choice set. But based on the actual observations, we can assume these alternatives that have not been observed are simply not perceived as feasible by the decision-maker. OD pairs also must have at least two feasible alternatives, OD pairs with fewer is discarded.

We use *PandasBiogeme* for the estimation of the DCMs (Bierlaire, 2018). This requires constructing the choice set in a correct format for *Biogeme* which means variables (e.g. traveller ID number or route attributes like travel time or waiting time) correspond to columns and observations to rows. Furthermore, since we are dealing with multiple OD pairs, each OD pair will have a different choice set size and it is important to correctly account for this in the availability conditions for the choice model.

4.7. Model Specification

To investigate the inertia effects on route choice when individuals face L6, we specify a MNL model as comparison, a MNL model with L6 dummy variable and a MNL model with inertia. By quantifying habitual behaviour using the SI prior L6, we want to investigate whether people who are classified as habitual, would be less likely to use L6 as compared to others. This leads us to formulate the following hypothesis:

Travellers who exhibit habitual route choice behaviour prior L6 are less likely to use L6 after it becomes an available route alternative

To test the hypothesis we include a simplified SI[2] as a dummy variable in the route DCM framework. Since habitual behaviour can lead to inertia, the SI indicator in this DCM framework reflects the inertia effect. Due to the relatively short period of analysis, we assume a traveller is habitual if all journeys

[2]Disclaimer: We want to emphasize that we do not use the SI in its full account. We use a simplified SI where it is reduced to a simple dummy variable. We consider those travellers with a SI of 1 as habitual and those with a SI lower than 1 as non-habitual due to the short period of analysis. Nevertheless, Kim et al. (2017) does address the possibility of using their analytical framework in changing urban design

are repeated. Therefore, we classify a person as habitual if their SI equals 1 and non-habitual if their SI is smaller than 1. Additionally, a dummy variable for L6 must be included to investigate how both segments perceive L6, which can be considered the baseline for perceiving L6 within the sample. The choice modelling strategy is conducted by first starting with a base MNL model that includes no inertia effect and no L6 dummy variable. The MNL model has been used in many studies that investigate travel behaviour of public transport passengers (Jánošíková et al., 2014) due to its simplicity. Because the MNL model does not account for correlation among alternatives with overlap in route segments, we modify this model into the PSL which accounts and corrects for route overlap on stop level.

Summarizing, this study estimates three models. A base MNL model, a MNL model with L6 dummy variable and MNL model with inertia effects. The base MNL model is used as comparison to highlight the implications for demand estimations if inertia exists. The MNL model with L6 includes a dummy variable for L6 which represents the perception of both segments for L6. The MNl model with inertia effects has an additional interaction effect that accounts for the additional effect for L6 of travellers being habitual. The estimation itself is done using *PandasBiogeme* package (Bierlaire, 2018).

4.7.1. Model 1: MNL (base model)

The deterministic part of utility consists of the following attributes: in-vehicle travel time for metro and bus, waiting time at transfers, number of transfers, path-size factor and mode-specific constants for bus and metro. For the number of transfers, we make distinction between metro-metro, bus-metro, metro-bus and bus-bus. Waiting time has the following components: waiting time, transfer time and walking time. Only the waiting time for the subsequent trips after the first trip is available in the data. All alternatives have the same attributes. We define the travel time attribute separately per mode for bus and metro (formula 4.12). The taste parameters for each attribute are to be estimated. Travel costs have not been included in the systematic component due to the almost flat fare between modes. It is expected travel time for bus and metro, waiting time and transfer to have a negative sign for the taste parameters when estimated. Parameter for Path-Size factor is expected to be positive as it decreases the utility of overlapping alternatives.

$$\begin{aligned} V = \beta_{bus,TT} * TT_{bus} + \beta_{metro,TT} * TT_{metro} + \beta_{WT} * WT + \beta_{Transfer_{busbus}} * Transfer_{busbus} + \\ \beta_{Transfer_{busmetro}} * Transfer_{busmetro} + \beta_{Transfer_{metrobus}} * Transfer_{metrobus} + \\ \beta_{Transfer_{metrometro}} * Transfer_{metrometro} + \beta_{PSF} * PSF + \\ \beta_{MSC_{bus}} * MSC_{bus} + \beta_{MSC_{metro}} * MSC_{metro} \end{aligned} \tag{4.12}$$

4.7.2. Model 2: MNL With L6 Dummy Variable

Before we include the inertia effect, we first estimate a model where we assess how both segments, habitual and non-habitual, perceive L6. Model 2 is an extension of model 1 by adding a dummy variable for those alternatives that have L6. The deterministic part of utility is as follows:

$$\begin{aligned} V = \beta_{bus,TT} * TT_{bus} + \beta_{metro,TT} * TT_{metro} + \beta_{WT} * WT + \beta_{Transfer_{busbus}} * Transfer_{busbus} + \\ \beta_{Transfer_{busmetro}} * Transfer_{busmetro} + \beta_{Transfer_{metrobus}} * Transfer_{metrobus} + \\ \beta_{Transfer_{metrometro}} * Transfer_{metrometro} + \beta_{PSF} * PSF + \\ \beta_{MSC_{bus}} * MSC_{bus} + \beta_{MSC_{metro}} * MSC_{metro} + \beta_{L6} * L6 \end{aligned} \tag{4.13}$$

Where β_{L6} is the parameter to be estimated and L6 is the dummy variable defined as 1 for alternatives with L6 and 0 for those alternatives that do not have L6.

4.7.3. Model 3: MNL With Interaction Effect

For model 3 we adopt a novel approach by including the *Stickiness Index* (SI) variable in the DCM framework. In section 2.2 we discussed how habitual behaviour may lead to inertia. Although the

SI is simply a quantitative measure for habitual route choice and has not been included in a DCM framework before as far as the authors know, by including the variable as an indicator for the inertia effect in the model we hypothesize that habitual travellers are less willing to use L6. Important note, we use a simplified version of the SI as defined in Kim et al. (2017) for the reason that the data only contains one single week. Model 3 is an extension of model 2 by including an interaction effect of L6 with SI indicator to the deterministic part of utility as seen in formula 5.1. The additional term is considered to be the inertia effect. The dummy variable for L6 equals 1 if an alternative has L6 and 0 otherwise. The SI indicator equals 1 if a traveller is habitual and 0 in case of a non-habitual traveller. The perception of habitual travellers of L6 therefore is equal to the baseline (only L6 dummy variable) which consists of both segments (habitual and non-habitual) and an additional interaction effect of SI * L6 which only applies to habitual travellers. If no interaction effect is estimated, this would imply that there are no differences between habitual and non-habitual travellers and their perception of L6. A positive interaction effect would indicate that there is an additional preference towards L6 by habitual travellers and a negative effect would indicate there is an additional dislike of L6 by habitual travellers.

$$\begin{aligned} V = \beta_{bus,TT} * TT_{bus} + \beta_{metro,TT} * TT_{metro} + \beta_{WT} * WT + \beta_{Transfer_{busbus}} * Transfer_{busbus} + \\ \beta_{Transfer_{busmetro}} * Transfer_{busmetro} + \beta_{Transfer_{metrobus}} * Transfer_{metrobus} + \\ \beta_{Transfer_{metrometro}} * Transfer_{metrometro} + \beta_{PSF} * PSF + \\ \beta_{MSC_{bus}} * MSC_{bus} + \beta_{MSC_{metro}} * MSC_{metro} + \beta_{L6} * L6 + \beta_{stickinessL6} * L6 * SI \end{aligned} \tag{4.14}$$

It is noteworthy, that since the SI indicator developed by Kim et al. (2017) is a continuous variable, we set a threshold to classify a person as habitual on the assumption that we only consider a person habitual if all choices are repeated. Therefore the SI indicator is:

$$SI = \begin{cases} 1, & \text{If travellers repeat only one route within a given OD pair} \\ 0, & \text{otherwise} \end{cases}$$

4.8. Model Estimation

Estimation of the models is done by likelihood maximization. We use the maximum Likelihood-principle:

$$LL(\beta) = ln(\prod_n \prod_i P_n(i|\beta)^{y_n(i)}) \tag{4.15}$$

Where $P_n(\beta)$ is the probability of choosing alternative *i* by decision maker *n* and y_n is 1 if the alternative is chosen and 0 otherwise. The aim is to find the value of the taste parameters β that maximizes $LL(\beta)$ (Train, 2009). For the ML with panel effects, the estimation procedure is almost the same except that now we must integrate conditional logit probability over a probability density function.

$$P_n(\theta) = \int S_n(\beta_n) f(\beta_n|\theta) d\beta_n \tag{4.16}$$

Since the integral cannot be solved analytically in order to estimate the exact maximum likelihood, this is solved using simulation. We start first by randomly choosing values for β, we take draws from θ then we evaluate the conditional probability. These steps are repeated *R* times until we compute the following formula which is the average of the resulting choice probabilities:

$$SP_n(\theta) = (1/R) \sum_{r=}^{R} S_n(\beta_n^{r|\theta}) \tag{4.17}$$

Where *SP* is the simulated choice probability as a sequence of choices of decision maker *n*, *R* is the number of draws (Revelt and Train, 1998).

4.9. Model Fit and Comparison

After estimating the models, we assess how well the model fits given the data and how the models perform against each other. To assess these performances, we use the log-likelihood (LL) indicator. Assessing the model fit is done using McFadden's rho-squared (McFadden et al., 1973). McFadden's rho-squared is formulated as follows:

$$\rho^2 = 1 - \frac{LL_\beta}{LL_0} \tag{4.18}$$

Where ρ is McFadden's rho-squared, LL_β is the LogLikelihood of the estimated model and the LL_0 is the LogLikelihood when all betas are zero. The rho-squared parameter can be interpreted as a relative fit of the estimated model with the null-model. Where a rho-squared of 1 indicates a perfect fit of the model given the data and the lower the value the 'worse' the model fits the data.

In our study, we would like to assess model 3 against model 1. Does accounting for inertia effects improve the model fit? Cherchi and Manca (2011) which tested different forms of inertia showed that revealing inertia already results in significant model estimates. Based on the work by Cherchi and Manca (2011) it is expected that model 3 will show significant results. To assess the model fit across different models we adopt the Likelihood Ratio Statistic (LRS). The LRS is a statistical measure which its formula is as follows:

$$LRS = -2 * (LL_A - LL_B) \tag{4.19}$$

The Chi-squared distribution table is used to determine the model fits across models. The difference in likelihoods of the two models is taken and multiplied by 2. The LRS is then used to assess for example model B against model A at a given significance level. This statistical perspective allows us to determine whether the probability that model B is a better fit is due to coincidence or not. Additionally, we use the AIC and BIC to compare the models. Both measures penalize the models as they also take into account the number of parameters which the LL does not. The lower the values for AIC and BIC the better.

4.10. Predicting L6 Market Share

DCMs remain a powerful tool to estimate travel demand by aggregating individual choice preferences (Chorus, 2012). In the stable situation prior L6, we quantify habitual route choice behaviour by determining the *Stickiness Index* for a traveller within a given OD pair. Habitual behaviour can lead to inertia when a person is faced with a new transport alternative (Cherchi and Manca, 2011). Based on this notion, we hypothesise that travellers classified as habitual prior to L6 are less willing to use L6 when it becomes available in their choice set. Consequently, this means that if the inertia effect is significant and we do not account for the inertia effect in the route choice model, the prediction for shares of L6 will be overestimated due to habitual travellers being less willing to use L6.

To estimate the travel demand for L6 using model 3 (MNL with inertia), there are several factors to consider. For estimating the models we use the sample after L6. As mentioned in section 4.1 (Selection OD pairs), it is important to filter the sample after L6 with those travellers who travel before and after L6 within the same OD pair. For including the SI variable, this means that we filter the data after L6 with only those travellers for whom we estimated the SI prior L6. Secondly, since we are using unlabelled alternatives in the DCM (e.g. it does not matter that alternative 1 is different for traveller 1 and for traveller 2), we have to indicate which alternatives use L6. As already mentioned in the model specification, a dummy variable for L6 is used to specify whether an alternative uses L6 or not. By doing so, we are able to predict the shares for L6 after the estimation of the models.

After the models have been estimated, we are able to use the estimated parameters to predict the market share for L6. Since we are using revealed preference data, we use the same sample for the prediction as for the estimation. For prediction power and validation, we do however split the data into an estimation and validation sample as we further discuss in the following section. The demand per OD pair for L6 becomes:

$$W_{OD} = N_{OD} * \sum_{n=1}^{N_{OD}} P_n(i|x_n, C_n, Dummy_{L6}) \tag{4.20}$$

Where W_{OD} is the demand of L6 for a given OD pair, N_{OD} number of travellers for a given OD pair, P_n probability that individual *n* chooses alternative *i* conditional on attribute values x_n, choice set C_n and dummy variable L6. By aggregating the shares of L6 over entire set of OD pairs, we are able to predict the total demand for L6.

4.10.1. Hold-Out Validation

Although it is possible to estimate the demand for L6 using the same full sample as for the estimation process, to validate the models on their prediction power it is a good approach to test the model performance on unseen data and assess whether the models are generic. We use the hold-out validation approach where we split our sample randomly into two non-overlapping parts where 80% is the estimation sample and 20% is the validation sample. We estimate our models on the estimation sample and validate their performance on the validation sample which for the trained model is unseen data. For each model, we repeat this process five times to eliminate the role of randomness when selecting the estimation and validation data. The hold-out validation method can be done using different estimation-validation percentages, for instance a 90% estimation and 10% validation distribution. This may lead to over-fitting if the data for the estimation sample differs vastly from the test sample (Yadav and Shukla, 2016).

4.11. Summary

This chapter presents the methodology for this research. The method starts with a literature review to understand how habit and inertia are understood in the field of psychology and transportation. By reviewing earlier literature on the inertia effect in DCMs, we are able to understand how inertia can be accounted for in the DCM framework. From the literature review, it becomes clear that habitual behaviour can lead to inertia. To quantify habitual behaviour we use the method of *Stickiness Index*, where a high stickiness indicates a person has the tendency to stick to a single route within an OD pair and low stickiness indicates variety-seeking behaviour. To include the SI in our DCM framework, we define a person habitual if their SI equals 1 and non-habitual if their SI is lower than 1. To assess the effect of inertia in route DCM, we estimate a base MNL model and a MNL model with inertia. Finally, we use the model estimates to predict the market share for L6.

5
Results

This chapter presents the results that follow from the research methodology as described in chapter 4. The method of *Stickiness Index* has been applied to the sample prior L6. We present the results for both traveller-level SI and OD-level SI. Next, we include the traveller-level SI into our DCM framework to account for inertia effects after L6. We estimate a base MNL model for comparison and a MNL with inertia model. Estimations of both models are used for market share prediction of L6 and evaluated for their prediction power.

5.1. Results Estimation of Stickiness-Index (SI)

Following the data preparation of Figure 4.2, the sample prior L6 has been further narrowed down in order to obtain a representative sample for SI estimation. The final sample of 51,898 journeys for SI estimation contains a relevant set of 458 OD pairs with 270 origins and 167 destinations. A total of 13.618 unique travellers-OD were observed within these OD pairs.

5.1.1. Estimation Traveller-Level Stickiness-Index

Within the sample of 13.618 unique traveller-OD (i,k) pairs observed, a total of 3661 travellers-OD have a SI smaller than 1, with 0.51 as the second highest value after 1. This translates to 27% of the travellers-OD choosing at least two different routes to travel within a given OD pair. Assuming the week prior to L6 is a normal week (e.g. no drastic changes to the network or services), it is expected that a majority of the sample repeats the same route within a given OD pair since we include only travellers who make 3 or more journeys within a given OD pair. We speculate that people who travel frequently between the same origin and destination, usually commute to school or work. These daily activities are usually associated with habitual behaviour (Verplanken et al., 1997). Figure 5.1 shows the distribution of travellers that have a SI smaller than 1. Table 5.1 shows statistics on the entire sample, with mean, standard deviation and min. and max. value. We observe that SI values with the largest number of traveller-OD are SI of 0, 0.11 and 0.25. To illustrate what this means in terms of how the routes are distributed for an individual for a given OD pair, Figure 5.2 shows for a given OD pair, the representations behind these SI values. If SI is 0, this means a traveller has no tendency to still to any particular route and every route used is evenly distributed. When the SI is 0.11, we observe that a traveller uses route A twice and route B once. We see the value of SI increase as a single route becomes more dominant over the other routes used within a given OD pair.

Important to note is that we assume that the type of behaviour is the same prior to and after our week of data. In reality, it might be that someone repeats this type of behaviour over a longer period of time. If so, a person might be non-habitual for a given week based on our definition, but over a longer period of time might be habitual if they repeat the same pattern of behaviour. In order to analyse this, a longer period of time (months) would be able to capture variability and capture a more complete picture of a person's travel behaviour. However, since our data is limited to one week only, we assume a traveller is only habitual if their SI occurs to be 1 which means a traveller only chooses one alternative route within a given OD pair despite having other route alternatives available to the traveller.

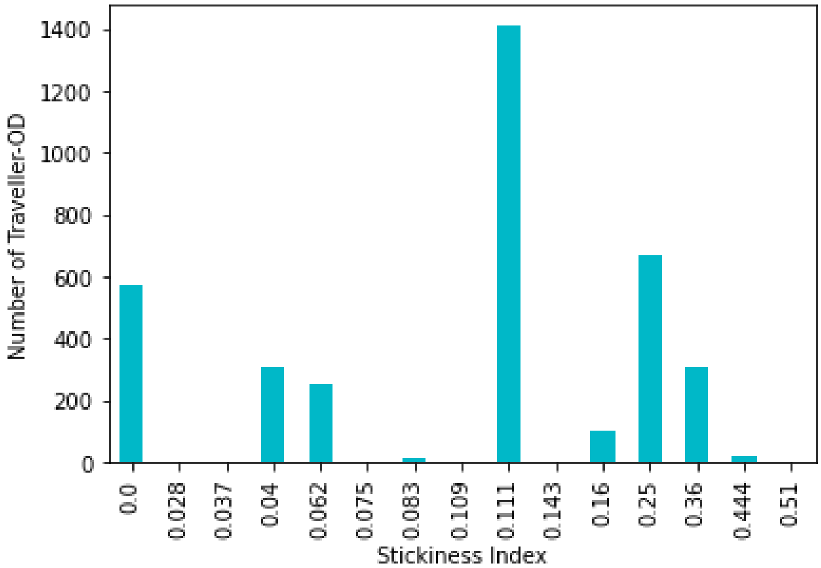


Figure 5.1: Distribution of SI values smaller than 1 (threshold 3 journeys)

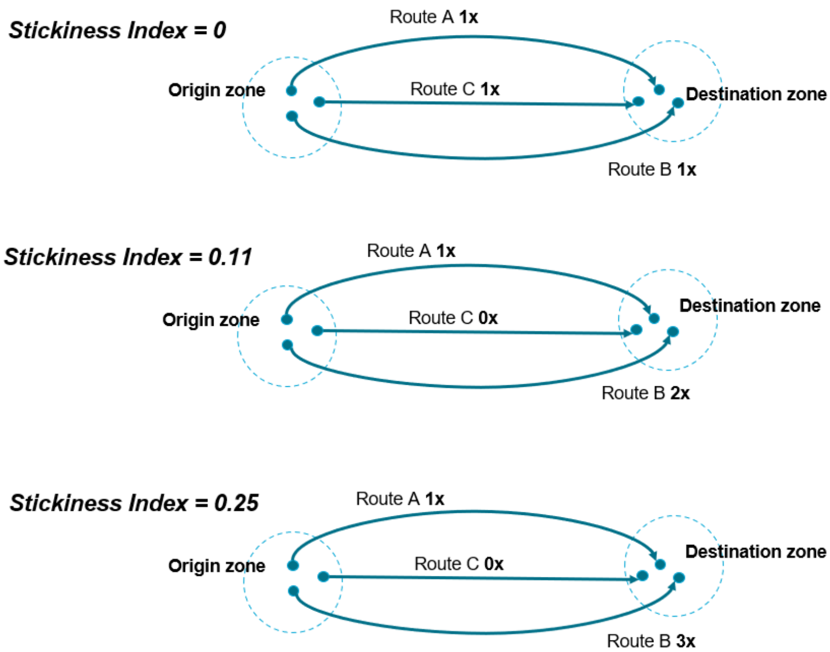


Figure 5.2: SI values and their representations for a given OD pair

Table 5.1: Estimation Stickiness-Index traveller-level

Observations (traveller-OD)	Mean	Std. Dev.	Min	Max
13,618	0.767	0.388	0	1

We impose the requirement that we only include travellers in our sample who make a minimum of 3 journeys within a given OD pair. To investigate how this threshold affects the distribution of SI among individuals, we tested several thresholds for minimum number of journeys. The caveat with higher thresholds is that the sample becomes increasingly smaller which may affect the statistical precision in the choice estimation process. For the threshold for 2 journeys or more, we see obtain a sample of 23.132 traveller-ODs. Within this sample, 27% have a SI smaller than 1. When increasing the threshold to 4 journeys, the sample becomes relatively small with 4651 traveller-OD pairs. The number of traveller-OD pairs that have a SI smaller than 1 is 20%. For all three thresholds, we observe that within the segment that has a SI smaller than one, the majority has a single dominant route and uses another route only once.

If we want to include the SI variable in the DCM framework, the threshold of 4 journeys results in a relatively small sample which may have implications for the parameter estimates in terms of significance. A threshold of 2 journeys does lead to a large sample which is preferred when estimating a choice model since a larger sample would lead to better statistical precision. However, going by our definition of habitual behaviour as repetition of past choices, we hypothesize that the higher the threshold, the more likely a person is habitual. For this reason, for our final model estimations we include only travellers who make a minimum of 3 journeys within a given OD pair.

5.1.2. Estimation Stickiness-Index OD-level

Aggregating the results of the *Stickiness Index* per traveller-OD, we gain insight on the average OD-level SI. This allows us to determine the average stickiness tendency of users for a particular OD pair and see if there is variation among OD pairs and understand the underlying factors causing this. We selected four OD pairs with the largest number of travellers travelling between the OD. Figure 5.3 and 5.4 shows the four largest origins and destinations respectively. Origin or destination is highlighted with a white triangle symbol. We observe that the OD-level stickiness indeed varies among OD pairs.

Differences in OD-level SI can be explained both by travel behaviour and network structure. From a travel behaviour point of view, it can be that travellers for a particular OD pair may be stickier than travellers of other OD pairs. For example, an OD pair that includes large number of home-work people may lead to a higher average SI than an OD pair where there is more variation on the type of travellers. Besides travel behaviour, also the network structure can be an explanatory factor for the differences in SI of different OD pairs. Assuming a traveller chooses the service with the highest frequency, an OD pair with a reliable transport service and high frequency may lead to higher average SI, as opposed to an OD pair where there is less variation in terms of frequency among the alternatives (Durán-Hormazábal and Tirachini, 2016).

Figure 5.3 shows the origins, they're located further away from the centre of Santiago. The average OD-level stickiness has little variation among the OD pairs. This can be explained by for example mainly home-work commuting where people are usually habitual in their behaviour. We speculate that these OD pairs are mainly travellers who travel to the city centre for work, hence relatively small differences can be seen here between the OD pairs and most have a high average OD-level SI.

Figure 5.4 shows the four largest destinations and their corresponding origins. We notice here that the variation among OD pairs is larger when compared to the origins. The destinations are located near or around the city centre. Their origins are spatially more distributed over the city centre. The larger variation among the SI of these OD pairs can be explained by the network structure and services available. We see much lower values for the average SI for these OD pairs. Lower values might indicate that for these given OD pairs, little difference in service frequency across available routes is observed. If travellers tend to choose a route with a higher frequency more likely, it indeed would result in lower SI for these OD pairs.

5.2. Results Discrete Choice Analysis

This section presents the empirical results of our choice modelling estimation based on the *Stickiness Index* sample. The models that have been described in the methodology chapter have been estimated using PandasBIOGEME package (Bierlaire, 2018). Full estimation reports for all estimated models are to be found in the Appendix.

(a) First origin

(b) Second origin

(c) Third origin

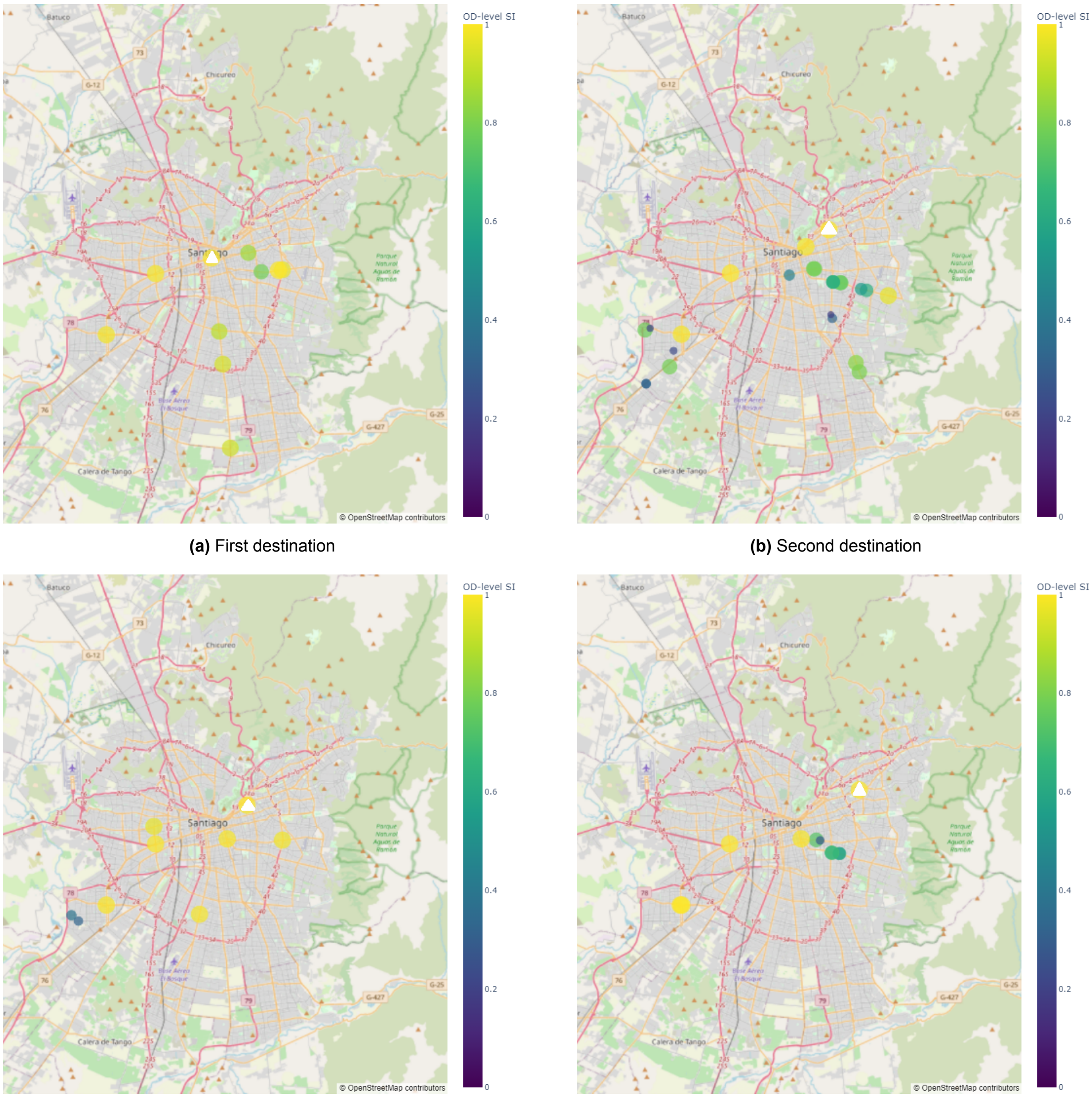
(d) Fourth origin

Figure 5.3: Geographical distribution of OD-level *Stickiness-Index*. Four largest origins are represented and their destinations (origins and destinations can be either metro station or bus stop)

5.2.1. Choice Set Results

We filtered the data after L6 with travellers for whom we determined the SI. This resulted in a sample of 11.245 traveller-OD pairs. The average choice set for an OD pair is 3.47 routes. The average Path-Size factor[1] (PSF) which was computed beforehand, has an average value of -0.42. Table 5.2 shows the minimum, maximum and mean values for each attribute considered in our models. It is important to note that for the presented table, route alternatives may comprise a single mode of transportation, hence the minimum travel time for either bus or metro can be zero for a given choice set.

[1]A PSF value of 0 indicates that there is no overlap with other route alternatives. It decreases as the route overlap with other route alternatives increases



(a) First destination

(b) Second destination

(c) Third destination

(d) Fourth destination

Figure 5.4: Geographical distribution of OD-level *Stickiness-Index*. Four largest destinations are represented and their origins (origin or destination can be either metro station or bus stop)

5.2.2. MNL Model

The models presented are considered our final model, although we did test several variations of our model specification. We decided to leave explanatory variable *transfer metro to metro* (TMM) out of the final model specification. Including the variable lead to a positive parameter estimate of *metro in-vehicle time*. When analysing the covariance matrix, the coefficients of metro in-vehicle time and transfer metro to metro are moderately correlated with a value of -0.619. Estimation reports of main models and other variations are found in A.1. Earlier studies on route choice models on the multimodal transport network of Santiago also excluded the variable transfer metro to metro with reliable model outcomes (Arriagada et al., 2022). Table 5.3 presents the results of the estimation of the three models. We included the estimated parameters, number of observations, final log-likelihood, rho-square bar, AIC and BIC. The final base model has the attributes: *in-vehicle time for bus and metro* (IVTB and IVTM),*waiting time* (which is composed of walking time, transfer time and waiting time), *number of transfers for metro to bus* (TMB), *bus to metro* (TBM) and for *bus to bus* (TBB), *PSF* and mode-specific constants for bus and metro. Due to overlapping alternatives (alternatives with both bus and metro),

Table 5.2: Statistics of attributes used in MNL and MNL with inertia models

Attribute description	Min	Max	Mean
Metro travel time (TT_{metro})	1.35	53.28	25.94
Bus travel time (TT_{bus})	1.45	93.56	18.87
Waiting time at transfers (WT)	0	89.4	3.72
PSF (PSF)	-1.95	0	-0.42
Transfer bus to bus (TR_{busbus})	0	2	0.0146
Transfer metro to bus ($TR_{metrobus}$)	0	1	0.076
Transfer bus to metro ($TR_{busmetro}$)	0	1	0.32
Transfers total	0	3	0.82
Bus dummy	0	1	0.58
Metro dummy	0	1	0.816

Note: waiting time = waiting time, walking time and transfer time

we obtain different final results depending on which mode-specific constant to normalize. The model with mode-specific constant bus fixed to zero, has a slightly lower final log-likelihood and lower model fit. Therefore, we continue with the estimation process with mode-specific constant metro fixed to 0 for both our models. All parameters that have been estimated are significant at $p < 0.05$ level, as can be seen from the t-ratio which is presented in parentheses.

For the PSF we estimated a negative parameter with a magnitude of -0.734. The magnitude of the PSF parameter is in line with Tomhave and Khani (2022) who defined the PSF based on stop overlap and found values for PSF between -0.6 and -0.7. For the multimodal public transport network in Greater Copenhagen Area, authors found magnitude for the PSF parameter of around -0.7 (Anderson et al., 2017)

The mode-specific constants show that there is a preference among the sample towards the metro relative to the bus, which is in line with other studies on multimodal network route choice (Dixit et al., 2021). We estimated different types of transfers, all three types are negative as expected. The TBM is considered less of disutility compared to the TMB. This can be explained due to several reasons. Buses are more irregular in frequencies and have a larger travel time variability (Arriagada et al., 2022; Durán-Hormazábal and Tirachini, 2016) and the mode-specific constants show there is a preference for the metro over the bus. The type of transfer that is disliked most is the TBB. These findings have been in line with other research on the multimodal network of Santiago that includes these types of transfers (Arriagada et al., 2022).

The parameter for waiting time is negative and has a value of -0.357. This tells us that increased waiting time is associated with a decrease in the utility of the route alternative. Arriagada et al. (2022) estimated a route choice model in Santiago but differentiated between actual waiting time and walking time. But similar to Anderson et al. (2017) who estimated a route choice model in a multimodal public transport network found that walking time to be more burdensome than actual waiting time. We did test models where we separated the waiting time components, however we found insignificant parameter estimates for the different waiting time components and therefore decided to use the formulation where the waiting time components are aggregated into a single waiting time variable. IVTM is considered to be preferred over IVTB with values of -0.177 and -0.265 respectively. This finding is contrary to other research on public transport route choice in Santiago, who found that bus in-vehicle time is actually preferred over metro in-vehicle time (Arriagada et al., 2022). Other route choice studies in different multimodal transport networks found values for bus in-vehicle time ranging from -0.11 to -1.7 (Anderson et al., 2017; Dixit et al., 2021) and metro in-vehicle time ranging from -0.09 to -0.113 (Anderson et al., 2017; Dixit et al., 2021).

5.2.3. MNL Model with Line 6

Table 5.3 presents the estimations for the MNL model with L6 which represents how both segments, non-habitual and habitual, perceive L6. All parameters are significant at $p < 0,05$ level and have expected signs. The MNL model with L6 shows an improvement in model fit and the increase in final log-likelihood from -9400 to -8975 is substantial when compared with the MNL model. The LRS test shows a value of 850.52, which exceeds the chi-square value of 6.635 at 1% significance level with one degree of freedom. When comparing with the base MNL model, we see that the dislike for IVTM, waiting time and PSF has decreased. It is interesting that the PSF decreased considerably from -0.734 to -0.387. When we accounted for the interaction effect of habitual travellers with the PSF, we found a significant positive interaction effect. This reveals the marginal utility for PSF is comparatively smaller when travellers are habitual as opposed to others. This would mean that habitual travellers prefer distinct routes over overlapping routes when we include L6 as opposed to other travellers. A possible explanation can be that habitual travellers prefer distinct routes over the robustness of the network if L6 is included (assuming habitual travellers are less willing to use L6). The parameter for metro travel time has turned out to be less negative, possibly indicating that people prefer longer metro travel times as they avoid L6. Waiting time is perceived as marginally less negative when including L6.

5.2.4. MNL Model with Inertia

Following, we investigate how travellers who are labeled as habitual perceive L6. Table 5.3 shows the results of model 3 (with inertia). The model as described in 4.7.2 was specified as follows:

$$
\begin{aligned}
V = \beta_{bus,TT} * TT_{bus} + \beta_{metro,TT} * TT_{metro} + \beta_{WT} * WT + \beta_{Transfer_{busbus}} * Transfer_{busbus} + \\
\beta_{Transfer_{busmetro}} * Transfer_{busmetro} + \beta_{Transfer_{metrobus}} * Transfer_{metrobus} + \\
\beta_{Transfer_{metrometro}} * Transfer_{metrometro} + \beta_{PSF} * PSF + \\
\beta_{MSC_{bus}} * MSC_{bus} + \beta_{MSC_{metro}} * MSC_{metro} + \beta_{L6} * L6 + \beta_{stickinessL6} * L6 * SI
\end{aligned} \tag{5.1}
$$

All parameters are significant at $p < 0.05$ level. Including the interaction effect shows a small improvement in model fit when compared to model 2, going from a final log-likelihood of -8975.092 to -8900.279. The core parameters, L6 and interaction effect are both negative and significant, which is in line with earlier studies on inertia effects (Cherchi and Manca, 2011; González et al., 2017). More importantly, the interaction effect is negative which indicates that the marginal utility for L6 is comparatively larger for travellers classified as habitual than others. This finding confirms there is indeed an additional effect for L6 when accounting for inertia effect of habitual travellers.

Table 5.4 presents the rates of substitution in order to understand the trade-off in utility by travellers. For all three models, we determined the rates of substitution of each attribute with respect to bus in-vehicle time which was set to 1. Additionally, the parameter for L6 and inertia effect is also compared with respect to metro in-vehicle time which is presented within the table in parentheses. For all models, in-vehicle time for metro is perceived as less than in-vehicle time for bus where for the MNL model we find 0.66 min in-vehicle time metro represents 1 min of in-vehicle time bus. The MNL model with inertia reveals that 0.36 min in-vehicle time metro represents 1 min in-vehicle time bus. Furthermore, the rates of substitution suggest that transfers represent roughly between 2 to 5 min of IVTB. For the MNL model with inertia, we find that using L6 for both segments (habitual and non-habitual) represents 4 min of IVTB. When we consider the additional effect for L6 of habitual travellers, using L6 represents an additional 5.7 minutes of IVTB for habitual travellers. Thus the inertia effect in model 3 is equivalent to the utility of roughly 10 minutes of reduction in bus in-vehicle time according to the marginal utility of bus in-vehicle time.

5.2.5. Sensitivity Analysis to Minimum Number of Journeys

We performed a sensitivity analysis of the interaction effect to the minimum number of journeys for travellers to include within the sample. For the estimation sample of SI and DCMs, we imposed two requirements to include valid travellers and valid OD pairs. For the valid traveller requirement, we only included those travellers who make a minimum of three journeys. A traveller is considered habitual,

Table 5.3: Estimates MNL model, MNL baseline model and MNL with inertia model

Description	**Model 1 (MNL)**	**Model 2 (L6)**	**Model 3 (Inertia)**
Metro in-vehicle time	-0.177 (-5.41)	-0.0945 (-2.77)	-0.095 (-2.71)
Bus in-vehicle time	-0.265 (-9.57)	-0.286 (-10.2)	-0.263 (-9.21)
Waiting time	-0.357 (-9.32)	-0.349 (-9.17)	-0.328 (-8.68)
Mode-specific constant for metro (fixed)	0	0	0
Mode-specific constant for bus	-2.52 (-24.3)	-2.35 (-24.4)	-2.57 (-25.2)
Transfer bus to bus	-1.34 (-14.9)	-1.35 (-15)	-1.37 (-15.1)
Transfer bus to metro	-0.636 (-9.38)	-0.7 (-10.8)	-0.727 (-11)
Transfer metro to bus	-1.08 (-8.68)	-0.947 (-6.9)	-0.943 (-6.87)
Path-Size correction	-0.734 (-10.6)	-0.387 (-5.18)	-0.492 (-6.49)
L6	-	-1.64 (-20.5)	-1.05 (-11.9)
Stickiness * L6	-	-	-1.5 (-9.09)
Number of observations	11245	11245	11245
Final Log-Likelihood	-9401.18	-8975.092	-8900.279
Rho-square bar	0.281	0.314	0.32
AIC	18818.36	17968.18	17820.56
BIC	18876.98	18034.13	17893.83
LRS (Against MNL)	-	850.52	1001.82

Table 5.4: Rates of substitution model estimates (with respect to bus in-vehicle time)

Description	**Model 1 (MNL)**	**Model 2 (L6)**	**Model 3 (Inertia)**
Metro in-vehicle time	0.66	0.33	0.36
Bus in-vehicle time	1	1	1
Waiting time	1.34	1.22	1.24
Transfer bus to bus	5.05	4.72	5.2
Transfer bus to metro	2.4	2.44	2.76
Transfer metro to bus	4.07	3.31	3.58
L6	-	5.73 (**17.35**)	3.99 (**11.5**)
Stickiness * L6	-	-	5.7 (**15.78**)

Note: values in parentheses represent the rates of substitution with respect to metro in-vehicle time

if they repeat routes within a given OD pair. But there may be a difference if someone is considered habitual if they only have to make a minimum of 2 journeys, versus for example a minimum of 4 journeys. In the first situation, the threshold is lower and thus a person might be labelled as habitual but in reality, the person might not and repeat the two journeys out of sporadic behaviour. If that is the case, we expect a mixture of people consisting of habitual and non-habitual travellers within the group that is considered as habitual. While in the case where the threshold is 4 minimum journeys, it is more likely someone is habitual if they repeat all 4 journeys. We hypothesize that the larger the threshold, the more likely a person is habitual. For the model estimations of the different thresholds we refer to Appendix A.1.

Table 5.5 shows the estimation results of models where travellers had to make a minimum of 2 journeys, 3 journeys and 4 journeys. For all three models, we estimate a significant interaction effect. We presented the rates of substitution of the L6 parameter and the interaction effect with respect to IVTB which was set to 1. For all three models, we observe that the marginal utility of L6 is larger when travellers are habitual. The rates of substitution for the dislike for L6 with respect to IVTB become larger as the threshold increases. This leads us to believe that due to the low threshold, we included travellers who are not 'habitual' and therefore the effect is relatively small. For the models with a higher threshold, we see that the additional effect of being a habitual traveller increases the rates of substitution for L6 with respect to IVTM. It is noteworthy, that the estimated parameters are significant for all three models, except when we raise the threshold to 4 journeys. The parameters for in-vehicle time for bus and metro for this threshold become insignificant at $p < 0.05$ level. This confirms our concerns with too high thresholds leading to relatively small samples and implications for estimation. Further empirical research is needed to confirm the change in rates of substitution with respect to the minimum number of journeys.

We also tested the model sensitivity to the minimum number of travellers an OD pair must have in order to be valid for our SI and DCMs sample. For our main models, this threshold was set to 10 travellers for a given OD pair as adopted from Kim et al. (2017). Various thresholds were tested such as 100 and 250 travellers, however this lead to complications in the choice model estimations as most parameters became insignificant.

Table 5.5: Model sensitivity to minimum number of journeys

Description	2 journeys	3 journeys	4 journeys
Bus in-vehicle time	1	1	1
L6	1.93	3.99	32.89
Stickiness * L6	1.58	5.70	55.78
Number of observations	23132	11245	4367
Estimated parameters	10	10	10
LRS (against respective base MNL)	1377.44	1001.82	271.148
Rho-square	0.239	0.32	0.45

Note: parameter estimates for bus in-vehicle time were not significant at $p < 0.05$ level for the model with a minimum of 4 journeys

5.3. Predicting L6 Market Share

The aim of this section is to validate the models on their prediction power for shares of L6. For the estimations on the training sample we refer to Appendix A.1. The estimates of the training sample show significant results for all parameters at $p < 0.05$ level. The interpretation of the parameters and statistical diagnostics of the estimations can be found in section 5.2 where all three models were estimated on the full sample.

5.3.1. Comparison Aggregated Shares L6: Actual versus Predictions

Figure 5.5 shows the aggregated average prediction for the number of journeys for L6 on the validation sample. The observed values are compared with the three models. It shows that not including inertia effects when travellers face a new transport alternative, considerably overestimates the shares for the new service. We observe an average of 119 journeys that use L6. For the base MNL, the results show a share of roughly 179 journeys with L6, which is 8% of the total sample. Comparing the prediction of the base MNL with the observed, we see an overestimation of roughly 50% of shares for L6. Next, we determine the share of L6 based on the results of models 2 and 3. The MNL model with L6 predicts roughly 144 journeys with L6. This is 6.4% of the total sample. Using the approach of hold-out validation, we find that the model that accounts for inertia improves the predictive power by 33% over the base MNL model which is a substantial improvement.

Table 5.6 shows the predicted average shares for L6 on the validation sample for all three models where the journeys are differentiated based on whether people are habitual and whether L6 is used or not. On an aggregate level, we see that the usage of L6 consists largely of non-habitual people. It is clear that the share for L6 as discussed earlier is relatively small compared to other alternatives. For the MNL model with inertia effects, it can be seen that the predicted shares for L6 when travellers are habitual are relatively close to the observed when compared with the other two models. From this table an interesting question would be how this table would change over a longer period of time, starting from the opening of L6. Does the share of habitual travellers on L6 increase, and for how long? These travel behaviour dynamics over time would be worth investigating.

Table 5.6: Average predictions for journeys with L6 and journeys without L6: MNL, MNL with L6 and MNL with Inertia (20% entire sample). Also the distinction between whether traveller is habitual (SI =1) or non-habitual (SI = 0)

Description	**Observed**	**MNL**	**MNL with L6**	**MNL with Inertia**
L6 = 0 | SI = 0	734.2	669.2298	697.2	706.7
L6 = 0 | SI = 1	1395.8	1370.152	1407.448	1402.5
L6 = 1 | SI = 0	69	107.522	78.1	93.15
L6 = 1 | SI = 1	50	72.1	66.353	46.83

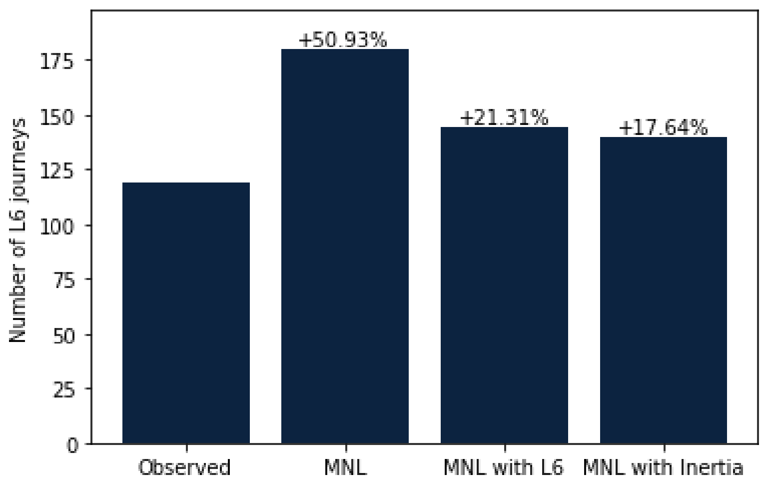


Figure 5.5: Market share L6 of observed and model predictions based on validation sample (20% of full sample)

5.3.2. Assessment Accuracy of Prediction Models

The prediction in Figure 5.5 shows the aggregated L6 share difference between the MNL model, MNL with L6 and MNL with inertia. However, it does not explain the prediction accuracy of both models with respect to L6. To assess the prediction accuracy we perform a False Positive Rate (FPR) analysis. Using the FPR approach we highlight which portion of the shares for L6 is explained by including the inertia effect and which portion is explained by journeys without L6. Table 5.7 shows the measures to assess the predictive ability of the three models. The measures include the true positives (TP), true negatives (TN), false positives (FP), false negatives (FN), accuracy (ACC), sensitivity (SENS), specificity (SPEC) and FPR. Additionally, the average final log-likelihood of the three models is presented in the table. To review the average predicted numerical values differentiated by journeys with L6 and without L6 we refer to Appendix 5.6.

Sensitivity or True Positive Rate (TPR) tells us that if the journey actually *includes* L6, how often does our model predict the journey *with* L6. The MNL model with inertia has a value of 0.83[2] and outperforms the base MNL model with a value of 0.49, as expected. Furthermore, the accuracy of the

[2] The score of SENS is between 0 and 1. The higher the score the better

models is high, indicating that it accurately predicts journeys with and without L6. For the FPR, we see that the MNL model with inertia scores lower than the base MNL model. The FPR tells us that when the journey is actually *without* L6, how often our model predicts that the journey is *with L6*. The FPR of 0.057 for base MNL model indicates that when the journey is actually without L6 it predicts that it is L6 in 5.7% of the cases. For instance, if 1000 journeys are observed, the MNL model predicts 57 journeys with L6 while actually these are journeys without L6. From the FPR analysis and the average log-likelihood, we assess that both models that account for L6 perform considerably better than the MNL model. The MNL model with inertia performs marginally better than the MNL model with L6. The aggregated prediction and the FPR analysis show that if habitual behaviour exists, not including the inertia effect in route choice models overestimates the share of a new alternative considerably. Overestimating shares of new services using a model without inertia was also found by Chatterjee (2011) who investigated bus dynamics of a new bus service.

Table 5.7: Accuracy prediction power of models using FPR analysis on validation sample

Model	TP	TN	FP	FN	ACC	SENS	SPEC	FPR	Average LL
MNL	58.38	2008.7	121.3	60.6	0.91	0.49	0.94	0.057	-1868
MNL with L6	93.6	2079.3	50.72	25.36	0.966	0.78	0.976	0.0238	-1781.9
MNL with Inertia	98.01	2088.03	41.97	20.98	0.97	0.83	0.98	0.019	-1764.5

Number of observations is 2249

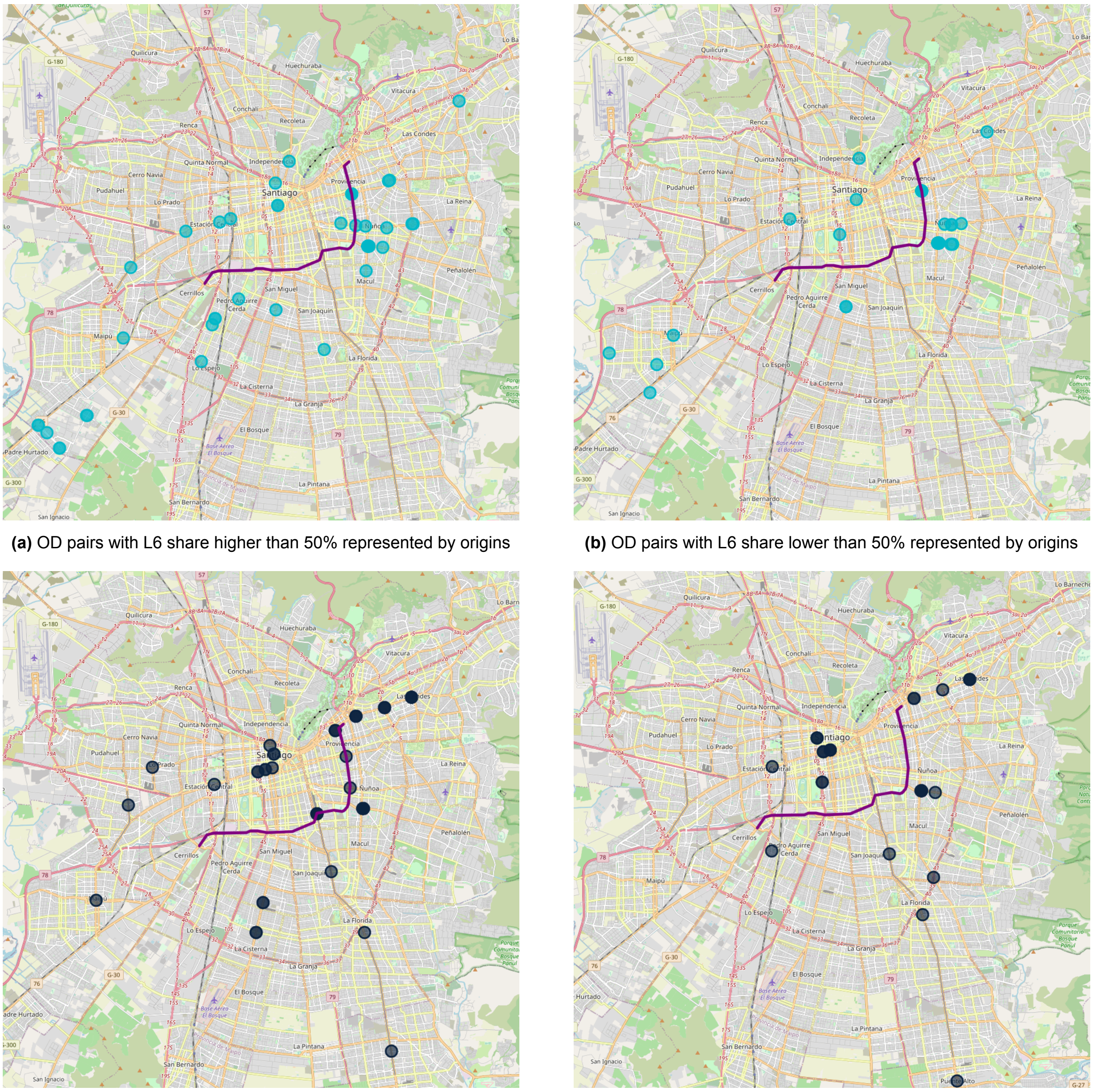
5.3.3. Distribution OD pairs Based on Shares L6

Figure 5.6 shows the distribution of OD pairs based on their share for L6. For the purpose of a clear overview, we show the OD pairs represented by their origin and destination. We distinguished between OD pairs that have a share higher than 50% (Figure 5.6a and Figure 5.6c) and those lower (Figure 5.6b and Figure 5.6d). When comparing OD pairs with high and low shares, we see that OD pairs with high shares can be found directly on the stations of L6. We also notice that certain stations of L6 are not visible on the map, which would be expected since people in these areas would have direct access to the new line. However, due to data filtering and imposed requirements throughout the process, a substantial number of journeys have been left out (OD pairs longitudinally consistent, journeys threshold, removing invalid data). A larger database would be helpful to reveal each station and its shares.

5.4. Summary

This chapter presents the empirical results from quantifying habitual route choice in a large multimodal network and estimating a route choice model including inertia effects. The sample of 11245 observations, consists of travellers for whom we estimated the *Stickiness-Index*. The SI indicates to what extent a person is habitual in their route choice for a given OD pair. To include this indicator in the DCM framework, we only included travellers who travelled prior to and after the opening of L6 within the same OD pair. If a traveller would change OD pair, their situation changes and we would not be able to investigate the effect of L6 on their usual route choice set.

Estimating the SI variable for each traveller-OD, results show that 27% of the sample have an SI lower than 1 and are considered non-habitual. We defined someone as habitual if a person would repeat every choice within a given OD pair. This is in line with expectations as people who commute within the same OD pair tend to be habitual. Aggregating individual SI-levels per OD pair allowed us to gain insight into how different OD pairs compare. For the four largest OD pairs, origins are located on



(a) OD pairs with L6 share higher than 50% represented by origins

(b) OD pairs with L6 share lower than 50% represented by origins

(c) OD pairs with L6 share higher than 50% represented by destinations

(d) OD pairs with L6 share lower than 50% represented by destinations

Figure 5.6: Spatial distribution of OD pairs based on their predicted L6 share. Purple line indicates L6

the outskirts of the city. OD-level for these origins are relatively high, and their destinations lie in the city centre. The relatively high level of OD-level SI for these origins can be explained by their activity (e.g. school/work) and network structure and transport services. On the other hand, destinations show a much more diverse range in SI-levels. The destinations lie usually in the city centre. Their origins are much more distributed over the city with OD-level SI with more variations in OD-level SI. This can be explained by the more diverse activities and less variation in service frequency among alternatives.

We took a novel approach by first quantifying habitual behaviour in a stable condition and using the habitual behaviour as an indicator to reflect the inertia effect when a new metro is implemented. Habitual behaviour can lead to inertia and therefore our hypothesis is that those travellers classified as habitual are less willing to use L6. A model with L6 was estimated to reflect how everyone perceives L6. Additionally, another model was estimated that included an interaction effect of L6 with the habitual indicator. Both parameters were found to be negative and significant. This reveals there is an initial dislike for L6 and there is an additional effect for the dislike of L6 when travellers are habitual. We validated our model and its prediction power using a hold-out validation approach where we train our model on 80% of the full sample and test its predictive power on 20% of the hold-out sample. Our aim here is to understand what effect not including the inertia effect has on travel demand estimations. We observe that the difference between the predictions and observed is relatively smaller for the MNL model with L6 and MNL model with inertia compared to the base model. Furthermore, the FPR analysis reveals that the MNL model with inertia outperforms the MNL model on observed journeys with L6. This study confirms that if people are habitual, inertia exists and should be accounted for in route choice models which are in line with earlier studies (Cherchi and Manca, 2011; González et al., 2017; Vacca et al., 2019. Not doing so, fails to accurately predict travel demand for new transport alternatives (Chatterjee, 2011).

6 Discussion

This chapter presents the discussion of this research. The main points of discussion are the outcomes of the *Stickiness Index* estimation and choice model estimations, as well as the limitations of this study.

6.1. Stickiness Index Estimation

To answer the question to what extent is route choice habitual, we also raised the question of what is habitual travel behaviour? An indicator to often measure habitual behaviour has been the frequency of past choices (Ouellette and Wood, 1998). But in what sense is repetition habitual? To actually distinguish choices as repetition due to habit or every time be the outcome of rational decision-making remains a challenge. Whether people repeat behaviour is due to habit or deliberation has implications for policies which focus on changing people's travel behaviour. Fujii and Kitamura (2003) tested how habit may be broken by offering a month-free bus ticket to a sample of car drivers. After the experiment, the researchers saw an increase in bus frequency and a positive attitude towards public transport. Together with this promising result, they also saw the usage of cars becoming less habitual. On contrary, Bamberg et al. (2003) questioned whether habit plays a role when changing people's travel behaviour. The authors conducted an experiment where car users were given a free public transport ticket. They saw an increase in public transport usage irrespective of the drivers' frequency of car usage. Rather awareness of a new transport alternative seemed to be important in getting people to change their behaviour. These studies reveal it is not always evident to what extent habitual behaviour plays a role in travel choices and this makes it difficult for transport planners to design effective policies to tackle habitual behaviour.

Using repetition of past choices as an indicator of habitual behaviour is limited, as habitual behaviour is also explained by personal motives and travel context (Verplanken et al., 1997). Nevertheless, this study uses a quantitative approach in quantifying habitual behaviour using passive anonymized observations where only repetition of choices is observable. The method of *Stickiness Index* by Kim et al. (2017) tries to do exactly this by quantifying to what extent route choice is habitual in a public transport network using SC data. It may not be able to explain habitual behaviour in its full account, but it is habitual in the sense of repetition of past choices which is a necessary condition to consider behaviour as habitual (Verplanken et al., 1997). As other indicators for habitual behaviour have been developed by using surveys (Verplanken and Orbell, 2003), a more comprehensive study in which passive observations over a longer period of time in combination with a qualitative approach will provide a more complete analysis of a person's habitual travel behaviour.

Regarding the outcomes of the SI estimation, this study found that roughly 70% of travellers are habitual within the context of this research. The mean value for SI was found higher than the outcomes obtained by Kim et al. (2017). However, they only considered travellers who have at least chosen two different routes in order to identify their choice set. Their period of analysis is six months which possibly captures more travel variability and may lead to lower SI values. The number of habitual travellers in this research may be overestimated due to the travel behaviour analysis during a single week only. It is expected that the mean value for SI would decrease if travellers of Santiago were observed over a longer period of time. People would be subject to factors such as disruptions of services or operations on the network that influences their route choice behaviour and consequently their SI values. In this research, the definition of habitual travel behaviour was defined as the repetition of route choices. If travellers were observed for months, it would be unreasonable to assume a traveller is only habitual if every single journey was repeated. We would relax the assumption to also account for disruptions for example or lower the threshold of the SI for someone to be considered habitual.

6.2. Discrete Choice Estimation Results

6.2.1. Results model 1 (MNL)

The results of the MNL model show overall plausible relationships, but we particularly want to discuss the PSF, waiting time and in-vehicle times for bus and metro. The parameter for PSF is initially expected to be positive, which suggests that the overlap of route alternatives reduces the utility of these competing alternatives. However, earlier research on multimodal transit route choice has also found negative estimates for the PSF (Anderson et al., 2017). In the case of a multimodal network, a negative parameter suggests that travellers actually prefer overlap between alternative routes over distinct routes. As it is not uncommon for multimodal transit networks to have delays and disruptions, overlap in route alternatives offers travellers the opportunity to have other travel options available en route. The Santiago public transport network is also subject to disruptions and delays, therefore the negative estimate for the PSF in this study does not come as unexpected. The empirical finding of the PSF adds to the existing literature that found negative estimates for the PSF in a multimodal transport network (Anderson et al., 2017; Dixit et al., 2021).

We estimated the waiting time component, but it is noteworthy that the waiting time variable differs from the study by Arriagada et al. (2022). Whereas Arriagada et al. (2022) differentiated between actual waiting time, walking time and transfer time, our research combined the three elements into a single waiting time component. Model specifications with separate waiting time components were tested, but estimating the three waiting time elements resulted in insignificant parameter estimates. Therefore, it was decided to specify a single waiting time component where waiting time, walking time and transfer time were aggregated into one component. Arriagada et al. (2022) found rates of substitution of waiting components with respect to bus in-vehicle time of 1.29 and 1.47 for waiting time and walking time respectively. We found that travellers value waiting time as 1.24 min in-vehicle time for bus.

In-vehicle time for metro is considered to be preferred over in-vehicle time for bus in this research. This finding is contrary to other research on public transport route choice in Santiago, which found that in-vehicle time for bus is actually preferred over in-vehicle time for metro (Arriagada et al., 2022). Although Arriagada et al. (2022) acknowledge the positives of the metro such as high frequency and reliable service as opposed to the bus, they argue the significance of crowding levels which explains the higher preference for bus in-vehicle time over metro in-vehicle time in their study. The argument for our case can be made that buses in Santiago have a high variability in travel time and irregular service as opposed to metro who offers a high frequency and reliable service (Durán-Hormazábal and Tirachini, 2016). Additionally, one major difference with the work by Arriagada et al. (2022), is that our estimation is based on the sample where L6 just opened within the set of OD pairs where L6 is part of at least one of the alternatives. More importantly, it is difficult to confirm whether one week after the opening, crowding levels would have just been as high as during normal operations and within the entire metro network. To add, Pineda and Lira (2019b) performed research on travel time savings due to L6. Their period of analysis was April of 2018 and found that during that time, the crowding levels for L6 were not perceived as high by travellers.

6.2.2. Results model 2 and 3 (L6 and inertia effect)

When comparing model 3 with model 2, the interaction effect of L6 with SI is significant. This reveals that the marginal utility for L6 is comparatively larger when travellers are classified as habitual prior-L6 than others. This is in line with earlier studies which found that habitual behaviour leads to inertia (Cherchi and Manca, 2011). Other studies used a more direct approach to express the inertia effect such as a dummy variable if the current choice is similar to the previous choice (Vacca et al., 2019) or a valuation of previous choice utilities with the current one (González et al., 2017). Due to the different definitions of inertia in those studies, it is difficult to compare the magnitude of the inertia effect since each study has its own behavioural assumptions and the magnitude of the effect depends on the specific context in those studies (Cherchi and Manca, 2011). Nevertheless, the interpretation of the inertia effect is in line with previous studies that found that the inertia effect is significant when repetition of past choices is present and is to be understood as the resistance to change (Cherchi and Manca, 2011; González et al., 2017; Vacca et al., 2019). If a fully revealed preference data set is available, our approach of quantifying habitual behaviour in a stable condition using a binary classification of habitual behaviour and using the habitual indicator in the choice model makes our method relatively simple to use. Especially when compared to methods where the inertia effect is expressed as a weighted average of past choices (Swait et al., 2004) or valuation of previous utilities with the current one (Cantillo et al., 2007). Cherchi and Manca (2011) mention that simple expressions of inertia effects such as a dummy variable, could get significant model estimations and that complex expressions are not necessarily better than simpler inertia expressions. Additionally, the use of RP data based on a large number of smart card observations has it advantage that actual choices are observed contrary to majority of RP/SP studies with inertia effects. Regarding practically, a clear and well-constructed SP survey is a challenge and time consuming. However, it is not always easy in practice to collect a large number of RP data based on smart card observations.

Regarding the marginal rates of substitution (MRS), we compare the inertia effect with respect to earlier studies which used joint RP/SP data sets. This research found that the inertia effect is equivalent to roughly 10 minutes of bus in-vehicle time. Cantillo et al. (2007) and González et al. (2017) found much lower values for the inertia effect represented as average travel time and in-vehicle time for bus-tram, respectively. Cantillo et al. (2007) found the inertia effect to be equivalent of 4.7 minutes of average travel time, whereas González et al. (2017) found the inertia effect for car to represent roughly 3 minutes of in-vehicle time for bus-tram. The lower values found in RP/SP studies can be the result of the bias that is inherent in SP studies. As people do not experience the real outcome of SP experiments, the mean value for the inertia effect may be underestimated (Cantillo et al., 2007). More empirical research is needed to confirm the outcomes of this study regarding the magnitude of the inertia effect. But it is not unlikely that the inertia effect in SP studies is underestimated and therefore leading to lower MRS with respect to travel times.

When comparing the MRS of other parameters between the two models, earlier studies on the Santiago public transport network revealed higher values for transfers with respect to bus in-vehicle time (Arriagada et al., 2022). This can be explained as Arriagada et al. (2022) only include travellers who make 15 or more journeys and their period of analysis is during the morning peak where they focus mainly on work or school commute. Transfers during peak period has its downside due to the large number of people travelling during these hours with the consequence of high crowding levels. Garcia-Martinez et al. (2018) found the effect of crowding to be significant when considering transfers. Our sample includes travellers during the whole day and the type of traveller might be more varied. If the effect of crowding on transfer is significant, transfers may be perceived differently throughout the day due to different crowding levels, which explains why our rates of substitution for transfers are lower than Arriagada et al. (2022).

We hypothesised that the higher the number of repeated past choices, the more likely a traveller is habitual. The sensitivity analysis on the minimum number of journeys shows that including travellers who make 2 journeys or more, the rates of substitution of L6 with respect to bus in-vehicle time is less large when compared to the models with a minimum of 3 or 4 journeys. The rate of substitution for the model with 3 journeys shows that the usage of L6 by habitual travellers represents 11 min of bus in-vehicle time which is an increase compared to the model with 2 journeys. These results might therefore indicate that the higher the number of repeated choices the more likely a person is habitual and therefore leading to an inertia effect.

The prediction of L6 shares using model 2 and 3, reveal that by accounting for inertia effects, the models more accurately predict the shares for the new transport alternative. The MNL model with inertia shows that not including inertia effects has considerable effects on demand estimation. It shows that model 1 (without inertia) has a higher percentage of predicting journeys with L6 while they actually do not have L6. When comparing model 2 with model 3, it can be seen that the difference in model accuracy is marginally better. The large difference can especially be seen between the model 1 and the models that account for inertia effects for L6. These findings confirm our belief that inertia should be accounted for if it exists and improves the travel demand estimations for new transport alternatives.

6.3. Limitations

The estimation of our model comes with certain limitations. Our study uses Santiago as case study, and therefore the empirical results are limited to this specific city. For this reason, it is difficult to generalize these results. As travel behaviour is related to a place and time, factors such as environment and culture will have an effect on habitual travel behaviour. For instance, the metro network of Santiago is subject to high levels of crowding (Arriagada et al., 2022) which may influence the use of metro and thereby the willingness to use a new metro line by non-metro users. Whereas other cities for example with moderate crowding levels, may reveal divergent results. However, our findings suggest that ignoring inertia effects when travellers are habitual could have implications for travel demand models that try to forecasts travel demand for new transport services.

The definition of habitual travel behaviour in our study is limited to only repetition of past choices. As we mentioned earlier in literature study, frequency cannot be the only indicator for habit and a more specified model may explain more to what degree an individual is habitual and which factors influence the inertia effect. However, when using passive observations based on smart card data, socio-demographic data is still not widely included in SC data which makes it difficult to assess the habitual behaviour by other personal factors. Additionally, complementing quantitative approaches such as the *Stickiness Index* with qualitative research will help gain an understanding in underlying factors for habitual behaviour and inertia effects.

The period of analysis of this research is bound to a single week prior to and after the opening of L6. We assumed the type of behaviour of an individual would be the same outside of these periods of analysis. This limits this study, since the short period of analysis does not allow to capture variability in travel behaviour.

The choice set per OD pair was largely determined by the radius of the cluster zone, which we based on the work by Arriagada et al. (2022). We did not consider it within the scope of the study to investigate the walking behaviour for access or egress for the city of Santiago. To identify the choice set per traveller, we used the Historical/Cohort approach which assumes that the identified choice set per traveller is based on the observed choices in the data set. Its limitation is that possible viable route choices may have not been included in the choice set of a traveller. Due to this dependency of choice set on observed choices, the choice set can vary between different samples.

7 Conclusion and Recommendations

The research aim was to investigate inertia effects in multimodal route choice in the case of a new metro line. Not accounting for the inertia effect in route discrete choice models may have an impact on travel demand predictions for new public transport infrastructure projects or services. As a case study, we used the public transport network of Santiago, Chile. The period of analysis was before and after the opening of L6 on 2^{nd} November 2017. Revealed preference data in the form of smart card data was used as input for our methodology. The method of *Stickiness-Index* was used to first quantify prior L6 whether route choice is habitual and to what extent a traveller is habitual. Based on the literature, we defined habitual as the repetition of past choices under stable conditions. Habitual behaviour can then lead to inertia (Cherchi and Manca, 2011), expressed as resistance to change or in our case less willingness to use L6. To include the inertia effect in the DCM framework, we included a simplified*Stickiness-Index* as a dummy variable in the route discrete choice model. We estimated the inertia model with an interaction effect with L6 in order to understand whether habitual travellers are less willing to use L6 as opposed to other travellers. Results from the DCM estimation were used to test the inertia model on its predictive performance.

The remaining part of this chapter will present the main findings, limitations of this study and recommendations for future research and policy.

7.1. Findings

The methodology as described above, allowed us to give an answer to our research sub-questions. We present step-wise per sub-question its main finding.

1. To what extent is travellers' route choice habitual in a non-changing public transport network?

If we base this question on the definition that habitual behaviour is purely a repetition of choices, then indeed route choice within a given OD pair is habitual given a non-changing public transport network. However, habit as literature describes is not purely based on the repetition of choices but also includes factors such as context and personal motives (Thøgersen, 2006). Literature tells us that repetition of choices is a necessary condition for habitual behaviour but does not entirely capture habitual behaviour (Verplanken et al., 1997). Whether a choice made is due to habit or deliberation remains unanswered in this research. Nevertheless, we tried to measure to what extent travellers in Santiago exhibit habitual travel behaviour before L6 by using the method of *Stickiness-Index*. A high 'stickiness' would indicate that a traveller prefers one single route over other alternatives, whereas a low 'stickiness' would indicate that a traveller is more variety-seeking. Results reveal that a minority of travellers within this research context are variety-seeking (SI lower than 1) and majority are habitual travellers (SI is 1). We assume a traveller is only habitual if that person repeats a single route out of multiple available routes within a given OD pair. Despite the 'variety' in behaviour for those travellers who have a SI lower than one, it is plausible that some of these travellers exhibit a pattern of habitual behaviour. For example, given two routes A and B within a given OD pair. A traveller may repeat route A three times and route B once which may appear sporadic for a single week based on our definition. However, if this pattern repeats over an extended period of time, it raises questions about their habitual behaviour. To be able to analyse this, data extending over a longer period of time is necessary in order to take variability of behaviour into account and accurately evaluate the presence of habitual behaviour.

2. How can inertia be quantified and be included within a route discrete choice model?

The literature review showed us that inertia can be quantified in the DCM framework in various ways each differing in behavioural assumptions. The inertia effect can be defined as a dummy variable (Vacca et al., 2019), a weighted average of past experience (Swait et al., 2004 or as an evaluation of previous choice utilities (Cantillo et al., 2007). All under the notion that past experiences have an effect on current choices. Cherchi and Manca (2011) shows that simpler expressions such as a dummy variable already show promising results in the estimation process. For this research, a novel approach is tried by including a simplified SI as an indicator in the DCM framework. The SI indicator described whether a person was habitual or not prior L6 during a stable travel environment. Since we investigate the effect of L6 on travellers, we included the SI binary classification as an interaction effect with L6. We hypothesise that habitual travellers (SI is 1), are less willing to use L6 as opposed to other travellers (SI smaller than 1). We did not attempt other expressions for the inertia effect as described in the literature chapter. The goal of this research was to reveal whether inertia exists in route choice when travellers face a new transport alternative, rather than investigate how different inertia expressions affect the model estimation outcomes.

3. After the opening of a new metro line, to what extent does inertia play a role in people's route choice decision-making?

We hypothesised that travellers that are labelled as habitual are less willing to use L6 as opposed to other travellers. A base MNL model was estimated as comparison and a MNL model with L6 and MNL model with interaction effect of L6 with SI to reflect the inertia effects. The MNL model with L6 reflects how both segments (habitual and non-habitual perceive L6) while the MNL model with inertia effects reflects the additional effect for L6 when travellers are habitual. The interaction effect of 'stickiness' with L6 was found to be significant and negative. The parameter L6 was also found to be positive and negative for both models. The interaction effect reveals that the marginal utility of L6 is comparatively larger for travellers who make repeated choices in the past than others. Compared to the majority of inertia effect studies which use a joint RP/SP data set, this study found that the inertia effect represents larger values of in-vehicle times. This is likely due to the underestimation of the inertia effect in SP studies where people do not experience the real outcome of the SP experiments. Further empirical research is needed to confirm the magnitude of the inertia effects based on fully RP data sets. In terms of model performance, the MNL model with inertia outperforms the basic MNL model. A large increase is observed for the final log-likelihood between the MNL model and MNL model with inertia effects. Our sample only includes travellers who make 3 journeys or more, it is interesting to therefore investigate the effect of the minimum of journeys on the interaction effect. We performed a sensitivity analysis where we test a minimum of 2,3 and 4 journeys for travellers to make in order to be included in the estimation sample. For all three models, we determined the marginal rates of substitution of dislike for L6 with respect to IVTB. As the threshold becomes higher, we observe that the marginal utility of L6 becomes larger for habitual travellers and see the rates of substitution increase with higher thresholds. This might indicate that by increasing the threshold, it is more likely a traveller is habitual and thus leads to a larger inertia effect for L6. Our findings show that inertia indeed does exist in multimodal route choice under changing environments, which is in line with previous literature including inertia in discrete choice modelling framework in a transport context. Furthermore, inertia should be accounted for in choice models if habitual behaviour plays a role.

4. To what extent does accounting for inertia improve the accuracy of route travel demand prediction?

All three models were tested for their prediction power for shares of L6 against the observed. Since revealed preference data is used, the prediction was performed using the numerical values of the estimation sample. Using the approach of hold-out validation, the MNL model overestimates the shares

for L6 substantially. The MNL model with inertia effect is able to more accurately predict journeys with L6 as opposed to the MNL model. When comparing the MNL model with L6 and the MNL model with inertia, we observe that the latter is marginally better in terms of travel demand prediction for L6. Concluding, by not including inertia effects, traditional route choice models overestimated the share of the new L6.
Estimating our model with inertia shows us that if inertia exists, it should be accounted for in multimodal route choice. Not including it, has implications both for travel demand predictions but also for travel demand strategies. For the latter, we need to ask whether habitual behaviour is due to deliberate choice-making or non-deliberate. Because if habitual behaviour is non-deliberate, travel demand strategies that focus on the rational (e.g. lower costs) would be ineffective. As for travel demand prediction, not including inertia effects can have implications when predicting demand for new services or infrastructure. Traditional models that do not include inertia effects would overestimate the shares for the new services or infrastructure.

We synthesize the above to come to the final conclusion for answering the main research question:

To what extent (if any) does inertia have an effect on the route choice behaviour of travellers when faced with a new metro line in a multimodal public transport network?

This study reveals that habitual behaviour leads to inertia effects when individuals face a new metro line. The inertia effect is significant and should be accounted for in route choice models. The outcome of the DCMs reveals that the marginal utility for the new metro line is comparatively larger when travellers are classified as habitual than others. Finally, validating the prediction power of our model reveals that the model that accounts for inertia effects outperforms traditional route choice models that do not include inertia effects on predicting shares for the new metro line.

7.2. Limitations Study

This research was carried out knowing its limitations in data and methodology. Assumptions made throughout the process also add to the limitations of this study. The first limitation concerns the data and the period of analysis. The data only contains one week before and one week after the opening of L6. Due to this limited data set, it is difficult to capture variability in habitual travel behaviour. During this research, we label travellers based on the assumption that the type of behaviour is the same before and after the period of analysis. An extended period of time would give a better representation of a traveller's travel behaviour. Someone might be non-habitual in our data of one week, but if that person repeats the same pattern over a longer period of time, is that same person then habitual or still non-habitual? To measure variability, a period of analysis of months would have been needed or at least a minimum of two weeks (Gärling and Axhausen, 2003). The relatively short period of analysis also limited our analysis after model estimation. As we impose requirements on the data during the process of the study, the final data set for SI estimation and DCM estimation of only one week suddenly becomes relatively small, even though we started with data set with over 20 million observations per week.

As previously stated, habitual behaviour is defined as the repetition of choices within this research. While it is acknowledged that the repetition of past choices is a necessary condition for behaviour to be considered habitual, it does not explain the behaviour in its full account. Rather, habitual behaviour also depends on contextual factors and personal motives. So to say whether a traveller is habitual or not based on repetition, works within the scope of this study. Accordingly, a more comprehensive evaluation of a traveller is needed in order to define someone as habitual where both qualitative and quantitative methods should be integrated into the habitual behaviour evaluation process.

Regarding the methodology, one of the assumptions made was to consider choice alternatives within a 100m Euclidean distance of every origin and destination stop, based on the work by Arriagada et al. (2022). This is a rather conservative number and has a considerable impact on the final choice sets for each traveller and consequently for the DCM estimation. We also assumed the choice set remains the same for every traveller and throughout the day. In reality, there can be differences in choice sets during morning and evening for example. Furthermore, we identified the choice sets for travellers based on observations from the revealed preference data. This has its limitations in that possible viable routes are not included in the choice sets since they have not been observed. The variability of observed routes may cause dependence of choice sets on such routes, therefore variations in choice sets may occur among different samples.

For the validity of our research method and empirical results, the research should also be extended to other transport networks and cities. This research is limited due to its application to the city of Santiago, therefore the empirical results are limited to this specific city. The effect of inertia, its magnitude and habitual behaviour may depend on the transport network and culture.

7.3. Recommendations for Future Research

It is important when planning and designing urban space to take into account travel behaviour dynamics which makes investigating inertia effects and its implications on new transport services an interesting topic for further research. While we only tested fairly simple choice models, it is likely that travel behaviour dynamics and choices vary across individuals. Estimating a random parameter model would capture unobserved heterogeneity for the interaction effect. If socioeconomic data was available on these travellers, it would also be interesting to investigate the taste differences among groups of individuals using a latent class choice model approach. Smart card data is anonymized in most countries, but if there are countries that allow for such data, investigating inertia effects for different groups of individuals under changing travel environments would be interesting.

As aforementioned, quantitative analysis of travel behaviour might not be sufficient to capture habitual behaviour in its full account (Verplanken et al., 1997). Qualitative research might fill in the gaps that quantitative research does not allow to investigate. It helps understand which other factors play a role in habitual travel behaviour and their influence on inertia. Besides frequency as indicator for habitual behaviour, Verplanken and Orbell (2003) also addresses the role of automaticity by measuring how fast people respond under given conditions and goals. Although combining qualitative research with large scale observations is a difficult task. Furthermore, as inertia can be explained by a combination of reduction of mental effort and risk aversion (Chorus and Dellaert, 2012), it is interesting and challenging to develop a model that accounts for frequency, cognitive processes and risk aversion.

Future research on modelling travel behaviour dynamics over time would also be very interesting to capture. Our study, unfortunately only contains one week of data which was not sufficient to do such an analysis. How would the mechanism of inertia change over time with respect to new transport alternatives? Does the inertia effect of habitual travellers with respect to the new alternative decrease? Do they stay with the new alternative, or do they return to their old routes and why? These are all interesting questions that might have been possible to answer with the availability of a data set extending over months for instance. To the contribution of empirical evidence, future research directions can be done using larger databases as well as extending this research to other cities and networks. Additionally, model specifications can be improved as we used a fairly simple indicator for the inertia effect.

7.4. Recommendations for Policy

The results of this study show that if habit exists, this should be accounted for in route choice models to capture travel behaviour dynamics also confirmed by earlier studies (Bogers et al., 2007; Cherchi and Manca, 2011; González et al., 2017; Vacca et al., 2019). When planning and designing urban transport systems, policy makers and transport planners should model these systems using data that captures both inertia effects and effect of new transport services. These data characteristics with panel effects and surrounding the implementation of a new transport alternative make it difficult to collect in practice. Not including the inertia effect when estimating demand models will have implications for travel demand estimation when aggregating these different travel behaviour dynamics. In practice, as transport systems are designed, not including inertia effects in route or mode choice models overestimates the share of those travellers who are less willing to use the new transport alternative.

If policy makers aim to change travel behaviour, we need to ask how these habits may be broken in order for travellers to change behaviour. Whether repetition of choice is due to habit or deliberate decision-making remains a complex issue and therefore challenging for policy makers to formulate a fitting travel demand strategy. As pointed out by Fujii and Kitamura (2003) and Bamberg et al. (2003), the act of travelling also might involve a sense of awareness of other transport alternatives. Making travellers aware of a new transport alternative may be of great aid in designing a well-balanced transport system. In addition, policy makers should provide effective strategies that help travellers use the new alternative in a stable environment. This gives travellers the opportunity to repeat a travel behaviour and therefore aid in attaining the new habits. If the outcome of these new habits is rewarding within a stable environment (Ouellette and Wood, 1998), repeating the behaviour can then lead to travellers using the new transport alternative as intended by transport planners.

As this research was carried out using the case study of Santiago, temporary conclusions and policy recommendations are useful for Santiago only. Since 2007, Santiago made a large reform plan for the transit system and since then the public transport ridership has increased substantially (Mcfarlane, 2022). Work already begins for new lines adding to the existing metro network. Line 7 (L7) which spans from northwest to northeast of the city is added with its goal to add a reliable and frequent service in the northwest and relieve the pressure of Line 1 (Rogers, 2022).
The unique RP data set of this research included both inertia effects and the effect of a new transport alternative. However, transport planners in Santiago who aim to assess the travel demand prediction for new transport services may not have the availability yet of this unique data set. In case only inertia effects are observed, transport planners may for instance include the inertia effect within the set of OD pairs where the new transport alternative will be implemented in the future. By including the binary classification of habitual behaviour as an interaction effect with for instance specific routes or metro stations, represented as dummy indicators, it might be possible to assess whether the inertia effect is stronger for specific OD pairs or stations. The outcome can then be used to give an initial indication of whether the new transport alternative will be subject to the resistance of using it due to inertia effects within given OD pairs. Data sets containing months of smart card observations are necessary to investigate the inertia effects on station level as this research found that with the current data set this was not possible to analyse.

Transport policies should aim at developing strategies to break habits in order to attract travellers who currently use other routes in using the new L7. For instance, making travellers aware of the new L7. This can be done by making L7 accessible and providing sufficient information to promote the new line. Even though there is an almost flat fare for metro usage, policy makers might even consider a discount for the new metro line in the starting phase to promote the usage of the new line (Bamberg et al., 2003) and may even lead to repeated use (Thøgersen, 2006). In case of the multimodal network in Santiago, there is a discrepancy between the bus and metro in terms of crowding levels (Arriagada et al., 2022). Additionally, Gao et al. (2021) revealed the significant interaction effect of inertia with LOS variables. Bus users due to their experience of low crowding levels in buses, may exhibit larger inertia effects with respect to using the metro (and thus the new line) (Gao et al., 2021). By making the new metro line easy to use for bus users, the role of experience will be an effective approach in order to discard negative misconceptions of other transport modes. The practical experience may also push people to change their evaluation of known attributes such as crowding levels in this case(Thøgersen, 2006).

In order to facilitate the adoption and maintenance of new travel habits among travellers, it is imperative to establish a stable environment for the use of L7. If the operation of the new line during its initial phase comes with complications (e.g. disruptions, delays), this will have an effect on the stable environment in which travellers best thrive in developing and maintaining new habits (Ouellette and Wood, 1998). Failure in doing so, might return people back to their usual travel habits, thereby rendering the implementation of the new line ineffective. If the intended objective of implementing L7 is to alleviate pressure on other lines, if people are not willing to use L7 due to inertia it will have consequences for the quality of the public transport system. As Arriagada et al. (2022) mentioned, the Santiago metro network is subject to high levels of crowding. Failure to shift travellers to the new line due to inertia effects may result in continual high levels of crowding on other lines, ultimately leading to poor quality of the multimodal public transport. To continue to improve the public transport system, transport planners and policy makers must be aware of the role of travel behaviour and its complexity when designing urban spaces.

References

Aarts, H., Verplanken, B., & Van Knippenberg, A. (1998). Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of applied social psychology*, *28*(15), 1355–1374.

Adamowicz, W. L. (1994). Habit formation and variety seeking in a discrete choice model of recreation demand. *Journal of Agricultural and Resource Economics*, 19–31.

Alós-Ferrer, C., Hügelschäfer, S., & Li, J. (2016). Inertia and decision making. *Frontiers in psychology*, *7*, 169.

Anderson, M. K., Nielsen, O. A., & Prato, C. G. (2017). Multimodal route choice models of public transport passengers in the greater copenhagen area. *EURO Journal on Transportation and Logistics*, *6*(3), 221–245.

Arnott, R., de Palma, A., & Lindsey, R. (1990). Departure time and route choice for the morning commute. *Transportation Research Part B: Methodological*, *24*(3), 209–228.

Arriagada, J., Munizaga, M. A., Guevara, C. A., & Prato, C. (2022). Unveiling route choice strategy heterogeneity from smart card data in a large-scale public transport network. *Transportation Research Part C: Emerging Technologies*, *134*, 103467.

Bamberg, S., Rölle, D., & Weber, C. (2003). Does habitual car use not lead to more resistance to change of travel mode? *Transportation*, *30*, 97–108.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. *Handbook of transportation science* (pp. 5–33). Springer.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D. S., et al. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters*, *13*(3), 163–175.

Ben-Akiva, M. E., Lerman, S. R., Lerman, S. R., et al. (1985). *Discrete choice analysis: Theory and application to travel demand* (Vol. 9). MIT press.

Bierlaire, M. (2018). Pandasbiogeme: A short introduction. *EPFL (Transport and Mobility Laboratory, ENAC)*.

Bliemer, M. C., & Bovy, P. H. (2008). Impact of route choice set on route choice probabilities. *Transportation Research Record*, *2076*(1), 10–19.

Bogers, E. A., Bierlaire, M., & Hoogendoorn, S. P. (2007). Modeling learning in route choice. *Transportation Research Record*, *2014*(1), 1–8.

Brands, T., Dixit, M., & van Oort, N. (2020). Impact of a new metro line in amsterdam on ridership, travel times, reliability and societal costs and benefits. *European Journal of Transport and Infrastructure Research*, *20*(4), 335–353.

Cantillo, V., Ortuzar, J. d. D., & Williams, H. C. (2007). Modeling discrete choices in the presence of inertia and serial correlation. *Transportation Science*, *41*(2), 195–205.

Chatterjee, K. (2011). Modelling the dynamics of bus use in a changing travel environment using panel data. *Transportation*, *38*, 487–509.

Cherchi, E., & Manca, F. (2011). Accounting for inertia in modal choices: Some new evidence using a rp/sp dataset. *Transportation*, *38*(4), 679–695.

Chorus, C. G. (2012). Random regret-based discrete choice modeling: A tutorial.

Chorus, C. G., & Dellaert, B. G. (2012). Travel choice inertia: The joint role of risk aversion and learning. *Journal of Transport Economics and Policy (JTEP)*, *46*(1), 139–155.

de Dios Ortúzar, J., & Willumsen, L. G. (2011). *Modelling transport*. John wiley & sons.

Di, X., & Liu, H. X. (2016). Boundedly rational route choice behavior: A review of models and methodologies. *Transportation Research Part B: Methodological*, *85*, 142–179.

Dixit, M., Cats, O., Brands, T., van Oort, N., & Hoogendoorn, S. (2021). Perception of overlap in multimodal urban transit route choice. *Transportmetrica A: Transport Science*, 1–23.

Duncan, L. C., Watling, D. P., Connors, R. D., Rasmussen, T. K., & Nielsen, O. A. (2020). Path size logit route choice models: Issues with current models, a new internally consistent approach,

and parameter estimation on a large-scale network with gps data. *Transportation Research Part B: Methodological*, *135*, 1–40.
Durán-Hormazábal, E., & Tirachini, A. (2016). Estimation of travel time variability for cars, buses, metro and door-to-door public transport trips in santiago, chile. *Research in Transportation Economics*, *59*, 26–39.
Fu, X., & Gu, Y. (2018). Impact of a new metro line: Analysis of metro passenger flow and travel time based on smart card data. *Journal of advanced transportation*, *2018*.
Fujii, S., & Kitamura, R. (2003). What does a one-month free bus ticket do to habitual drivers? an experimental analysis of habit and attitude change. *Transportation*, *30*(1), 81–95.
Gao, K., Shao, M., Axhausen, K. W., Sun, L., Tu, H., & Wang, Y. (2021). Inertia effects of past behavior in commuting modal shift behavior: Interactions, variations and implications for demand estimation. *Transportation*, 1–35.
Garcia-Martinez, A., Cascajo, R., Jara-Diaz, S. R., Chowdhury, S., & Monzon, A. (2018). Transfer penalties in multimodal public transport networks. *Transportation Research Part A: Policy and Practice*, *114*, 52–66.
Gärling, T., & Axhausen, K. W. (2003). Introduction: Habitual travel choice. *Transportation*, *30*(1), 1–11.
González, R. M., Marrero, Á. S., & Cherchi, E. (2017). Testing for inertia effect when a new tram is implemented. *Transportation Research Part A: Policy and Practice*, *98*, 150–159.
Hoogendoorn-Lanser, S., van Nes, R., & Bovy, P. (2005). Path size modeling in multimodal route choice analysis. *Transportation research record*, *1921*(1), 27–34.
Jánošíková, L., Slavík, J., & Koháni, M. (2014). Estimation of a route choice model for urban public transport using smart card data. *Transportation planning and technology*, *37*(7), 638–648.
Kahneman, D. (2017). Thinking, fast and slow.
Kim, J., Corcoran, J., & Papamanolis, M. (2017). Route choice stickiness of public transport passengers: Measuring habitual bus ridership behaviour using smart card data. *Transportation Research Part C: Emerging Technologies*, *83*, 146–164.
Manski, C. F. (1977). The structure of random utility models. *Theory and decision*, *8*(3), 229.
McFadden, D. et al. (1973). Conditional logit analysis of qualitative choice behavior.
Mcfarlane, C. (2022). Santiago metro - growth to 2030 overview - ax: Legal. https://ax.legal/2022/02/23/3434/
Morikawa, T. (1994). Correcting state dependence and serial correlation in the rp/sp combined estimation method. *Transportation*, *21*(2), 153–165.
Newton, I. (1833). *Philosophiae naturalis principia mathematica* (Vol. 1). G. Brookman.
Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological bulletin*, *124*(1), 54.
Pineda, C., & Lira, B. M. (2019a). Travel time savings perception and well-being through public transport projects: The case of metro de santiago. *Urban Science*, *3*(1). https://doi.org/10.3390/urbansci3010035
Pineda, C., & Lira, B. M. (2019b). Travel time savings perception and well-being through public transport projects: The case of metro de santiago. *Urban Science*, *3*(1), 35.
Prato, C. G. (2009). Route choice modeling: Past, present and future research directions. *Journal of choice modelling*, *2*(1), 65–100.
Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of economics and statistics*, *80*(4), 647–657.
Rogers, D. (2022). Work begins on $2.5bn metro line in santiago, chile. https://www.globalconstructionreview.com/work-begins-on-2-5bn-metro-line-in-santiago-chile/
Swait, J., Adamowicz, W., & van Bueren, M. (2004). Choice and temporal welfare impacts: Incorporating history into discrete choice models. *Journal of Environmental Economics and Management*, *47*(1), 94–116.
Thøgersen, J. (2006). Understanding repetitive travel mode choices in a stable context: A panel study approach. *Transportation Research Part A: Policy and Practice*, *40*(8), 621–638.
Thorhauge, M., Swait, J., & Cherchi, E. (2020). The habit-driven life: Accounting for inertia in departure time choices for commuting trips. *Transportation Research Part A: Policy and Practice*, *133*, 272–289.

Tomhave, B. J., & Khani, A. (2022). Refined choice set generation and the investigation of multi-criteria transit route choice behavior. *Transportation Research Part A: Policy and Practice*, *155*, 484–500.

Ton, D., Cats, O., Duives, D., & Hoogendoorn, S. (2017). How do people cycle in amsterdam, netherlands?: Estimating cyclists' route choice determinants with gps data from an urban area. *Transportation research record*, *2662*(1), 75–82.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Vacca, A., Prato, C. G., & Meloni, I. (2019). Should i stay or should i go? investigating route switching behavior from revealed preferences data. *Transportation*, *46*(1), 75–93.

Verplanken, B., Aarts, H., & Van Knippenberg, A. (1997). Habit, information acquisition, and the process of making travel mode choices. *European journal of social psychology*, *27*(5), 539–560.

Verplanken, B., & Orbell, S. (2003). Reflections on past behavior: A self-report index of habit strength 1. *Journal of applied social psychology*, *33*(6), 1313–1330.

Verplanken, B., & Orbell, S. (2022). Attitudes, habits, and behavior change. *Annual review of psychology*, *73*, 327–352.

Wood, W., & Rünger, D. (2016). Psychology of habit. *Annual review of psychology*, *67*(1), 289–314.

Yadav, S., & Shukla, S. (2016). Analysis of k-fold cross-validation over hold-out validation on colossal datasets for quality classification. *2016 IEEE 6th International conference on advanced computing (IACC)*, 78–83.

Yáñez, M. F., Cherchi, E., Ortúzar, J.-D., & Heydecker, B. G. (2009). Inertia and shock effects on mode choice panel data: Implications of the transantiago implementation.

A

Estimation Reports

Estimation report

Number of estimated parameters:	11
Sample size:	11245
Excluded observations:	0
Null log likelihood:	-13080.44
Init log likelihood:	-9769.169
Final log likelihood:	-8836.106
Likelihood ratio test for the null model:	8488.662
Rho-square for the null model:	0.324
Rho-square-bar for the null model:	0.324
Likelihood ratio test for the init. model:	1866.126
Rho-square for the init. model:	0.0955
Rho-square-bar for the init. model:	0.0944
Akaike Information Criterion:	17694.21
Bayesian Information Criterion:	17774.82
Final gradient norm:	4.6368E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	3.253989e-06
Relative change:	0.00016702596651785306
Number of iterations:	5
Number of function evaluations:	16
Number of gradient evaluations:	6
Number of hessian evaluations:	6
Cause of termination:	Relative gradient = 3.3e-06 <= 6.1e-06
Optimization time:	0:00:00.558771

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-0.709	0.0922	-7.69	1.49e-14
B_PSF	-0.278	0.0782	-3.55	0.000384
B_STICKINESSL6	-1.39	0.158	-8.78	0
B_TR_BB	-1.36	0.0897	-15.1	0
B_TR_BM	-0.833	0.067	-12.4	0
B_TR_MB	-1.23	0.154	-7.99	1.33e-15
B_TR_MM	-0.853	0.0796	-10.7	0
B_TT_BUS	-0.257	0.0285	-8.99	0
B_TT_METRO	0.209	0.0469	4.45	8.55e-06
B_WT	-0.302	0.0365	-8.28	2.22e-16
MSC_BUS	-2.33	0.104	-22.3	0

Figure A.1: Estimation report of MNL model (full sample) including transfer type metro to metro

Estimation report

Number of estimated parameters:	8
Sample size:	11245
Excluded observations:	0
Null log likelihood:	-13080.44
Init log likelihood:	-9444.031
Final log likelihood:	-9401.18
Likelihood ratio test for the null model:	7358.515
Rho-square for the null model:	0.281
Rho-square-bar for the null model:	0.281
Likelihood ratio test for the init. model:	85.70172
Rho-square for the init. model:	0.00454
Rho-square-bar for the init. model:	0.00369
Akaike Information Criterion:	18818.36
Bayesian Information Criterion:	18876.98
Final gradient norm:	3.6816E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	5.744601e-06
Relative change:	9.46914585675529e-06
Number of iterations:	5
Number of function evaluations:	16
Number of gradient evaluations:	6
Number of hessian evaluations:	6
Cause of termination:	Relative change = 9.47e-06 <= 1e-05
Optimization time:	0:00:00.359646

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_PSF	-0.734	0.0689	-10.6	0
B_TR_BB	-1.34	0.0904	-14.9	0
B_TR_BM	-0.636	0.0679	-9.38	0
B_TR_MB	-1.08	0.125	-8.66	0
B_TT_BUS	-0.265	0.0277	-9.57	0
B_TT_METRO	-0.177	0.0327	-5.41	6.33e-08
B_WT	-0.357	0.0382	-9.32	0
MSC_BUS	-2.52	0.104	-24.3	0

Figure A.2: Estimation report of MNL model on full sample (model 1)

Estimation report

Number of estimated parameters:	9
Sample size:	11245
Excluded observations:	0
Null log likelihood:	-13080.44
Init log likelihood:	-13080.44
Final log likelihood:	-8975.092
Likelihood ratio test for the null model:	8210.691
Rho-square for the null model:	0.314
Rho-square-bar for the null model:	0.313
Likelihood ratio test for the init. model:	8210.691
Rho-square for the init. model:	0.314
Rho-square-bar for the init. model:	0.313
Akaike Information Criterion:	17968.18
Bayesian Information Criterion:	18034.13
Final gradient norm:	5.1843E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	2.507251e-06
Relative change:	0.0011326198439173905
Number of iterations:	5
Number of function evaluations:	16
Number of gradient evaluations:	6
Number of hessian evaluations:	6
Cause of termination:	Relative gradient = 2.5e-06 <= 6.1e-06
Optimization time:	0:00:00.508266

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-1.64	0.0799	-20.5	0
B_PSF	-0.387	0.0747	-5.18	2.21e-07
B_TR_BB	-1.35	0.0902	-15	0
B_TR_BM	-0.7	0.0648	-10.8	0
B_TR_MB	-0.947	0.137	-6.9	5.23e-12
B_TT_BUS	-0.286	0.028	-10.2	0
B_TT_METRO	-0.0945	0.0341	-2.77	0.00565
B_WT	-0.349	0.0381	-9.17	0
MSC_BUS	-2.35	0.0963	-24.4	0

Figure A.3: Estimation report of MNL model with L6 on full sample (model 2)

Estimation report

Number of estimated parameters:	10
Sample size:	11245
Excluded observations:	0
Null log likelihood:	-13080.44
Init log likelihood:	-8928.947
Final log likelihood:	-8900.279
Likelihood ratio test for the null model:	8360.317
Rho-square for the null model:	0.32
Rho-square-bar for the null model:	0.319
Likelihood ratio test for the init. model:	57.33691
Rho-square for the init. model:	0.00321
Rho-square-bar for the init. model:	0.00209
Akaike Information Criterion:	17820.56
Bayesian Information Criterion:	17893.83
Final gradient norm:	3.7399E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	4.938083e-06
Relative change:	0.0003014051476971465
Number of iterations:	3
Number of function evaluations:	10
Number of gradient evaluations:	4
Number of hessian evaluations:	4
Cause of termination:	Relative gradient = 4.9e-06 <= 6.1e-06
Optimization time:	0:00:00.311404

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-1.05	0.088	-11.9	0
B_PSF	-0.492	0.0757	-6.49	8.46e-11
B_STICKINESSL6	-1.5	0.165	-9.09	0
B_TR_BB	-1.37	0.0908	-15.1	0
B_TR_BM	-0.727	0.0663	-11	0
B_TR_MB	-0.942	0.137	-6.87	6.4e-12
B_TT_BUS	-0.263	0.0285	-9.21	0
B_TT_METRO	-0.095	0.0351	-2.71	0.00682
B_WT	-0.328	0.0378	-8.68	0
MSC_BUS	-2.57	0.102	-25.2	0

Figure A.4: Estimation report of MNL model with Inertia on full sample (model 3)

Estimation report

Number of estimated parameters:	10
Sample size:	23132
Excluded observations:	0
Null log likelihood:	-28709.48
Init log likelihood:	-22214.69
Final log likelihood:	-21845.23
Likelihood ratio test for the null model:	13728.5
Rho-square for the null model:	0.239
Rho-square-bar for the null model:	0.239
Likelihood ratio test for the init. model:	738.9298
Rho-square for the init. model:	0.0166
Rho-square-bar for the init. model:	0.0162
Akaike Information Criterion:	43710.45
Bayesian Information Criterion:	43790.94
Final gradient norm:	1.1758E-01
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	5.44344e-06
Relative change:	8.688401607725993e-06
Number of iterations:	4
Number of function evaluations:	13
Number of gradient evaluations:	5
Number of hessian evaluations:	5
Cause of termination:	Relative change = 8.69e-06 <= 1e-05
Optimization time:	0:00:00.967512

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-0.783	0.047	-16.6	0
B_PSF	-0.471	0.0501	-9.39	0
B_STICKINESSL6	-0.64	0.0743	-8.61	0
B_TR_BB	-1.38	0.0571	-24.1	0
B_TR_BM	-0.939	0.0439	-21.4	0
B_TR_MB	-0.911	0.0823	-11.1	0
B_TT_BUS	-0.405	0.0186	-21.8	0
B_TT_METRO	-0.312	0.023	-13.5	0
B_WT	-0.294	0.022	-13.3	0
MSC_BUS	-2.06	0.0611	-33.7	0

Figure A.5: Estimation report of MNL model with Inertia on full sample (threshold 2 journeys)

Estimation report

Number of estimated parameters:	10
Sample size:	4367
Excluded observations:	0
Null log likelihood:	-4573.145
Init log likelihood:	-2647.891
Final log likelihood:	-2512.317
Likelihood ratio test for the null model:	4121.656
Rho-square for the null model:	0.451
Rho-square-bar for the null model:	0.448
Likelihood ratio test for the init. model:	271.1485
Rho-square for the init. model:	0.0512
Rho-square-bar for the init. model:	0.0474
Akaike Information Criterion:	5044.633
Bayesian Information Criterion:	5108.452
Final gradient norm:	1.1852E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	3.801828e-06
Relative change:	0.004368229260546237
Number of iterations:	4
Number of function evaluations:	13
Number of gradient evaluations:	5
Number of hessian evaluations:	5
Cause of termination:	Relative gradient = 3.8e-06 <= 6.1e-06
Optimization time:	0:00:00.149839

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-1.25	0.182	-6.88	5.91e-12
B_PSF	-1.96	0.221	-8.85	0
B_STICKINESSL6	-2.12	0.507	-4.18	2.97e-05
B_TR_BB	-1.31	0.21	-6.23	4.54e-10
B_TR_BM	-0.358	0.136	-2.64	0.0083
B_TR_MB	-0.789	0.343	-2.3	0.0216
B_TT_BUS	-0.038	0.0634	-0.6	0.549
B_TT_METRO	0.05	0.0712	0.703	0.482
B_WT	-0.602	0.098	-6.14	8.32e-10
MSC_BUS	-3.16	0.197	-16	0

Figure A.6: Estimation report of MNL model with Inertia on full sample (threshold 4 journeys)

Estimation report

Number of estimated parameters:	10
Sample size:	8996
Excluded observations:	0
Null log likelihood:	-10485.92
Init log likelihood:	-10485.92
Final log likelihood:	-7148.873
Likelihood ratio test for the null model:	6674.091
Rho-square for the null model:	0.318
Rho-square-bar for the null model:	0.317
Likelihood ratio test for the init. model:	6674.091
Rho-square for the init. model:	0.318
Rho-square-bar for the init. model:	0.317
Akaike Information Criterion:	14317.75
Bayesian Information Criterion:	14388.79
Final gradient norm:	1.3715E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	1.528799e-06
Relative change:	0.001943976594783292
Number of iterations:	5
Number of function evaluations:	16
Number of gradient evaluations:	6
Number of hessian evaluations:	6
Cause of termination:	Relative gradient = 1.5e-06 <= 6.1e-06
Optimization time:	0:00:00.364900

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-0.998	0.0957	-10.4	0
B_PSF	-0.503	0.0831	-6.05	1.42e-09
B_STICKINESSL6	-1.59	0.184	-8.62	0
B_TR_BB	-1.41	0.104	-13.5	0
B_TR_BM	-0.684	0.0731	-9.35	0
B_TR_MB	-0.954	0.149	-6.41	1.44e-10
B_TT_BUS	-0.267	0.0322	-8.31	0
B_TT_METRO	-0.108	0.0392	-2.74	0.00606
B_WT	-0.328	0.0419	-7.82	5.33e-15
MSC_BUS	-2.62	0.115	-22.8	0

Figure A.7: Estimation report of MNL model with Inertia on estimation sample (80% of full sample, randomly selected)

Estimation report

Number of estimated parameters:	10
Sample size:	2249
Excluded observations:	0
Null log likelihood:	-2599.686
Init log likelihood:	-1821.946
Final log likelihood:	-1810.924
Likelihood ratio test for the null model:	1577.524
Rho-square for the null model:	0.303
Rho-square-bar for the null model:	0.3
Likelihood ratio test for the init. model:	22.04423
Rho-square for the init. model:	0.00605
Rho-square-bar for the init. model:	0.000561
Akaike Information Criterion:	3641.848
Bayesian Information Criterion:	3699.031
Final gradient norm:	1.2862E-02
Nbr of threads:	20
Algorithm:	Newton with trust region for simple bound constraints
Proportion analytical hessian:	100.0%
Relative projected gradient:	5.240763e-06
Relative change:	0.0015968823689704 7
Number of iterations:	3
Number of function evaluations:	10
Number of gradient evaluations:	4
Number of hessian evaluations:	4
Cause of termination:	Relative gradient = 5.2e-06 <= 6.1e-06
Optimization time:	0:00:00.168938

Estimated parameters

Name	Value	Rob. Std err	Rob. t-test	Rob. p-value
B_L6	-0.72	0.172	-4.18	2.86e-05
B_PSF	-0.273	0.172	-1.58	0.114
B_STICKINESSL6	-1.62	0.327	-4.95	7.6e-07
B_TR_BB	-1.48	0.196	-7.54	4.75e-14
B_TR_BM	-0.988	0.157	-6.3	2.95e-10
B_TR_MB	-1.03	0.322	-3.21	0.00135
B_TT_BUS	-0.249	0.0679	-3.66	0.000249
B_TT_METRO	-0.0216	0.0793	-0.273	0.785
B_WT	-0.266	0.0834	-3.19	0.00142
MSC_BUS	-2.19	0.223	-9.83	0

Figure A.8: Estimation report of MNL model with Inertia on validation sample (20% of full sample, randomly selected)

B
Academic Paper

Accounting for inertia in multimodal route choice behaviour: the case of a new metro line in Santiago

Hoang Nguyen

Department of Transport and Planning, Delft University of Technology, Delft, Netherlands

April 3, 2023

Abstract

If people repeat choices in daily travel behaviour under stable conditions, over time this can form habitual travel behaviour and lead to inertia. If travellers face a new metro line, to what extent does their habitual travel behaviour affect their willingness to use this new transport alternative. This study investigate the inertia effects in a multimodal public transport network using a fully revealed preference data set. Habitual route choice behaviour is quantified prior to the opening of the new metro line. We then use the quantitative metric for habitual behaviour as an indicator in the situation after the metro line opens to reflect the inertia effects of individuals. The outcome of the route discrete choice model reveal that the inertia effects for the new metro line are significant. The interaction effect of habitual travellers with the new transport alternative show that there is an additional effect for the new alternative if travellers are classified as habitual. Furthermore, not accounting for inertia effects leads to bias in travel demand estimations of the new transport alternative. The model with the inertia effect improves model fit and is able to more accurately predict shares for the new metro line.

Keywords: *smart card data, inertia, habitual travel behaviour, multimodal route discrete choice*

1 Introduction

In everyday life, people's route choices associated with travel activities such as going to work or school tend to repeat themselves under stable conditions. As the choices people make while performing these activities repeat, a person may become habitual over time due to this repetitive travel behaviour (Thøgersen, 2006). People's travel behaviour has often been modelled using Discrete Choice Models (DCM) based on the notion of Random-Utility Maximisation (RUM) (Manski, 1977). The aforementioned notion assumes that a person has perfect knowledge of their choice situation and the cognitive capability to evaluate their entire choice set in order to make a deliberate choice. However, in a stable travel environment, a person has the tendency to automatize certain decisions in order to economize their cognitive resources by making repeating choices (Kahneman, 2017).

But what if the travel conditions are not stable and the travel environment changes, how does habitual behaviour play a role in people's route choice decision-making? When people are faced with new transport alternatives, habit can play a role in people's decision-making process and prevent people to pursue these new transport alternatives. This willingness to not change is also known as the inertia effect (Cherchi and Manca, 2011). The inertia effect is usually framed as the result of minimizing mental effort where the context associated with performing the repeated choices is stable over place and time (Gärling and Axhausen, 2003; Ouellette and Wood, 1998). On the other hand, Chorus and Dellaert (2012) argues that complementary to the aforementioned reason for inertia, the effect of inertia emerges as a combination of risk aversion and learning expenses. They postulate that if people are risk averse and choices are risky because of the uncertainty that comes with unknown alternatives, people have the disposition to maintain their usual choices.

While DCMs based on RUM paradigm are often used in route choice modelling and are considered superior to other route choice models, that for example assume people only minimize costs (Jánošíková et al., 2014), the RUM paradigm does not explain behaviour (e.g. habit) that deviates from utility maximisation (Ben-Akiva et al., 2002; Di and Liu, 2016). For this reason, there are trends in the past decades to develop models that expand on the RUM paradigm such as the Hybrid Choice Model (HCM). The HCM expands on the utility maximisation framework by including dependency on history, attitudes and preferences of individuals (Ben-Akiva et al., 2002). Bounded Rationality (BR) takes a different stance and opposes the aforementioned notion. BR assumes that people are actually limited in their knowledge of choice situations and cognitive abilities. Di and Liu (2016) addresses evidence for behaviour deviating from perfect rationality such as heuristics in decision-making leading to systematic errors and violation of taking the shortest path. This underscores why perfect rationality is not able to capture people's cognitive processes and why a more realistic assumption like BR is needed in travel behaviour modelling.

It is clear that the micro-economic theory of utility maximisation is not able to capture the full account of human behaviour. Especially in travel behaviour context such as route choice, where people repeat behaviour and become habitual, their route choice behaviour may not only be expressed in 'hard information' such as travel time and costs (Gao et al., 2021). Nevertheless, in the case of repetitive travel behaviour, attempts have been made to account for habit in DCMs and are successfully incorporated in various models such as mode choice (Gao et al., 2021; González et al., 2017; Yáñez et al., 2009) and car route choice (Bogers et al., 2007; Vacca et al., 2019). The majority of these studies support the significance of inertia in repetitive travel behaviour and therefore should be accounted for in choice modelling. Gao et al. (2021) included the inertia effect in mode choice using mixed revealed preference (RP) and stated preference (SP) data and found that the inertia effect is mode specific and influences the perception of choice attributes. González et al. (2017) and Yáñez et al. (2009) tested inertia effects in case of a new transport alternative for mode choice in a public transport system using mixed RP/SP data and found that the effect is significant and should be accounted for in travel behaviour modelling. The former study did however have a relatively small sample focusing only on students, while the latter study used a pseudo diary of 300 individuals.

To the author's knowledge, no studies investigated the role of inertia in multimodal route choice in case of a new transport alternative based on fully revealed preference data set. The contribution of this study is that we include the inertia effect in large multimodal public transport route choice when travellers are faced with a newly opened metro line. Habitual route behaviour of individuals is quantified prior to the opening of a new metro line in Santiago, Chile. This individual habitual route choice indicator, which reflects the inertia effect, is used in a route discrete choice model after the opening of the new metro line to investigate the willingness of habitual travellers to use the new transport alternative. Furthermore, the aim is to address the implications for demand estimations when not including the inertia effect. The relevance for society is that we aim to aid in developing travel demand models that are able to capture more behavioural realism in order to more accurately predict travel demand for new transport services. If travellers due to inertia, stick to their usual choices, transport planners that design transport alternatives with the intention to alleviate the pressure of other lines might see their strategy be attenuated. By including the inertia effect in choice models, transport planners and policy makers are able to better predict the travel flow and design effective policies in addressing habitual travel behaviour. As for scientific relevance, this study contributes by using a data set based on real observations. Using a RP data set eliminates the bias in people's choices when using a SP data set.

This paper is organised as follows. Section 2 describes how habit and inertia are understood in literature and have been included in the DCM framework. Section 1 presents the case study and data. Following, the methodology of this research is presented in 4. The results and core findings are presented in section 5. Finally, we conclude this paper with a discussion of the results in section 6 and conclusion in section 7.

2 Literature review

2.1 Theoretical framework

Within the field of psychology, the concept of habit is described as a sequence of learned acts that eventually can lead to automatic choices when a person is faced with certain situations which are characterised by specific goals or cues (Verplanken et al., 1997). Habits are then tendencies grounded in memory that react automatically to the cues associated with these aforementioned goals that led to similar behaviour in the past. People therefore reduce mental effort by repeating choices under stable conditions (Ouellette and Wood, 1998; Verplanken et al., 1997; Wood and Rünger, 2016). Chorus and Dellaert (2012) argues that complementary to the view of individuals economising on cognitive resources as a reason for inertia, the effect of inertia emerges as a combination of risk aversion with the perceived costs of learning new alternatives. If people are risk averse and the expected gains of new alternatives are uncertain, people become behaviourally inert and reuse past solutions to simplify decision-making and mitigate risks (Chorus and Dellaert, 2012).

The formation of habit occurs in everyday life and is strongly associated with pursuing goals (Wood and Rünger, 2016). Built on the fundamental principle that responses with positive rewards are repeated (Wood and Rünger, 2016), habit forms over time when the same response is repeated to attain these goals. Ouellette and Wood (1998) differentiates between long-term and short-term positive rewards. People are more likely to change their behaviour if their responses show positive rewards on short-term rather than long-term. Conversely, a negative reward will weaken the link between goal and behaviour and therefore decrease the probability that a person will continue with the behaviour (Aarts et al., 1998).

The frequency of behaviour in the past has been the standard to measure habit (Ouellette and Wood, 1998). However, repeated choices in the past do not imply that behaviour is habitual, it is a necessary condition for habitual behaviour but does explain the full account of habitual behaviour (Gärling and Axhausen, 2003). Other factors such as personal motives and external constraints play a role in the formation of habit (Thøgersen, 2006). Verplanken and Orbell (2003) developed a Self-Report Index (SRHI) to measure habit strength of students with respect to mode choice. Repetition of behaviour is only a proxy of true habitual behaviour, hence why the authors developed the SRHI to add value to the residual effect of past behaviour. The disadvantage of such qualitative measurement of habit is that people had the tendency to report in a desirable way or provide answers to only appear consistent. Kim et al. (2017) quantitatively measured habitual behaviour of bus users using smart card data by introducing the *Stickiness Index* (SI). Within a given origin-destination (OD) pair and stable environment, the authors expressed habitual behaviour as how often a route was used and how the chosen routes were distributed among a person's choice set.

2.1.1 Definitions

Literature study shows that the terms habit and inertia are used interchangeably. In this study, a similar definition of habitual behaviour is adopted from Kim et al. (2017) which is based on frequency of past behaviour under stable conditions. This research investigates the effect of the opening of a new metro line on travel behaviour. Consequently, two situations occur: the first situation is prior to the opening and the second situation is after the opening. To remain consistent with terminology throughout this paper, we refer to *habit* or *habitual* behaviour *prior* to the opening of the new metro line when the travel conditions were stable (e.g. no significant changes) and is defined as the repetition of choices. Habitual behaviour can lead to inertia and thus we refer to *inertia* in the situation *after* the opening of the metro line and is defined as the resistance to change to the new transport alternative.

2.2 Modelling inertia effects in travel behaviour

In the context of repeated travel behaviour, many studies have accounted for inertia effects, each with different approaches and empirical findings in a different transport context. Morikawa (1994) conducted a mixed RP/SP research where the biased responses in the SP survey were controlled by including an inertia dummy variable that reflects the actual behaviour.Adamowicz (1994) expressed habit as a state-dependence dummy variable as to how often an alternative was chosen in the past. Gao et al. (2021) adopted the latter method in context of mode choice behaviour to investigate the interaction effect of inertia with travel attributes. They found that the inertia effect is mode specific and that inertia has an effect on the perception of travel attributes. Cantillo et al. (2007) proposed a more complex expression of habit. Habit was formulated as a function of evaluation of previous choice utilities to the current one. They highlight that if there are inertia effects, this should be accounted for in model specifications in order to avoid bias in parameter estimates and the implications for large policy impacts. The specification of the inertia effect by Cantillo et al. (2007) has later been adopted by González et al. (2017) and Yáñez et al. (2009). González et al. (2017) studied the inertia effect on mode choice as a result of the implementation of a new tram using mixed RP/SP and RP/RP data set but on a relatively small sample only comprising of students. They found no significant inertia effect between the SP/RP data set, indicating that the SP responses were led by bias as students did not experience the real outcome of the tram. Yáñez et al. (2009) additionally added a shock effect to control for the fact that travellers were suddenly confronted with a new change in the public transport system in Santiago, Chile. Both studies supported the significance of the inertia effect when travellers are faced with new changes in the public transport system. Since habitual behaviour can lead to inertia, we also highlight the work by Kim et al. (2017) who quantified habitual route choice behaviour in a public transport network based on entirely revealed preference data. The authors developed the *Stickiness Index*, as a metric to quantify the tendency for a traveller to stick to a particular route within a given OD pair.

Summarizing, the literature review reveals that the inertia effect has been defined in various ways and studied in different context. Cherchi and Manca (2011) conducted a research to test these various inertia definitions and found that using the relatively simple dummy variable for inertia could get meaningful results and more advanced expressions such as the one proposed by Cantillo et al. (2007) are not necessarily superior to simple definitions of inertia. Furthermore, the literature study reveals that the inertia effect has been studied in context of public transport mode choice and car route choice based on mixed RP/SP data sets. As González et al. (2017) mentioned the discrepancy between the RP and SP data sets as people do not experience the real outcome in a SP survey. This leads to bias in parameter estimates because of the hypothetical situation which is present in SP surveys. When compared to the observation of real behaviour, their preferences might be altered as people have problems imagining the real situation. This research tries to fill in these two gaps by using a fully revealed preference data set based on smart card observations and accounting for inertia effects in a multimodal public transport route choice when travellers are faced with a new transport alternative.

3 Data

To empirically investigate the inertia effects in a multimodal route choice, this paper uses the case study of the opening of Metro Line 6 in Santiago, Chile. The two data sources are the passive observations obtained from the smart card *Bip!* of the public transport system of Santiago and geographic data of the same public transport network.

3.1 Case study

The period of analysis is from 31 July - 6 August 2017 and from 10 November - 16 November 2017. During that period, Santiago has a multimodal public transport system consisting of a metro network, an urban bus network and a railway system. On a normal working day, 6.8 million people generate roughly 18 million trips. The share of these trips is 28% for cars and 25% for public transport (Pineda and Lira, 2019). Half of the public transport trips are comprised of metro trips, which underscores the importance of the metro system. By that time, the metro network consists of 5 metro lines working as a backbone of the multimodal public transport system. Expanding the metro network has been made a priority by the government of Santiago and sees the expansion of existing lines and the addition of completely new lines. One of those additions is Santiago Metro Line 6 (L6) which was realised on 2^{nd} November 2017.

This research focuses on the effect of a new metro line on travel behaviour, therefore we focus on the opening of L6. The new line added 10 new stations to the metro network with a total line length of 15.3 km connecting the southwest with the northeast of Santiago. One of its main goals was to relieve pressure on Line 1 and provide extra transport connections for the metro network. To use the transport system, travellers pay by the smart card *Bip!*. Although there are different tariffs for the metro depending on the time of day, the differences are negligible. For buses however, there is a flat fare upon usage. Furthermore, travellers only have to check-in upon entering the public transport system and are allowed to transfer up to two times within a period of 120 minutes.

We draw upon two weeks of processed[1] smart card (SC) data and geographic data on the bus and metro stops of the Santiago public transport network. The first week (31 July - 6 August 2017) is prior to the opening of L6 and the second week (10 November - 16 November 2017) is after the opening of L6. The first week contains 22.7 million journey observations and the second week contains 24 million journey observations. Furthermore, the data is anonymized which means each observation is identified by a traveller's smart card identification (id) number.

The second data source is the geographical coordinations of the bus stops and metro stations. The data source contains the *xy* UTM coordinates of bus stops and metro stations.

[1]The data from the smart card has been processed. The raw data which consists of only time and place of check-in has been processed in order to infer the alighting time and location. Additional data such as mode and line used have also been added.

3.2 Definitions

To clarify some terminology for the remainder of this paper, we define some terms. A person travels between a given OD pair and we will refer to this as a *journey*. While doing so, the person uses a *route* that consists of multiple single *trips*. Each trip has a board and alight stop and uses a single mode, either bus or metro.

3.3 Descriptive analysis

We are only interested in the effect of L6 on people's travel behaviour, we therefore select only a subset of OD pairs where L6 is at least part of one of the alternatives for a given OD pair. Selection of these OD pairs is done by selecting only those journeys where L6 is part of any trip of the journey. To identify the choice sets for each OD pair, the work by Arriagada et al. (2022) is used who estimated route choice models in Santiago, Chile. For each selected OD pair, stops surrounding the selected origin and destination stops are clustered if the stops are within a 100 Euclidean meters of the selected origin and destination stop. After identifying the subset of relevant OD pairs, the trips between these OD pairs are analysed during the period of analysis. Table 1 gives an overview of the initial data size and how this has been reduced after selecting the relevant OD pairs and the corresponding journeys.

Table 1: *Initial data size per week and final number of journeys after selecting relevant OD pairs*

	Initial journeys	**Final journeys**
31/07 - 06/08 (Prior L6)	22,7 million	565,998
10/11 - 16/11 (After L6)	24 million	987,044

3.3.1 Impact L6 in Santiago

Within the selected OD pairs, 429.229 unique travellers post-L6 are identified. The average number of trips taken is 1.44 trips per journey, where the majority of the travellers only have 1 trip in their journey. Prior-L6, we identify 302.653 unique travellers within the set of OD pairs. The average number of trips taken is 1.5 trips per journey. The effect of the new line shows that within these OD pairs, people have taken fewer transfers as the average number of trips has decreased from 1.5 to 1.44 due to the new line. This was also found by Pineda and Lira (2019) who analysed travel time savings due to the new L6.

Out of the 302.653 unique travellers prior-L6, 96.056 continue to travel after the opening of L6. Out of these travellers who continue to travel longitudinally between the two weeks, 42.232 travellers use L6 at least once after it became available. When analysing the week post-L6 and not considering whether people travelled prior-L6 within the same OD pairs, 221.370 travellers used L6 once or more. It is noteworthy that since each id is a smart card, there is the possibility that people have taken new smart cards therefore we have to be cautious with the number of people using L6 after it opened. Nevertheless, this shows a large increase in travellers due to L6 within the selected OD pairs.

Regarding changes in travel times, we differentiate between waiting time and in-vehicle time. It is noteworthy, that the number of travellers prior- and post-L6 differ in numbers. The average travel time prior-L6 was 32.8 minutes and has decreased to an average travel time of 29.46 minutes due to L6. The average waiting time has decreased from 6 minutes prior-L6 to 5.18 minutes.

The descriptive analysis also reveals substantial differences in total share of ridership per mode. Within the selected OD pairs, there is a clear increase in metro usage in Santiago due to L6. Figure 1 shows the difference between the situation before and after L6. We observe prior-L6, that the share for metro only is 37%, bus only is 18% and the combination bus and metro is 45%. After the introduction of L6, the number of journeys by bus only remained similar. We see a large increase in metro journeys and also a substantial increase in combination bus and metro. The shares post-L6 are 52% for metro only, 10% for bus only and 38% for combination bus and metro. This large increase in metro journeys shows the significant impact L6 has on Santiago. It is noteworthy, that the period of analysis represents a high-point in the usage of L6 since it was captured right after it opened. This might have attracted a substantial number of people who simply want to 'explore' the new line rather than consider it as a viable transport alternative. The large share for the combination bus and metro is also interesting and characterises the travel behaviour of Santiago. It indicates the importance of the bus as a complementary mode for the metro.

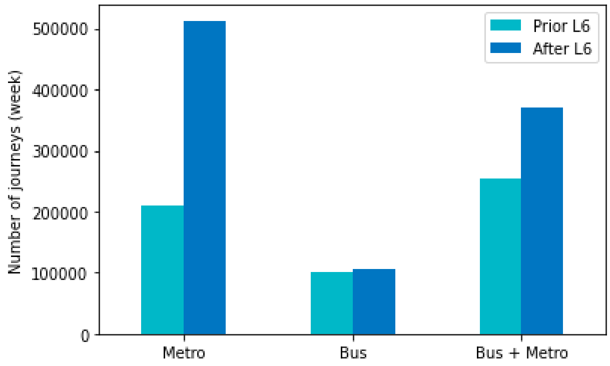


Figure 1: *Change in mode share ridership within selected OD pairs*

4 Methodology

4.1 Choice set construction

To specify the route choice model, we first have to identify the choice sets for each traveller within a given OD pair. Since we are only interested in the effect of L6, we select those OD pairs where L6 is part of any trip of a journey. This subset of journeys is further narrowed down by removing journeys with invalid or missing information. Furthermore, journeys are removed with ambiguous metro trips[2] since we cannot infer which metro line has been taken once a traveller checks in at a station. We are not able to 'look' underground past the point of check-in as to say. Finally, to study the effect of inertia, it is important that OD pairs remain consistent prior- and post-L6. If a traveller changes OD pair post-L6, for example, due to changing work, we would not be able to study how L6 affects the usual choice set of a traveller since the conditions have changed.

Once the relevant OD pairs have been selected, we identify the choice sets of travellers by first identifying the OD pair zones. These zones include stops that are within a 100 Euclidean meter distance of the selected journey origin and destination stops. We base this clustering method on the work by Arriagada et al. (2022) who studied the route choice behaviour of travellers in Santiago, Chile. They tested various distances for the OD pair zones and found 100 meters to give the best results regarding parameter estimates. Generating the choice set for each traveller is done based on the Historical/Cohort approach which identifies the choice set based on the observations from the smart card (SC) data. Its limitation is that possible viable alternatives are not included within the choice set. Based on the actual observations, we assume that these alternatives were simply not considered feasible by the decision-maker. Due to this dependency of the choice set on observed choices, choice sets may vary among different samples.

4.2 Quantifying habitual route choice behaviour

In the case of a new metro line, how does habitual behaviour affect people's willingness to pursue the new travel alternative? To answer this question, we have to ask to what extent is route choice habitual given

[2]Observations with for instance 'Line 1 - Line 4', indicating either one of the two has been taken

our data set in the situation prior to the opening of L6 when the conditions were stable. Consequently, we must specify when a traveller is classified as habitual, non-habitual or possibly something in between. We quantify habitual route choice based on the method by Kim et al. (2017). The method of *Stickiness Index* (SI) has been applied in their study in a public transport network based on smart card data, which makes it applicable to our study. The SI metric quantifies the tendency of a traveller to 'stick' to a particular route within a given OD pair. A high stickiness indicates that a person is often or always using the same route despite the availability of different routes to the user within the same OD pair. We consider this habitual due to the repetitive nature of choices. Conversely, a low stickiness indicates that a person is using the available routes within a given OD pair more evenly with no clear preference for a particular route. We consider this as non-habitual route choice behaviour or variety-seeking behaviour. Since we determine the habitual behaviour of a person for a given OD pair, a person can be considered habitual for a given OD pair but variety-seeking for another pair. Therefore, we emphasize that the SI is estimated for a traveller-OD.

4.2.1 Traveller-Level Stickiness Index

For each OD pair k, we construct a traveller-route matrix. The rows indicate the set of travellers I and the rows indicate the set of observed routes J for OD pair k. Each entry n represents the frequency a traveller i uses route j to travel within k.

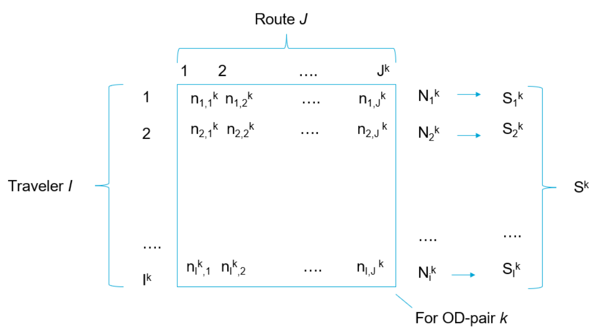


Figure 2: *Traveller-route matrix (based on Kim et al. (2017)*

Before we estimate the *Stickiness Index* we must prepare our sample prior-L6. We impose three requirements to the sample to include valid travellers, valid OD pairs and OD pairs with at least two alternatives or more. For the first requirement, we only include travellers who make 3 or more journeys. To quantify habitual behaviour travellers have to repeat a journey in the first place. We also hypothesize that the higher the number of repetitions, the more likely a person is habitual leading to a stronger inertia effect. The second requirement, we only include OD pairs that have at least 10 or more individuals travelling within a given OD pair. As a result of these requirements, the initial set of 646.391 traveller-OD journeys was reduced to 51.998 traveller-OD journeys. An OD pair has an average number of 113 journeys. Each traveller made on average 4.6 journeys.

The formulation for the *Stickiness Index* (Kim et al., 2017) is specified as follows:

$$S_i^k = \frac{J_i^k * D_i^k - 1}{J_i^k - 1} \tag{1}$$

where J_i^k represents the number of routes us by a traveller i and D_i^k the diversity index. The diversity index is specified as follows:

$$D_i^k = \sum_{j=1}^{J^k} (p_{i,j}^k)^2 = \sum_{j=1}^{J^k} (\frac{n_{i,j}^k}{N_i^k})^2 \tag{2}$$

where $n_{i,j}^k$ represents the number of journeys made by a traveller i using route j to travel within OD pair k, N_i^k is the total set of journeys made by traveller j to travel with OD pair k and $p_{i,j}^k$ is the proportion of journeys made using route j so that $\sum_{j=1}^{J^k} p_{i,j}^k = 1$. $D_i^k = 1$ if only one route is and indicates no diversity. Maximum diversity occurs when all routes are equally used with $D_i^k = 1/J_i^k$. We are only interested in how the routes are distributed over a choice set for traveller i and not the size of the choice set which formula 2 accounts for. For this reason, Kim et al. (2017) normalizes the diversity index by the choice set size as seen in formula 1 and resulting in the formulation of the SI.

A SI of 1 would indicate that a person always using the same route within a given OD pair and a SI of 0 would indicate that a person uses all the available routes evenly within a given OD pair. We explain how the SI changes and the difference between the diversity index and SI on the basis of three cases: 90% of journeys allocated to a single route with the rest of the journeys to the remaining routes, 50% of journeys allocated to a single route and the rest to the remaining routes and when all routes are distributed evenly.

- Low evenness (case 1), where 90% of routes used is allocated to one route and 10% to the rest. Starting value for SI would be high due to the dominance of a single route. SI would increase with increasing routes used which indicates a high stickiness to one particular route (fractions journeys with other routes becomes smaller). The diversity index would also have a high starting value (very low evenness) and would slowly decrease with increasing number of routes used. Although richness increases for the diversity index (number of routes used), since 90% of journeys is allocated to a single route, the fraction for the other routes becomes smaller as richness increases. Fraction of other routes used becomes smaller (e.g decreasing evenness).

- Medium evenness (case 2), 50% of journeys is allocated to a single route and 50% to remaining other routes used. The values for SI would be smaller than for case 1 because of increasing evenness. With increasing route used, the SI and diversity index would show similar patterns as for case 1.
- High evenness (case 3), all journeys made are distributed equally among all the routes used. Diversity index would decrease with number of routes used as both evenness and richness increases. SI would be zero indicating no stickiness to a particular route. Even if the number of routes increases, there is no tendency to stick to a particular route.

Figure 3 illustrates how frequency affects the SI when only one journey has been allocated to another route. It shows that the higher the number of journeys a traveller makes, the higher the SI is when the traveller allocates almost all except one journey to a single route.

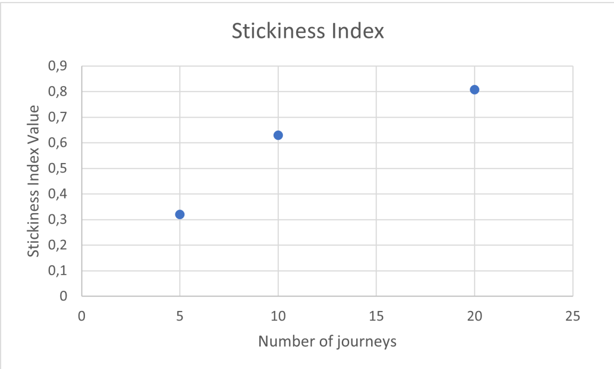


Figure 3: *SI values depending on frequency: the case of 2 routes used where only one journey has been allocated to the other route.*

4.2.2 OD-level Stickiness Index

By aggregating the traveller-level SI, we are able to gain insight in the average stickiness tendency for a given OD pair. This allows us to compare the average SI of different OD pairs to see whether there are any spatial differences among OD pairs. The OD-level SI (Kim et al., 2017) is formulated as a weighted average of each persons SI:

$$S^k = \sum_{i=1}^{I^k} w_i^k * S_i^k \tag{3}$$

where S_i^k denotes the individual traveller SI for a given OD pair k and w_i is the proportion of a travellers total set of journeys within the entire set of journeys for a given OD pair and I^k is the set of all travellers for OD pair k. The proportion is defined as follows:

$$w_i^k = \frac{N_i^k}{\sum_{i=1}^{I^k} N_i^k} \tag{4}$$

Where N_i^k is the total number of journeys made by traveller i travelling OD pair k and I^k is the set of all travellers for OD pair k

4.3 Route discrete choice model

Habitual behaviour can lead to inertia (Cherchi and Manca, 2011), therefore, we include the SI[3] as an indicator in the route discrete choice model (DCM) framework. Before we specify the route discrete choice models with inertia effects, we present the specification to account and correct for overlapping routes in a multimodal public transport network.

4.3.1 Account for route overlap

Our inertia model is based on the Multinomial Logit (MNL) model, which has been used often in multimodal route choice models due to its simplicity (Jánošíková et al., 2014). However, the MNL model exhibits the Irrelevant from Independent Alternatives (IIA) property (Prato, 2009). To address this problem in the route choice context, we use the Path-Size Logit (PSL) which is a modification of the MNL model. There are other MNL model modifications that account for commonality between routes such as the C-Logit (CL). Recent research points out that the CL has been outperformed by the PSL in terms of model estimations (Tan et al., 2015), hence why we use the PSL to correct and account for route overlap in this research.

The PSL is based on adding a correction term to the systematic part of utility in order to account for overlap between route alternatives. Ben-Akiva and Bierlaire (1999) introduced the PSL within the DCM because of the assumption that overlapping route alternatives may not be considered distinct alternatives. Their PSL model remains the Logit closed-form structure:

$$P_k = \frac{exp(V_k + \beta_{PS} * ln(PS_k))}{\sum_{l \in C} exp(V_l + \beta_{PS} * ln(PS_l))} \tag{5}$$

Where PS_k and PS_l are the path sizes of routes k and l, respectively. Parameter β_{PS} is to be estimated. Although the PSL due to its closed form is used often in route choice modelling, the model is limited by only

[3]Disclaimer: We want to emphasize that we do not use the SI in its full account. We use a simplified SI where we consider those travellers with a SI of 1 as habitual and those with a SI lower than 1 as non-habitual due to our short period of analysis. Nevertheless, Kim et al. (2017) does address the use of their analytical framework in changing urban design and how it affects travel behaviour.

capturing part of the correlation among route alternatives. Nevertheless, its interpretation and relative ease of use make it a preferable model to account for route overlap among alternatives.

The correction term can be specified in various overlapping elements, such as nodes or services (Hoogendoorn-Lanser et al., 2005). In this research, overlap will be accounted for on stop level. In practice, this means that routes that share the same stop for a given trip in a route share a commonality and thus are overlapping. Dixit et al. (2021) investigated various elements for route overlap and found that stops or legs (defined as a pair of stops served by the same mode) yield substantially better results than travel time or link length. This can be explained by the difference in service attributes (e.g. comfort, capacity) associated with a transport service even though travel time between the two services is similar. The Path-Size Factor (PSF) on stop level (Tomhave and Khani, 2022) is formulated as follows:

$$PSF_{i,n} = \sum_{s \in \Gamma_i} \frac{1}{N_i} ln(\sum_{j \in C_n} \delta_{s,j}) \tag{6}$$

where $PSF_{i,n}$ is the Path-Size Factor for route *i* and person *n*, Γ_i is the set of all stops for route *i*, N_i total number of stops served by path *i*, C_n is the choice set of person *n* and δ is 1 if stop *s* is on path *j*, 0 otherwise.

4.4 Model specification

We use the Random-Utility Maximisation (RUM) paradigm, where it is assumed that given a subjective choice set for each individual *n*, the probability *P* that the individual chooses alternative *i* from choice set C_n is given by:

$$P_n(i) = Pr(U_{in} \geq U_{jn} \forall j \in C_n) \tag{7}$$

Where *U* is the utility function which comprises a deterministic component and a random error component. The deterministic component is of linear additive form and consists of observable attributes and taste parameters for each attribute. The error component is identically and independently distributed (iid).

In this research, three route discrete choice models are estimated based on MNL. Model 1 is a MNL model without inertia effects and is used as a comparison for our inertia model. Model 2 is a MNL model with a dummy variable for L6 and an extension of model 1. It reflects how both segments, habitual and non-habitual travellers, in the sample perceive L6. Model 3 is an extension of model 2 and includes an interaction effect of L6 with SI indicator, which is the additional effect for L6 when travellers are classified as habitual. The SI in this research context is a binary classification and distinguishes between travellers who make repetitive choices (high SI) within a given OD pair and travellers who choose multiple routes (low SI) within a given OD pair. By including the SI indicator, we hypothesize that those travellers classified as habitual prior-L6 are less willing to use L6 after it becomes available.

For the choice model estimation sample, it is important that the data post-L6 is filtered with travellers for whom we estimated the SI prior-L6. Estimation of the three models is done using PandasBiogeme (Bierlaire, 2018) package.

4.4.1 Model 1: MNL model

Formula 8 shows the deterministic part of utility for model 1 without inertia effects. The attributes for the route DCM are in-vehicle time for bus (IVTB) and metro (IVTM), waiting time at transfers (WT), transfer type bus to metro (TBM), transfer type metro to bus (TMB), transfer type bus to bus (TBB), PSF and mode-specific constant (MSC) for bus and metro. Waiting time component has the elements: waiting time, walking time between transfers and transfer time. Several model specifications were tested and found that by including transfer type metro to metro led to positive parameter estimate for metro in-vehicle time which resulted in implications for demand estimations. Therefore, the transfer type metro to metro was left out of the model specification. The mode-specific constant metro is fixed at zero, this led to slightly better model fit and parameter estimates as compared to keeping mode-specific constant bus fixed at zero. Travel costs were not included in the specification due to the almost flat fare in the Santiago public transport system. The parameters β are to be estimated.

$$\begin{aligned} V = \beta_{bus,TT} * TT_{bus} + \beta_{metro,TT} * TT_{metro} + \\ \beta_{WT} * WT + \beta_{Transfer_{busbus}} * Transfer_{busbus} + \\ \beta_{Transfer_{busmetro}} * Transfer_{busmetro} + \\ \beta_{Transfer_{metrobus}} * Transfer_{metrobus} + \\ \beta_{Transfer_{metrometro}} * Transfer_{metrometro} + \beta_{PSF} * PSF + \\ \beta_{MSC_{bus}} * MSC_{bus} + \beta_{MSC_{metro}} * MSC_{metro} \end{aligned} \tag{8}$$

4.4.2 Model 2: MNL model with L6 dummy variable

Model 2 is an extension of model 1 and includes a dummy variable for L6. The dummy variable is 1 for alternatives with L6 and 0 for alternatives without L6. By including this variable, we want to investigate how everyone in the sample perceives L6 and can be considered the baseline for the inertia model.

4.4.3 Model 3: MNL model with inertia effects

Formula 9 shows the deterministic part of utility for our main model with inertia effects. Model 3 is an extension of model 2, by including an interaction effect of SI with L6. The SI indicator is 1 for travellers classified as habitual prior-L6 and 0 for travellers classified as non-habitual prior-L6. The interaction effect reflects the additional effect for L6 and only applies to habitual travellers. The parameters β_{L6} and $\beta_{stickinessL6}$ are to be estimated.

$$V = \beta_{bus,TT} * TT_{bus} + \beta_{metro,TT} * TT_{metro} + \beta_{WT} * WT + \beta_{Transfer_{busbus}} * Transfer_{busbus} + \beta_{Transfer_{busmetro}} * Transfer_{busmetro} + \beta_{Transfer_{metrobus}} * Transfer_{metrobus} + \beta_{Transfer_{metrometro}} * Transfer_{metrometro} + \beta_{PSF} * PSF + \beta_{MSC_{bus}} * MSC_{bus} + \beta_{MSC_{metro}} * MSC_{metro} + \beta_{L6} * L6 + \beta_{stickinessL6} * L6 * SI \quad (9)$$

4.5 Validation and market share prediction of L6

DCMs remain a powerful tool for demand estimation for new services or products (Chorus, 2012). To estimate the demand for L6, we include a L6 indicator for those alternatives with L6. This is necessary since unlabelled route alternatives were used in the DCMs. To validate our models for their prediction power, we use the approach of hold-out validation. This approach splits the full sample randomly into two non-overlapping parts where 80% is the estimation sample and 20% is the validation sample. To test whether our models are generic, it is a good approach to test the models on unseen data (validation sample).

We use the estimations from the estimation sample and predict the market share for L6 on the validation sample. Since we are using RP data, we are able to use the numeric values of the sample to predict shares for L6. The demand per OD pair for L6 becomes:

$$W_{OD} = N_{OD} * \sum_{n=1}^{N_{OD}} P_n(i|x_n, C_n, dummy_{L6}) \quad (10)$$

Where W_{OD} is the demand of L6 for a given OD pair, N_{OD} number of travellers for a given OD pair, P_n probability that individual n chooses alternative i conditional on attribute values x_n, choice set C_n and dummy variable L6. By aggregating the shares of L6 over the entire set of OD pairs, we gain insight into the prediction power of the three models when compared with the observed. To assess the accuracy of the prediction power, a False Positive Rate (FPR) analysis is conducted on the models.

5 Results

5.1 Results Stickiness Index estimation

5.1.1 Traveller-level SI

Figure 4 shows the distribution of the SI estimation for values smaller than 1. Within the sample of 13.618 unique traveller-OD (i,k) pairs observed, a total of 3661 traveller-OD have a SI smaller than 1. In other words, 27% of the sample choose at least two different routes to travel within a given OD pair. Assuming the week of analysis is a normal week with no drastic changes to the network, the large number of travellers with a SI of 1 can be explained due to the threshold of 3 journeys and that people who travel between the same origin and destination usually commute to school or work. These daily activities are usually associated with habitual behaviour (Aarts et al., 1998). Figure 4 as well shows that the three largest SI values are 0, 0.11 and 0.25. We explain these SI values using the case when 3 routes are available within a given OD pair. In the case of SI is 0, all journeys made by a traveller are distributed equally among their routes used. If SI is 0.11, a traveller makes two journeys with a single route and one journey with a different route. Lastly, if SI is 0.25, we observe that a traveller repeats three journeys with a single route and one journey with a different route. Table 2 shows the mean, std. dev, min and max of the SI estimation.

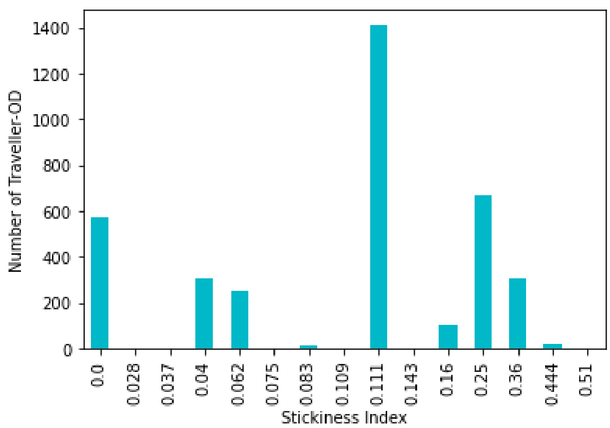


Figure 4: *Distribution of SI values smaller than 1 (threshold 3 journeys)*

Table 2: *Estimation Stickiness-Index traveller-level*

# Traveller-OD	Mean	Std. Dev.	Min	Max
13,618	0.767	0.388	0	1

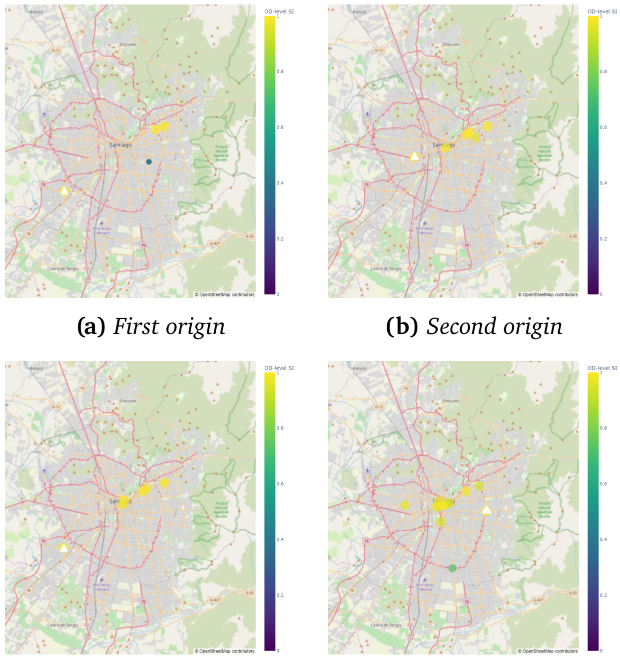
5.1.2 OD-level SI

Figure 5 and Figure 6 show the spatial distribution of the four largest origins and destinations, respectively. The selection of these OD pairs has been determined by the largest number of individuals travelling between them. The four largest origins and destinations are marked with a white triangle while their respective destinations (for given origin) and respective origins (for given destination) are marked with circles.

The difference in OD-level SI can be explained by travel behaviour and network service. From a travel behaviour point of view, an OD pair that includes large number of home-work behaviour may exhibit a higher level of average OD-level SI as opposed to an OD pair with more variation in travel behaviour type. The network service can also be an explanatory factor for the spatial differences among OD pairs. If we assume that travellers choose the alternative with the highest frequency, an OD pair with a reliable transport service and high frequency may lead to a higher average SI. Conversely, an OD pair with less variation among alternatives in terms of frequency may lead to a lower average SI (Durán-Hormazábal and Tirachini, 2016).

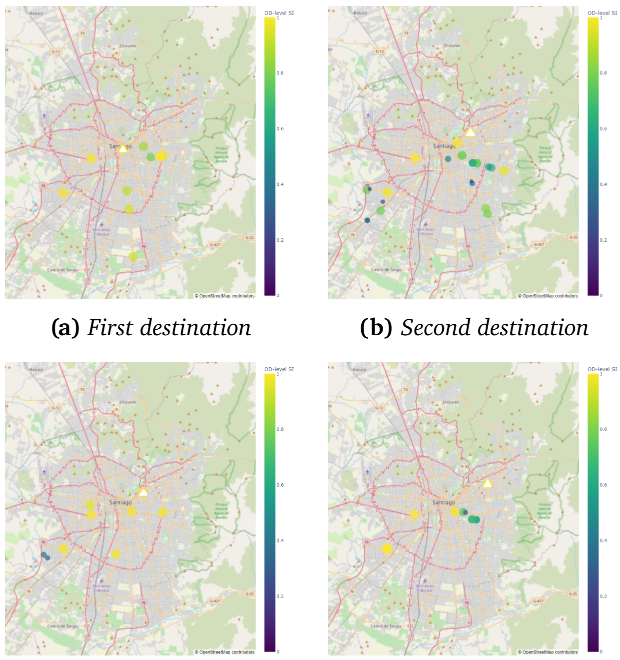
Figure 5 shows the four largest origins (white triangle) and their respective destinations. There is little variation among OD pairs in terms of average SI. We speculate that these origins are dominated by home-work behaviour as these origins lie further away from the city centre and their destinations are located in the centre. We also observe that the average SI per OD pair is relatively high, which can be explained by home-work behaviour as people are usually habitual due to repetitive daily activity.

Figure 6 shows the four largest destinations and their respective origins. Here more variation among the OD pairs in terms of average SI is observed. We speculate that since the destinations are located in the city centre, travel behaviour activity might be more diverse such as leisure or work.



(a) *First origin* **(b)** *Second origin* **(c)** *Third origin* **(d)** *Fourth origin*

Figure 5: *Geographical distribution of OD-level Stickiness-Index. Four largest origins are represented and their destinations (origins and destinations can be either metro station or bus stop)*



(a) *First destination* **(b)** *Second destination* **(c)** *Third destination* **(d)** *Fourth destination*

Figure 6: *Geographical distribution of OD-level Stickiness-Index. Four largest destinations are represented and their origins (origin or destination can be either metro station or bus stop)*

5.2 Results discrete choice analysis

Table 3 shows the minimum, maximum and mean values for each attribute considered in our choice models. The sample for estimation has 11.245 traveller-OD pairs. The average choice for an OD pair is 3.47 routes. It is important to note that for the minimum attribute values of in-vehicle time, route alternatives may comprise a single mode of transportation, hence why the minimum in-vehicle time for either bus or metro can be zero for a given choice set.

5.2.1 MNL model

Table 4 presents the results of the estimation of our models. Included are: the estimated parameters, number of observations, final log-likelihood, rho-square bar, AIC and BIC. All parameters that have been estimated are significant at $p < 0.05$ level, as can be seen from the t-ratio which is presented in paren-

Table 3: *Statistics of attributes used in MNL and MNL with inertia models*

Attribute description	Min	Max	Mean
Metro travel time	1.35	53.28	25.94
Bus travel time	1.45	93.56	18.87
Waiting time at transfers	0	89.4	3.72
PSF	-1.95	0	-0.42
Transfer bus to bus	0	2	0.0146
Transfer metro to bus	0	1	0.076
Transfer bus to metro	0	1	0.32
Transfers total	0	3	0.82
Bus dummy	0	1	0.58
Metro dummy	0	1	0.816

Waiting time = waiting time, walking time and transfer time

theses.

The model estimated a negative parameter for the PSF with a magnitude of -0.734. The magnitude of the PSF parameter is in line with Tomhave and Khani (2022) who defined the PSF based on stop overlap and found values for PSF between -0.6 and -0.7. Other research on multimodal public transport networks found magnitudes of -0.7 (Anderson et al., 2017).

The MSC reveals there is a preference among the sample towards the metro relative to the bus, which is in line with other studies on multimodal network route choice (Dixit et al., 2021). Different types of transfers are estimated and all three are negative as expected. Transfer type bus to metro is considered as less disutility as transfer type metro to bus. Buses are more irregular in frequencies and have a larger travel time variability (Durán-Hormazábal and Tirachini, 2016). Additionally, the mode-specific constants show a preference for the metro over the bus. The transfer type that is disliked the most is bus to bus. These findings are in line with earlier research on public transport route choice in Santiago (Arriagada et al., 2022).

Waiting time is negative with a value of -0.357. This tells us that increased waiting time is associated with a decrease in utility of the route alternative. Contrary to Arriagada et al. (2022) who estimated a multimodal route choice model in Santiago, our waiting time component comprises of waiting time at transfers, walking time at transfers and transfer time while Arriagada et al. (2022) estimated all three waiting time elements separately. We did test model specifications where waiting time was differentiated, however insignificant parameter estimates were found for the waiting time elements. In-vehicle time for bus is valued more negatively than in-vehicle time for metro. This is contrary to Arriagada et al. (2022) who actually found that IVTM is considered more negative than IVTB which is interesting. Regarding the magnitude, other route choice studies in different multimodal networks found values for in-vehicle time bus ranging from -0.11 to -1.7 (Anderson et al., 2017; Dixit et al., 2021) and metro in-vehicle time ranging from -0.09 to -0.113 (Anderson et al., 2017; Dixit et al., 2021)

5.2.2 MNL model with L6

All estimated parameters for model 2 are significant at $p < 0.05$ level and have expected signs. The MNL model with L6 shows an improvement in model fit when compared to model 1. The increase in final log-likelihood from -9400 to -8975 is substantial. The Likelihood Ratio Test (LRS) shows a value of 850.52, which exceeds the chi-square value of 6.635 at 1% significance level with one degree of freedom. When assessing the differences with model 1, the dislike for IVTM, waiting time and PSF has decreased. It is interesting that the PSF has decreased considerably from -0.734 to -0.387. We estimated a model specification with an interaction effect of SI with PSF and found the effect to be significant and positive. This reveals the marginal utility for PSF is comparatively smaller when travellers are habitual than others. This means that habitual travellers prefer distinct routes over overlapping routes when we include L6 as opposed to other travellers. A possible explanation can be that habitual travellers prefer distinct routes over the robustness of the network if L6 is included. The parameter for IVTM turned out to be less negative, possibly indicating that people prefer longer metro travel times as they avoid L6.

5.2.3 MNL model with inertia effects

The parameter estimations for model 3 are all significant at $p < 0.05$ level. Including the inertia effect shows a small improvement in model fit when compared to model 2. Final log-likelihood shows a small increase from -8975 to -8900. The core parameters, L6 and inertia effect, are both negative and significant. This is in line with earlier studies on inertia effects in public transport networks (Cherchi and Cirillo, 2010; González et al., 2017). More importantly, the interaction effect is negative which indicates that the marginal utility for L6 is comparatively larger when travellers are classified as habitual prior-L6 than others. This finding confirms there is indeed an additional inertia effect for L6 when we account for habitual travellers.

Table 5 presents the rates of substitution (RS) in order to understand the trade-off in utility by travellers. For all three models, we determined the RS of each attribute with respect to bus in-vehicle time which was set to 1. For model 2 and 3, we also present the rates of substitution for L6 and inertia effect against metro in-vehicle time in parentheses. Compared to other earlier research on inertia effects in travel behaviour,

Table 4: *Estimates MNL model, MNL baseline model and MNL with inertia model*

Description	Model 1 (MNL)	Model 2 (L6)	Model 3 (Inertia)
Metro in-vehicle time	-0.177 (-5.41)	-0.0945 (-2.77)	-0.095 (-2.71)
Bus in-vehicle time	-0.265 (-9.57)	-0.286 (-10.2)	-0.263 (-9.21)
Waiting time	-0.357 (-9.32)	-0.349 (-9.17)	-0.328 (-8.68)
Mode-specific constant for metro (fixed)	0	0	0
Mode-specific constant for bus	-2.52 (-24.3)	-2.35 (-24.4)	-2.57 (-25.2)
Transfer bus to bus	-1.34 (-14.9)	-1.35 (-15)	-1.37 (-15.1)
Transfer bus to metro	-0.636 (-9.38)	-0.7 (-10.8)	-0.727 (-11)
Transfer metro to bus	-1.08 (-8.68)	-0.947 (-6.9)	-0.943 (-6.87)
Path-Size correction	-0.734 (-10.6)	-0.387 (-5.18)	-0.492 (-6.49)
L6	-	-1.64 (-20.5)	-1.05 (-11.9)
Stickiness * L6	-	-	-1.5 (-9.09)
Number of observations	11245	11245	11245
Final Log-Likelihood	-9401.18	-8975.092	-8900.279
Rho-square bar	0.281	0.314	0.32
AIC	18818.36	17968.18	17820.56
BIC	18876.98	18034.13	17893.83
LRS (Against MNL)	-	850.52	1001.82

Table 5: *Rates of substitution model estimates (with respect to bus in-vehicle time)*

Description	Model 1 (MNL)	Model 2 (L6)	Model 3 (Inertia)
Metro in-vehicle time	0.66	0.33	0.36
Bus in-vehicle time	1	1	1
Waiting time	1.34	1.22	1.24
Transfer bus to bus	5.05	4.72	5.2
Transfer bus to metro	2.4	2.44	2.76
Transfer metro to bus	4.07	3.31	3.58
L6	-	5.73 (17.35)	3.99 (11.05)
Stickiness * L6	-	-	5.7 (15.78)

González et al. (2017) found RS for inertia effect of car compared to in-vehicle time bus-tram of 2.8 minutes.

5.3 Sensitivity analysis to minimum number of journeys

Table 6 presents the findings of the sensitivity analysis of the inertia effect on the minimum number of journeys for travellers to be included within the estimation sample. As mentioned earlier, we impose two requirements for the sample of SI and DCM estimation. We included travellers who only make a minimum of three journeys and included OD pairs with a minimum of 10 individuals travelling within a given OD pair.

We assume a traveller is habitual if they repeat choices within a given OD pair. But there is a differ-

Table 6: *Model sensitivity to journey threshold*

Description	2	3	4
Bus in-vehicle time	1	1	1
L6	1.93	3.99	32.89
Stickiness * L6	1.58	5.70	55.78
# observations	23132	11245	4367
Parameters	10	10	10
LRS*	1377.44	1001.82	271.2
Rho-square	0.239	0.32	0.45

Note: parameter estimates for bus in-vehicle time was not significant at $p < 0.05$ level for model with minimum of 4 journeys
* LRS against respective base MNL

ence if someone is considered as habitual if they have to make a minimum of 2 journeys versus someone who has to make a minimum of 4 journeys. In the former case, a person might repeat choices out of sporadic behaviour and is not habitual in reality. Thus we might expect a mixture of people within the habitual sample. In the latter case, it is more likely a person is habitual if they repeat 4 journeys. Based on this reasoning, we hypothesize that the larger the threshold, the more likely a person is habitual and thus leading to a greater inertia effect.

Model 3 is estimated using a threshold of 2,3 and 4 journeys. For all three models, a significant inertia effect is estimated. Table 6 presents the rates of substitution with respect to in-vehicle time bus which was set to 1. We observe that the marginal utility for L6 is comparatively larger when travellers are habitual than others for all three thresholds. However, we see that the marginal rates of substitution become larger as the threshold increases. We did find complications for model estimations when the threshold was set to 4 journeys as other parameters became insignificant. This confirmed our belief that the threshold with 3 journeys led to best model estimates and higher thresholds led to a relatively small sample. Further empirical research is needed to confirm the change in rates of substitution with respect to the minimum number of journeys.

Increasing the threshold of a minimum number of travellers for OD pairs to be valid was also tested, such as 100 and 250 travellers. Unfortunately, this did not lead to meaningful results in the model estimations.

5.4 Results predictions market share for L6

Table 7 presents the predicted average shares for L6 on the validation sample. The hold-out validation approach was repeated five times to eliminate the role of randomness when the sample is split randomly into an estimation and validation sample. The average was taken for further analysis. An average of 119 journeys were observed that used L6. For model 1 (MNL), the results show roughly 179 journeys with L6, which is 8% of the total sample. Comparing the prediction of the MNL with observed, the journeys with L6 were overestimated by roughly 50%. The shares for L6 of model 2 and model 3 are 144 and 140, respectively.

The aggregated average predictions give us an initial indication of the prediction power of the models but do not reveal the prediction accuracy of the models. For this reason, a FPR analysis is conducted to reveal how many journeys with L6 are actually predicted by the model and how many journeys are explained by not using L6. Table 8 shows measures of the FPR analysis to assess the prediction power of the models. These measures include true positives (TP), true negatives (TN), false positives (FP), false negatives (FN), accuracy (ACC), sensitivity (SENS), specificity (SPEC) and FPR. Additionally, the average final log-likelihood is presented.

Sensitivity quantifies that if the journey actually includes L6, how often does the model predict the journey with L6. The MNL model with inertia has a value of 0.83[4] and outperforms the MNL model substantially, while the difference with MNL model with L6 is marginally better. The FPR quantifies that when the journey is actually *without* L6, how often the model predicts the journey is with L6. The MNL model with FPR of 0.57 indicates that in practice if 1000 journeys are observed, 57 of those journeys are predicted with L6 while they actually are not. We see that the MNL with inertia performs better on this measure compared to the MNL model. Furthermore, accuracy of all three models is relatively high indicating that the accuracy of predicting journeys with L6 and without L6 is high.

The aggregated prediction in combination with the FPR analysis reveal that not accounting for inertia effects in route choice models when travellers face a new transport alternative leads to implications for demand estimation. The MNL model without inertia effects overestimates shares for L6 considerably. These findings are in line with earlier research on inertia effects, who supported the significance of accounting for inertia effects in choice models if inertia exists (Cherchi and Manca, 2011; González et al., 2017) and the implications for demand estimations (Chatterjee, 2011).

6 Discussion

Regarding the *Stickiness Index* estimation outcomes, this study found that within the SI sample, roughly 70% are habitual. The mean SI value was also found higher than the outcomes obtained by Kim et al. (2017) in their study. However, they considered only travellers who used at least two different routes in order to identify their choice set. Another main difference is that their period of analysis is 6 months which most likely captures more variability in travel behaviour and leading to a lower mean SI value. The number of habitual travellers (high SI) in this research may be overestimated and subject to bias to a single week. In the case travellers in Santiago would be observed over a longer period of analysis (e.g. months), we would expect the mean value for SI to decrease. People would be subject to disruptions or network operations that have effect on their route choice behaviour. We would adjust the definition of habitual travellers if larger number of journeys was observed. It would be unreasonable to assume a traveller is only habitual if every journey was repeated over a long period of time and not to take into account for instance network incidents which can influence the route choice behaviour. Furthermore,

[4] Score between 0 and 1. The higher the better

Table 7: *Average predictions for journeys with L6 and journeys without L6: MNL, MNL with L6 and MNL with Inertia (20% entire sample). Also distinction between whether traveller is habitual (SI = 1) or non-habitual (SI = 0)*

Description	Observed	MNL	MNL with L6	MNL with Inertia
L6 = 0 | SI = 0	734.2	669.2298	697.2	706.7
L6 = 0 | SI = 1	1395.8	1370.152	1407.448	1402.5
L6 = 1 | SI = 0	69	107.522	78.1	93.15
L6 = 1 | SI = 1	50	72.1	66.353	46.83

Table 8: *FPR analysis and average final log-likelihood on validation sample*

Model	TP	TN	FP	FN	ACC	SENS	SPEC	FPR	Average LL
MNL	58.38	2008.7	121.3	60.6	0.91	0.49	0.94	0.057	-1868
MNL with L6	93.6	2079.3	50.72	25.36	0.966	0.78	0.976	0.0238	-1781.9
MNL with Inertia	98.01	2088.03	41.97	20.98	0.97	0.83	0.98	0.019	-1764.5

Number of observations is 2249

a period of months would allow observing habitual behavior that conforms to a weekly rhythm instead of a daily one. For a given OD pair, an individual may exhibit varying route preferences within a given week. However, if this pattern recurs every week, the question arises as to whether the behavior in question constitutes variety-seeking or habitual behaviour.

The route choice model estimates overall show credible relationships. We particularly want to highlight the PSF, in-vehicle times and the inertia effects. The PSF is initially expected to be positive, since the overlap of route alternatives reduces the utility of these competing alternatives. Contrary, negative estimates were found which was also found in earlier studies in multimodal route choice studies (Anderson et al., 2017; Dixit et al., 2021). In case of a multimodal network, a negative parameter suggests that travellers actually prefer route overlap between competing alternatives over distinct routes. It is not uncommon for public transport networks to have delays and disruptions, the overlap in route alternatives offers travellers the opportunity to have other travel options available en-route.

The in-vehicle time for metro is preferred over in-vehicle time bus in this research. This differs from earlier route choice studies in Santiago. Arriagada et al. (2022) who studied route choice heterogeneity in Santiago actually found the reverse to be the case. While Arriagada et al. (2022) acknowledge the positives of the metro such as high frequency and reliable service as opposed to bus, they argue that the significant crowding levels in the metro network of Santiago contribute to the larger dislike for metro in-vehicle time as opposed to bus in-vehicle time in their study. It is important to note that our estimation is based on a sample in the week after L6 opened within the set of OD pairs where L6 is part of an alternative. The new L6 was accompanied by offering real-time information on waiting times and capacity per wagon in order for travellers to better distribute over the vehicles and platforms (Sice, 2018). It is also difficult to confirm whether crowding levels right after opening were just as high as during normal operations and within the entire metro network. To add, Pineda and Lira (2019) conducted research on the effect of L6 on travel time savings and found crowding levels not be perceived as high by travellers during the period of April 2018.

The parameter for the inertia effect was found to be negative and significant, this is in line with earlier studies on the effect of inertia on travel behaviour (Cherchi and Manca, 2011; González et al., 2017; Vacca et al., 2019). Although other studies defined the inertia effect differently and used in a different context, the interpretation of the effect is similar as the resistance to change. Regarding the marginal rates of substitution (MRS), comparing to studies with a joint RP/SP data set, Cantillo et al. (2007) and González et al. (2017) found much lower values for the inertia effect represented as travel time. The inertia effect was found to represent roughly 4.7 minutes of travel time by Cantillo et al. (2007). Our study found that by accounting for inertia effects, the effect was considered to represent roughly 10 minutes of bus in-vehicle time. The lower values in the mode choice RP/SP study can be subject to biases inherent in SP studies and overestimate the mean of the inertia effect in RP/SP studies (Cantillo et al., 2007). The SP study by Gao and Sun (2018) found the MRS of inertia effect for metro with respect to average travel time to be a reduction of roughly 9.7 minutes. Compared to this study, the additional inertia effect for L6 was up to 16 minutes with respect to the marginal utility of metro in-vehicle time. Based on these comparisons, our study based on entirely RP data found much higher values of MRS for the inertia effect compared to the in-vehicle times.

If revealed preference data is available, our approach of quantifying habitual behaviour in a stable condition and using the habitual indicator in the choice model makes our method relatively simple to use compared to other studies that define the inertia effect as a weighted average (Swait et al., 2004) or valuation of previous choices with the current choice (Cantillo et al., 2007). Additionally, the use of RP data based on smart card observations has it advantage that actual choices are observed. Regarding practicality, constructing, preparing and handing out stated preference (SP) surveys which is the case in joint RP/SP studies are time consuming. However, it is not always easy in practice to collect RP data based on smart card observations.

7 Conclusions

The research aim was to investigate the inertia effects in multimodal route choice when travellers face a new metro line. As a case study, we used the public transport network of Santiago and used a fully revealed preference data set surrounding the opening of metro Line 6. Our approach to tackle the research objective was done by first quantifying habitual route choice behaviour using the method of *Stickiness Index* prior-L6 when the conditions were stable. We then used a simplified SI as an indicator for inertia in the route discrete choice model. We assumed as traveller is habitual if their SI is 1 and non-habitual if their SI was lower than 1. This binary classification allowed us to hypothesize that habitual travellers were less willing to use L6 as opposed to others.

We found that the inertia effect is significant and negative. The effect indicates that the marginal utility for L6 is comparatively larger when travellers are classified as habitual than others. Furthermore, using the FPR analysis showed that not accounting for inertia effects when repetitive behaviour exists, has implications for demand estimations. The models with inertia effects showed that they were able to more accurately predict journeys with the new transport alternative due to inertia effects than the traditional route discrete choice model without inertia effects.

This study does come with its limitations. As this research was carried out specifically for the case of Santiago, the empirical results are limited to this city. The methodology should be extended to other public transport networks as well in order to validate the effect and magnitude of the inertia parameter. We also consider the period of analysis to be a limitation of this study. Due to the period of one week, we assumed a traveller is only habitual if all journeys were repeated. A longer period of analysis would allow capturing variability in travel behaviour (Gärling and Axhausen, 2003). A person may be considered non-habitual for a given week, but if this pattern repeats, the question arises whether the classification in this context is still true for a given individual.

As for future research, it is most likely that the inertia effect varies across individuals. Therefore possible research directions include capturing unobserved heterogeneity for the inertia effect. If more revealed preference data is available extending over a longer period of time, it would be interesting to also capture time dynamics of the inertia effect and how the effect for a new transport alternative changes over time.

References

Aarts, H., Verplanken, B., & Van Knippenberg, A. (1998). Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of applied social psychology*, *28*(15), 1355–1374.

Adamowicz, W. L. (1994). Habit formation and variety seeking in a discrete choice model of recreation demand. *Journal of Agricultural and Resource Economics*, 19–31.

Anderson, M. K., Nielsen, O. A., & Prato, C. G. (2017). Multimodal route choice models of public transport passengers in the greater copenhagen area. *EURO Journal on Transportation and Logistics*, *6*(3), 221–245.

Arriagada, J., Munizaga, M. A., Guevara, C. A., & Prato, C. (2022). Unveiling route choice strategy heterogeneity from smart card data in a large-scale public transport network. *Transportation Research Part C: Emerging Technologies*, *134*, 103467.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In *Handbook of transportation science* (pp. 5–33). Springer.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D. S., et al. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters*, *13*(3), 163–175.

Bierlaire, M. (2018). Pandasbiogeme: A short introduction. *EPFL (Transport and Mobility Laboratory, ENAC)*.

Bogers, E. A., Bierlaire, M., & Hoogendoorn, S. P. (2007). Modeling learning in route choice. *Transportation Research Record*, *2014*(1), 1–8.

Cantillo, V., Ortuzar, J. d. D., & Williams, H. C. (2007). Modeling discrete choices in the presence of inertia and serial correlation. *Transportation Science*, *41*(2), 195–205.

Chatterjee, K. (2011). Modelling the dynamics of bus use in a changing travel environment using panel data. *Transportation*, *38*, 487–509.

Cherchi, E., & Cirillo, C. (2010). Validation and forecasts in models estimated from multiday travel survey. *Transportation research record*, *2175*(1), 57–64.

Cherchi, E., & Manca, F. (2011). Accounting for inertia in modal choices: Some new evidence using a rp/sp dataset. *Transportation*, *38*(4), 679–695.

Chorus, C. G. (2012). Random regret-based discrete choice modeling: A tutorial.

Chorus, C. G., & Dellaert, B. G. (2012). Travel choice inertia: The joint role of risk aversion and learning. *Journal of Transport Economics and Policy (JTEP)*, *46*(1), 139–155.

Di, X., & Liu, H. X. (2016). Boundedly rational route choice behavior: A review of models and methodologies. *Transportation Research Part B: Methodological*, *85*, 142–179.

Dixit, M., Cats, O., Brands, T., van Oort, N., & Hoogendoorn, S. (2021). Perception of overlap in multi-modal urban transit route choice. *Transportmetrica A: Transport Science*, 1–23.

Durán-Hormazábal, E., & Tirachini, A. (2016). Estimation of travel time variability for cars, buses, metro and door-to-door public transport trips in santiago, chile. *Research in Transportation Economics*, *59*, 26–39.

Gao, K., Shao, M., Axhausen, K. W., Sun, L., Tu, H., & Wang, Y. (2021). Inertia effects of past behavior in commuting modal shift behavior: Interactions, variations and implications for demand estimation. *Transportation*, 1–35.

Gao, K., & Sun, L. (2018). Incorporating inertia in mode choice and influential factors of car stickiness: Implications for shifts to public transit. *Promet-Traffic&Transportation*, *30*(3), 293–303.

Gärling, T., & Axhausen, K. W. (2003). Introduction: Habitual travel choice. *Transportation*, *30*(1), 1–11.

González, R. M., Marrero, Á. S., & Cherchi, E. (2017). Testing for inertia effect when a new tram is implemented. *Transportation Research Part A: Policy and Practice*, *98*, 150–159.

Hoogendoorn-Lanser, S., van Nes, R., & Bovy, P. (2005). Path size modeling in multimodal route choice analysis. *Transportation research record*, *1921*(1), 27–34.

Jánošíková, L., Slavík, J., & Kohání, M. (2014). Estimation of a route choice model for urban public transport using smart card data. *Transportation planning and technology*, *37*(7), 638–648.

Kahneman, D. (2017). Thinking, fast and slow.

Kim, J., Corcoran, J., & Papamanolis, M. (2017). Route choice stickiness of public transport passengers: Measuring habitual bus ridership behaviour using smart card data. *Transportation Research Part C: Emerging Technologies*, *83*, 146–164.

Manski, C. F. (1977). The structure of random utility models. *Theory and decision*, *8*(3), 229.

Morikawa, T. (1994). Correcting state dependence and serial correlation in the rp/sp combined estimation method. *Transportation*, *21*(2), 153–165.

Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological bulletin*, *124*(1), 54.

Pineda, C., & Lira, B. M. (2019). Travel time savings perception and well-being through public transport projects: The case of metro de santiago. *Urban Science*, *3*(1), 35.

Prato, C. G. (2009). Route choice modeling: Past, present and future research directions. *Journal of choice modelling*, *2*(1), 65–100.

Sice. (2018). Sice improves the users' travel experience in metro line 6 in santiago de chile. https://www.sice.com/en/news/sice-improves-the-users-travel-experience-in-metro-line-6-in-santiago-de-chile

Swait, J., Adamowicz, W., & van Bueren, M. (2004). Choice and temporal welfare impacts: Incorporating history into discrete choice models. *Journal of Environmental Economics and Management*, *47*(1), 94–116.

Tan, R., Adnan, M., Lee, D.-H., & Ben-Akiva, M. E. (2015). New path size formulation in path size logit for route choice modeling in public transport networks. *Transportation Research Record*, *2538*(1), 11–18.

Thøgersen, J. (2006). Understanding repetitive travel mode choices in a stable context: A panel study approach. *Transportation Research Part A: Policy and Practice*, *40*(8), 621–638.

Tomhave, B. J., & Khani, A. (2022). Refined choice set generation and the investigation of multi-criteria transit route choice behavior. *Transportation Research Part A: Policy and Practice*, *155*, 484–500.

Vacca, A., Prato, C. G., & Meloni, I. (2019). Should i stay or should i go? investigating route switching behavior from revealed preferences data. *Transportation*, *46*(1), 75–93.

Verplanken, B., Aarts, H., & Van Knippenberg, A. (1997). Habit, information acquisition, and the process of making travel mode choices. *European journal of social psychology*, *27*(5), 539–560.

Verplanken, B., & Orbell, S. (2003). Reflections on past behavior: A self-report index of habit strength 1. *Journal of applied social psychology*, *33*(6), 1313–1330.

Wood, W., & Rünger, D. (2016). Psychology of habit. *Annual review of psychology*, *67*(1), 289–314.

Yáñez, M. F., Cherchi, E., Ortúzar, J.-D., & Heydecker, B. G. (2009). Inertia and shock effects on mode choice panel data: Implications of the transantiago implementation.