HABIT AND SHOCK EFFECTS IN PUBLIC TRANSPORT: THE CASE OF METRO LINE 6 IN SANTIAGO USING SMART CARD DATA

Jesper Bláfoss Ingvardson, Sebastián Raveau[2] and Jaime Soza-Parra[3]

jbin@dtu.dk
Transport Division, DTU Management, Technical University of Denmark, Kgs. Lyngby, Denmark.

sraveau@ing.puc.cl
Department of Transport and Logistics, Pontificia Universidad Católica de Chile, Santiago, Chile.

j.a.sozaparra@uu.nl
Human Geography & Spatial Planning Department, Utrecht University, Utrecht, the Netherlands

ABSTRACT

Traditional traffic forecasting previously relied solely on characteristics related to the services and the users. Recent research has highlighted the importance of also considering psychological factors of the travellers when explaining travel behaviour. While previous studies have incorporated the role of habits in travel choice behaviour, only a few have analysed the role of habit and shock in relation to major changes to the transport network. This study contributes to previous literature by revealing the changes in behaviour of public transport passengers over time after the inauguration of a new metro line in Santiago, Chile, using large-scale RP data from Automated Fare Collection systems. Through estimating a heteroskedastic mixed latent class public transport mode choice model, the study explicitly analyses the consequences of the new metro on passenger behaviour considering different passenger types. The model incorporates both inertia effects resulting from habitual behaviour and shock effects resulting from the large change to the public transport network. The results confirm significant habitual behaviour among passengers where metro users tend to stick to using metro whereas bus users tend to switch to other modes. However, after the introduction of the new metro line a significant shock effect is observed where users have an increased tendency to switch mode, and this effect increases slightly on the longer term. The results highlight the importance of incorporating habitual effects in behavioural studies.

Keywords: Discrete choice modelling, public transport, mode choice, smart card data

1. INTRODUCCIÓN

Public transport systems are important in ensuring sustainable mobility in dense urban areas. Increasing levels of urbanisation puts pressure on urban transport networks, which therefore requires extensive investments to ensure sufficient capacity and level-of-service. To ensure sufficient mobility an attractive public transport system is necessary. By offering much higher capacity public transport not only ensures mobility for a range of users, but also relieves road congestion representing significant socio-economic value for urban areas (Aftabuzzaman *et al*., 2010). However, implementing public transport systems is expensive, and thus it is important to plan coherently to consider the potential impacts of new infrastructure.

Traditionally, traffic forecasting models incorporated solely characteristics related to the improved services. Nevertheless, much research has highlighted the importance of also considering psychological factors of the travellers such as habits, e.g. Gärling and Axhausen (2003), Schlich and Axhausen (2003). Recently, the role of habits has also been incorporated in several mode choice studies through inclusion of inertia with studies suggesting that serious errors occur if not accounting for inertia (Cantillo *et al*., 2007) since inertia increases when using the same travel mode over time (Cherchi and Cirillo, 2014), which influences mode shifting behaviour, e.g. from car to public transport (Fan *et al*., 2018).

While previous literature has highlighted the importance of considering inertia in transport mode choice models only few studies have analysed inertia and shock effects when implementing new public transport infrastructure. Due to the expensive nature of collecting large-scale Revealed-Preference (RP) data, studies have relied on either Stated-Preference (SP) surveys, despite the potential bias resulting from using SP data (Ben-Akiva and Morikawa, 1990; Cherchi and Manca, 2011; González *et al*., 2017), or restricted samples of RP data in terms of size and composition. Johnson and Hensher (1982) was based on a sample of 163 commuters in the northern suburbs of Sydney, Australia, that either chose car or train for their commute; Ben-Akiva and Morikawa (1990) was based on two surveys of 107 and 428 commuter rail users in Yokohama, Japan; Yáñez *et al*. (2009) collected RP data from 303 workers at specific universities and hospitals; and González *et al*. (2017) used data from 350 students. Hence, there is a gap in research in investigating the role of inertia when implementing new public transport infrastructure using large-scale RP data. With the advancement of Automated Fare Collection (AFC) systems, large-scale RP data is readily available in many cities around the world, but to the knowledge of the authors has yet to be used for this type of analysis.

Thus, this study contributes to existing literature by revealing the change in behaviour of public transport passengers over time after the inauguration of a new metro line in Santiago, Chile. The study is based on large-scale RP data from AFC systems covering one full week before, during and after the opening of the new line. This ensures a large sample, which is not restricted to specific user types or geographical areas. The data allows for estimating mode choice models revealing the mode shifts of users in the public transport system. This will include specific focus on the role of inertia as well as the shock effects after the inauguration of the new metro line. In addition, we will analyse how the new metro has changed usage patterns through clustering analysis of users, thus enabling identification of various user types based on travel frequency and timing to reveal how inertia and shock effects vary across user types. This will provide further insights into how passengers adapt to new public transport infrastructure.

The rest of the paper is organised as follows. Section 2 reviews relevant literature on public transport mode choice in the context of habit and shock effects, implementation of new public transport systems, and relevant case-specific literature. In Section 3 the methodology based on clustering analysis and latent class mode choice modelling is described whereas Section 4 introduces the case study and the data used. Section 5 presents the results and analysis. Section 6 concludes the paper.

2. LITERATURE REVIEW

This section presents the state-of-the-art literature on mode choice modelling in transport that incorporates inertia and shock effects as well as relevant literature for the case study context of this study.

2.1. Inertia and shock effects in transport mode choice modelling

Travel behaviour has long been known to be highly influenced by psychological factors such as habits, in addition to traditional level of service characteristics (Gärling and Axhausen, 2003; Schlich and Axhausen, 2003). Incorporating habits in mode choice models has therefore been focus of many previous studies. In one of the first studies, Johnson and Hensher (1982) analysed a two-wave RP data set and found that car drivers were more likely to continue choosing the car in the second wave irrespective of changes to the remaining variables included in the utility function, hence suggesting effects of habit. Later, Ben-Akiva and Morikawa (1990) analysed mode shifting behaviour after opening of a metro line in Yokohama, Japan, while assuming explicitly that a mode shift to the new metro happens only if its utility is greater than the utility of the current choice by more than some threshold value, thus assuming a transaction cost, or inertia effect, representing a habitual effect.

More recent literature has also found significant effects of habits in terms of inertia effects in mode choice studies. Cantillo *et al*. (2007) incorporated habits through inclusion of inertia using both a synthetic and a combination of real-life SP/RP data, and their results suggested serious errors in model estimations if not accounting for inertia. Similarly, Cherchi and Manca (2011) tested different measures of inertia in mixed logit models using SP/RP data concluding that inertia is important in explaining mode choice behaviour among car, bus and train users in Cagliari, Italy. Similarly, Fan *et al*. (2018) found significant inertia effects in mode choice experiments from car to public transport. Cherchi and Cirillo (2014) analysed travel diary data over six weeks finding that inertia increases over time when using the same mode of transport. Finally, Wang *et al*. (2021) analysed the re-opening of the public transport network in New York City, USA, after COVID-19 using Matsim simulation models, which explicitly incorporated the role of inertia, also finding significant inertia effects at the aggregate level as people shifted mode during the pandemic and did not return to public transport even at a full re-opening of the public transport system. Hence, there is strong evidence of the importance of incorporating inertia when considering mode choice.

A few studies have analysed specifically the role of inertia when implementing new public transport infrastructure. Yáñez et al. (2009) analysed the impact of a radical change to public transport using RP panel data collected through four waves before and after the implementation of the Transantiago public transport network in Chile. Through estimating mode choice models, they found significant inertia effects, and shock effects, resulting from the changed public transport system while controlling for traditional modal attributes. Termida *et al*. (2016) performed quantitative data analysis based on survey data collected in relation to the implementation of a new tram line in Stockholm finding that reinforcement learning based on past experiences happened on the short term, but not on medium- and long-run. González *et al*. (2017) analysed the role of inertia related to the introduction of a new tram line in Tenerife, Spain. They found significant effect of inertia among car users, and thus a better model fit when this was correctly included in the model.

Generally, studies found larger inertia effects for the choice of car in the mode choice context. Similar to the users in Tenerife where only inertia for the car alternative was significant (González et al., 2017), the largest inertia effect was also observed among car users in the multi-modal network in Shanghai (Gao and Sun, 2018) with inertia for metro being lower and for buses the lowest. This is in line with results from the Netherlands travel survey panel where inertia was larger for car compared to public transport (La Paix *et al*., 2022).

Some studies have focused on how inertia and habit is related to respondents' characteristics. Şimşekoğlu *et al*. (2017) found stronger car use habits among males, and weaker among travellers belonging to low-income groups and those emphasising pro-environmental attitudes and personal norms. Thorhauge *et al*. (2020) analysed habits in departure time choice finding higher inertia among males, having children, and working fixed hours. Several studies also found significant interaction effects between habit and level-of-service characteristics. La Paix *et al*. (2022) found significant inertia related to travel costs for car and public transport, thus suggesting that existing users are relatively less cost-sensitive. Similarly, Gao *et al*. (2022) found that car travel time and costs were perceived relatively lower among car users than among public transport users, and public transport users perceived crowding as less of a nuisance than car users. In addition, they found large variation in inertia effects across individuals. Hence, these studies have highlighted the importance of considering user heterogeneity in habitual effects within mode choice.

Several studies have focused on using SP data only or in combination with RP data. While SP data are less expensive to collect and thus larger sample sizes are easier to achieve, multiple studies highlighted severe bias using such data. González *et al*. (2017) only found significant inertia effect when using RP data whereas no effects were observed when using SP data. Ben-Akiva and Morikawa (1990) found bias in reported mode choice, thus highlighting importance of using RP data. Cherchi and Manca (2011) found that inertia is not stable during SP experiments due to the misperception of past actions, thus also suggesting the importance of using RP panel data. This is in line with Ortúzar *et al*. (2011), which discusses the importance of panel data travel surveys for better travel mode choice analysis.

While the effects of inertia on travel behaviour have been the focus of much research as highlighted above there no studies have analysed mode shifting behaviour before and after the introduction of a new public transport system using large-scale RP data.

2.2. Public transport mode choice modelling

Previous studies have analysed passenger preferences among various public transport modes, e.g. whether passengers perceive rail-based modes as more attractive compared to buses. The so-called rail factor has been observed in several studies, denoting that passengers prefer trains over buses, all else equal, e.g. Axhausen *et al*. (2001); Fosgerau *et al*. (2007); Nielsen (2000). However, some studies found that the preference for trains over buses is due to observable characteristics such as improved comfort and better reliability (Ben-Akiva and Morikawa, 2002; Tørset, 2005). Anderson, *et al*. (2017) reviewed several route choice studies comparing rates of substitution of travel time components for public transport passengers and found that rail services (metro, suburban rail, and regional rail) are consistently preferred over buses. Similar findings were observed in a recent study where all rail services are preferred compared to buses (Nielsen *et al*., 2021).

In the case of Santiago, Yáñez et al. (2010) studied mode choices after a radical change to the public transport system, showing the importance of including latent variables such as accessibility, reliability, comfort and safety to properly capture travellers' preferences and perceptions in their decision-making process. Soza-Parra *et al*. (2021) also used latent variables related to crowding aversion and punctuality to model the travel preferences of public transport users in presence of unreliable services. Raveau *et al*. (2011) studied the preferences between bus and metro of public transport travellers. Traditional variables such as travel time, wait time and number of transfers were included in their model, as well as topological and infrastructure information. Tirachini *et al*. (2017) and Batarce *et al*. (2015) studied the impact of crowing in the perception of public transport travel time and therefore in the travel decisions of public transport travellers.

3. METHODOLOGY

The study is based on discrete choice modelling to estimate mode choice of public transport passengers within the public transport network. Considering that AFC data do not hold background information about the users, we suggest a two-fold analysis for incorporating traveller information within the mode choice model framework. Hence, the proposed methodology consists of i) segmentation analysis based on clustering analysis, and ii) a latent class mode choice model incorporating the identified traveller segments. This allows for incorporating differences across travellers despite having no background information on the users of the public transport smart cards. The latent class mode choice model incorporates inertia and shock effects in the context of a mayor change in the public transport network.

3.1. Segmentation analysis

The objective of the first step of the analysis is to differentiate between different user types of the public transport system. Segmentation analysis has been used in multiple studies for this specific purpose (Briand *et al*., 2017; Eltved *et al*., 2021; He *et al*., 2020; Morency *et al*., 2007). To differentiate between various travel patterns among users we consider three temporal indicators as listed in Table 1.

Table 1 Indicators used for the passenger segmentation analysis

Variable	Domain	Description
ShareWeekdays	0 to 1	Share of weekdays with trips
ShareWeekend	0 to 1	Share of trips on weekend days
SharePeakWeekdays	0 to 1	Share of trips during peak hours on weekdays

Considering that the AFC data used cover one full week of travel in each of the three analysis periods (before, during and after opening of the new metro line) the temporal indicators were chosen to allow for distinguishing between travellers in terms of travel frequency, travel timing, and travel purpose. Hence, the criteria include i) the share of weekdays with active trips, ii) the share of trips performed on weekend days (Saturday and Sunday), and iii) the share of trips performed during peak hours on weekdays. The first indicator measures travel intensity and regularity whereas the two latter indicators provide information on trip timing and hence main travel purposes, since commuters often travel regularly during weekdays at specific time periods whereas leisure users typically travel less frequently outside of peak hours.

The analysis of passenger types will be performed through clustering analysis, similarly to in Eltved *et al*. (2021). This will be based on temporal characteristics of the smart card data, such as the frequency of usage during a full week, the timing of the trip-making during the day and the distribution of trips between weekdays and weekends. This allows for estimating the user types in terms of use frequency and trip purpose.

3.2. Latent class choice model

This study will deploy discrete choice models to estimate mode choice of public transport passengers among three alternatives, namely i) bus, ii) metro and iii) bus/metro in combination. In addition to traditional level-of-service characteristics such as in-vehicle travel time, transfer times and walking times, the model formulation will explicitly consider shock effects after opening of the new metro line as well as inertia effects between the three waves of data collection (before, during and after). To explicitly incorporate the user segmentation into the choice modelling we deploy a latent class modelling approach:

$$P_{jq}^{w} = \sum_{s=1}^{S} \pi_{qs}^{w} \cdot P_{jq|s}^{w}\left(U_{jq}^{w}\right) \tag{1}$$

Where P_{jq}^{w} is the choice probability of alternative j for individual q in wave w, π_{qs}^{w} is the class membership function for individual q belonging to class s during wave w, $P_{jq|s}^{w}\left(U_{jq}^{w}\right)$ is the probability that alternative j is chosen by individual q given class s based on the utility specification V_{jq}^{w}.

The class membership functions π_{qs}^{w} are modelled as binary logit models depending on the clusters assigned to each individual based on the segmentation analysis results. The utility specification used in the study is adopted from Yáñez *et al*. (2009), in which the overall utility U_{jq}^{w} of individual q for alternative j during wave w is the sum of the observed utility component V_{jq}^{w}, the random inertia effect I_{jrq}^{w}, the random shock effect S_{jq}^{w}, and the error term ϵ_{jq}^{w}. The presence of these random effects and the assumption that the error terms ϵ_{jq}^{w} follow a Gumbel distribution results in a mixed logit model structure for $P_{jq|s}^{w}\left(U_{jq}^{w}\right)$.

$$U_{jq}^{w} = V_{jq}^{w} + I_{jrq}^{w} + S_{jq}^{w} + \epsilon_{jq}^{w} \tag{2}$$

The observed utility consists of traditional level-of-service characteristics, X_{jq}^{w}, which includes in-vehicle times, waiting times at transfers, walking times at transfers, and a transfer penalty.

$$V_{jq}^{w} = \beta_{jq}^{w} \cdot X_{jq}^{w} \tag{3}$$

The habit effect, as measured through inertia, compares the observed utility across alternatives within the same wave. Hence, for each alternative *j* the observed utility is compared to the utility of the alternative chosen in the previous wave *r*.

$$I_{jrq}^{w} = \Theta_{j}^{w} \cdot \left(V_{rq}^{w-1} - V_{jq}^{w-1}\right) \tag{4}$$

The shock effect compares the observed utility for the same alternative across waves. Hence, for each alternative *j* the observed utility in wave *w* is compared to the utility for the same alternative in the previous wave *w*-1.

$$S_{jq}^{w} = \alpha_{j}^{w} \cdot \left(V_{jq}^{w} - V_{jq}^{w-1}\right) \tag{5}$$

Finally, the error component ϵ_{jq}^{w} consists of ν_{jq} representing an individual-specific, time-invariant effect for individual *q* for alternative *j*, that is, serial correlation such as personal dispreference for buses, ζ_{j}^{w} representing a time-specific, individual-invariant effect, and ξ_{jq}^{w} is a purely random term, which we in this study assume to be independently and identically (i.i.d.) Gumbel distributed, similarly as proposed in Cantillo *et al*. (2007).

$$\epsilon_{jq}^{w} = \nu_{jq} + \zeta_{j}^{w} + \xi_{jq}^{w} S_{jq}^{w} = \alpha_{j}^{w} \cdot \left(V_{jq}^{w} - V_{jq}^{w-1}\right) \tag{6}$$

All model parameters are assumed to be constant across the population, and the proposed model is estimated in PandasBiogeme (Bierlaire, 2020).

4. CASE STUDY AND DATA

The study is based on AFC data from Santiago, Chile before, during and after the inauguration of a new metro line in November 2017. The aforementioned new line corresponds to Line 6, which connects the South West area of the city with the North East, where most of the business activities are carried out. The location of this new line as well as its corresponding stations are presented in Figure 1. As can be noted from the figure, multiple areas of the city had to rely on bus services to access either the more attractive areas or the metro networks. It is fair to expect then that this new metro line will significantly improve residents' accessibility and thus it should become a relevant transportation alternative. The opening of the new line constitutes a pertinent study case to explore the effect of a new transportation alternative on passengers' choices.

Data is available for three distinct one-week periods, namely approximately three months before, one week after, and five months after the opening of Line 6. The exact dates and the size of each data wave are presented in Table 2. The three periods each include more than 3 million smart cards totalling more than 70 million trips. Considering that the study periods cover a total of 6 months, it is necessary to consider that not all cards are used in all three study periods. The distribution of the presence of each unique smartcard is presented in Figure 2. Overall, we see that the most frequent scenario is when smartcards are only part of one period. In Santiago de Chile, public transport smartcards are anonymous, and thus, people get a new card when the old one gets lost or defective. We can also see that 18.2% of the cards are used in all three study periods. Given the big sample size, this relatively low proportion of multiple appearance cards still corresponds to a total of more than half a million smartcards. As we are interested in habit and shock effects, we will focus our analysis on this particular sub-sample of travellers during weekdays and morning peak hours (between 06:00 and 09:30 am).

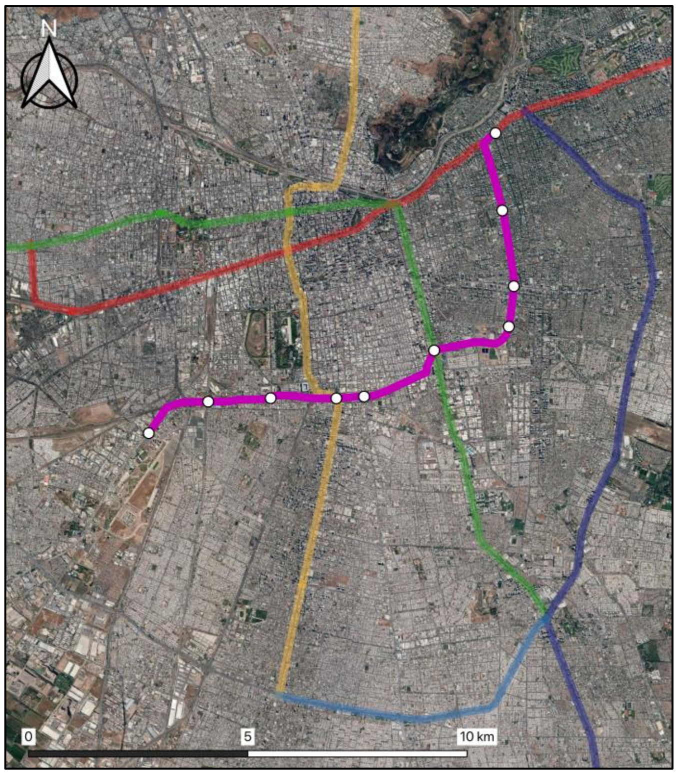

Figure 1 The Santiago metro network: Line 6 line in purple and stations in white

Table 2 Analysis periods

Period	Dates	Number of cards	Number of trips
Before	31 August - 6 September 2017	3,444,323	22,708,706
During	10 - 16 November 2017	3,586,492	24,026,260
After	9 - 15 April 2018	3,822,977	25,426,631

The public transport system in Santiago system operates by tapping only and the entrance of each bus or metro station. The fare collected only depends on the time of day and modes used and allows for up to two transfers within two hours. Because of this reason, people are not required to tap their cards when alighting any public transportation service. To estimate the alighting points of each trip, an estimation process is carried out by analysing the time and location of the following tap-ins (Munizaga and Palma, 2012). This procedure also allows joining multiple trips into journeys (i.e., chains of trips enabled by transferring), which provides more detailed information about passengers' destinations and choices.

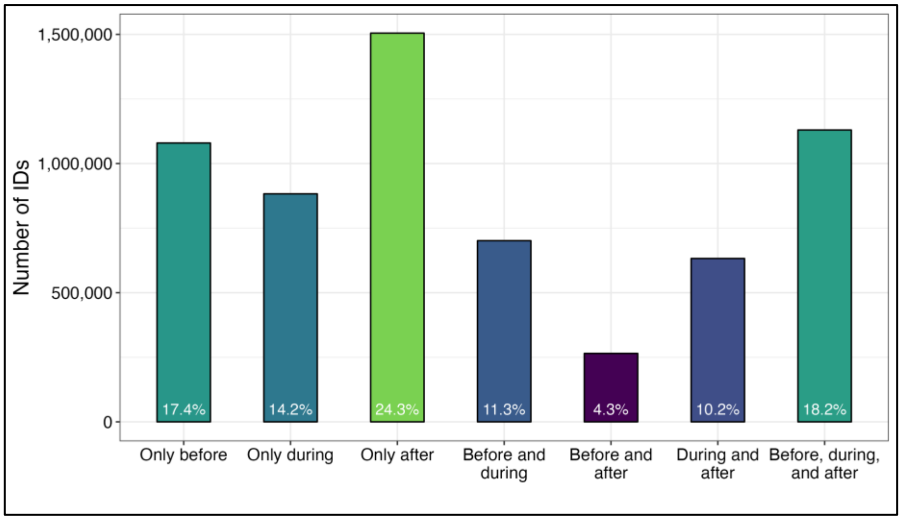

Figure 2 Smartcard ID distribution over the three studied periods: before, during, and after the opening of Line 6

As we are interested in the use of the new metro line, we made the decision to analyse the behavioural change from a mode choice perspective. To do so, we define three possible public transport alternatives: bus only, metro only, and a combined alternative. From a geographical point of view, each journey is associated with an origin and destination zone. This zoning comes from the planning authorities of the city, and thus it accurately reflects the transportation system from a behavioural and operational point of view. Thus, for each origin-destination pair and for each of the three possible modes, the levels of service are calculated by aggregating and averaging all the observations of the period. After following this procedure, in-vehicle travel time, waiting times, transfer times and the number of transfers are obtained for each alternative. This methodology is based on Soza-Parra *et al*. (2022), which was successful in estimating mode choice models in the same city of analysis.

5. RESULTS AND ANALYSIS

The results are divided into two section focusing on the initial segmentation analysis of the smart card data, and the subsequent mode choice model.

The segmentation analysis was performed using the entire dataset of smart cards for all three analysis periods covering 72,161,597 trips for 6,600,959 cards, of which 1,266,977 cards were active across all three periods. The number of clusters *k* was chosen through a combination of evaluating the cluster-within sum of squares while considering the cluster characteristics. The resulting cluster solution consists of six clusters for which the definition of the clusters based on the three temporal indicators are shown in Figure 3 as a boxplot, ordered by travel intensity. Table 3 shows the distribution of smart cards and trips according across the six identified travel type clusters for the three analysis periods.

Cluster 1 (Regular commuters) and cluster 2 (Regular non-commuters) represent those travelling the most in each of the periods as they travel almost every weekday, only rarely on week-end days and mostly inside or outside peak hours, respectively. Users in both clusters perform on average approx. 11 trips per week, and thus these two clusters combined represent approx. 71-73% of all trips, but only approx. 42-44% of cards. Cluster 3 (Occasional users) travel at a medium frequency with half of their trips on weekends and the other half spread out on approx. half of the weekdays, totalling approx. 6 trips per week. Clusters 4 (Irregular commuters) and 5 (Irregular non-commuters) travel irregularly at approx. 3 trips per week, mostly on weekdays inside or outside the peak hours, respectively. They represent 38-39% of cards, but only 16-17% of trips. Finally, Cluster 6 (Weekend users) travels the least with approx. 2.5 trips per week on average, with almost all trips on weekends.

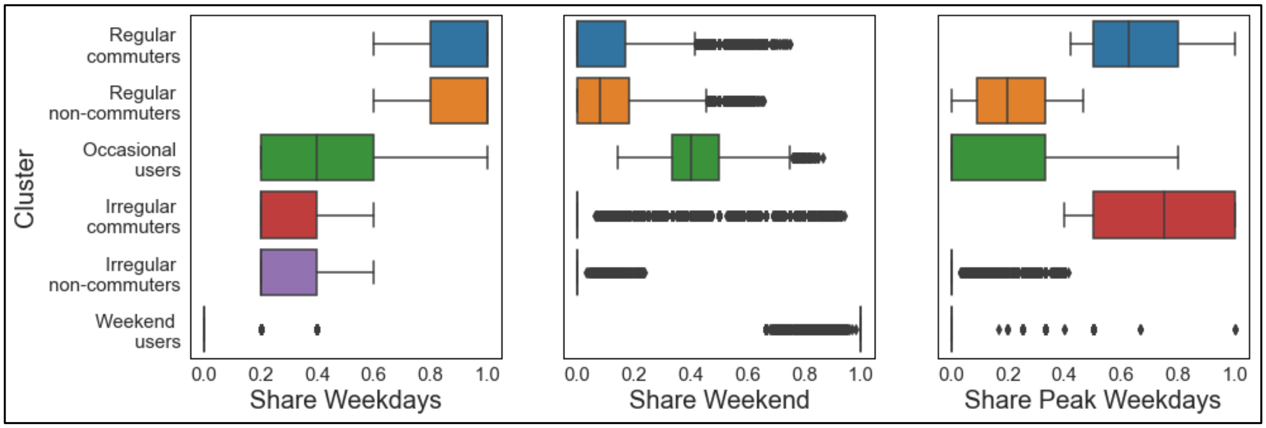

Figure 3 Cluster definitions, ordered by travel intensity

Table 3 Distribution of smart cards across cluster categories for the three analysis periods, based on all active cards

Cluster	Before		During		After	
	Card share	Trip share	Card share	Trip share	Card share	Trip share
Regular commuters	17.6%	29.2%	17.4%	28.3%	17.8%	29.2%
Regular non-commuters	24.9%	41.4%	26.7%	44.0%	26.5%	43.9%
Occasional users	10.3%	9.3%	9.9%	8.7%	9.0%	7.9%
Irregular commuters	11.5%	5.1%	11.9%	5.2%	11.5%	5.0%
Irregular non-commuters	27.1%	11.7%	26.7%	11.2%	26.9%	11.2%
Weekend users	8.6%	3.2%	7.4%	2.6%	8.3%	2.9%

The impacts of the metro on passenger behaviour across the various types of users are shown in Figure 4, which shows the distribution of travel cards belonging to each cluster, and how this evolves across the three analysis periods. Two important findings should be highlighted. First, many users change travel behaviour over time. Among the most frequent travellers most stay within the same cluster across analysis periods probably due to relying on using public transport for work or other regular activities. However, a notable share moves to other clusters with most being internally, e.g. between clusters 1 (Regular commuters) and 2 (Regular non-commuters). Among the clusters with lower travel frequency (Clusters 4-6) most cards change between clusters over time, which is not surprising since these users have a more changing travel behaviour, hence resulting in belonging to different low-frequency clusters over time. Similarly, this also applies to the users belonging to Cluster 6 (Weekend users) where only few stays within the cluster across analysis periods. This might be counter-intuitive, since these cluster could represent a specific user group that only use public transport regularly on weekends. However, the large cluster movements suggests that this group instead represent one type of irregular users. Finally, the movements over time of users belonging to Cluster 3 (occasional users) are less pronounced than the irregular travellers, but more than the regular travellers. Hence, this suggest that clusters can be categorised into three distinct traveller types, namely the regular users (Clusters 1 and 2), occasional users (Cluster 3), and irregular users (Clusters 4, 5 and 6).

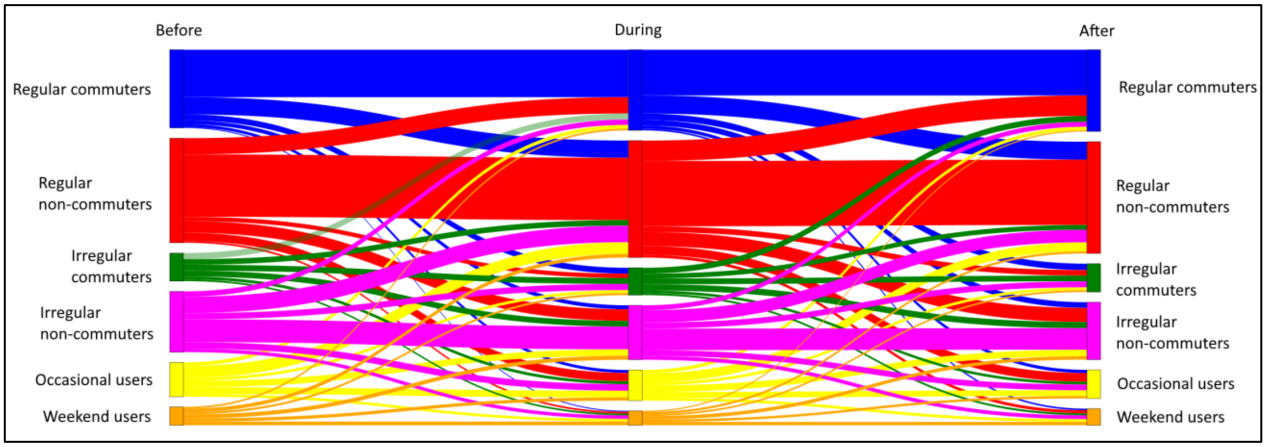

Figure 6 Sankey diagram showing the distribution and movements of cards among the six clusters. Based on all cards that are active in all three analysis periods

5.2. Mode choice model results

The mode choice model was estimated using a (random) sample of 100,000 individuals that travelled in all three analysis periods, i.e. before, during and after the opening of line 6. This was chosen due to the very long calculation times if using the full sample of 1,266,977 cards that were active in all three analysis periods. To ensure that the sampling did not induce bias to the results, the model was run using two independent samples. Since the model estimations did not vary notably, i.e. less than 0.5%, this method was assumed to not induce bias to the results.

Two latent classes were found among the travellers, namely i) a fully compensatory class that chooses based on all level-of-service characteristics (in-vehicle time, transfer time, waiting time, and number of transfers), and ii) a lexicographic class that minimises the number of transfers and if two or more alternatives have the same minimal amount of transfers then chooses based on in-vehicle time only. Heteroskedasticity was found between the second wave (during) and the first (before) and third (after). This heteroskedasticity was incorporated into the model through a scale factor in the utilities for the second wave.

Table 4 presents the model estimation results. Each parameter is accompanied by its *t*-Value to assess its statistical significance. The shock and inertia effects are random and follow a Normal distribution. All the parameters from the class membership model and the attributes in the mode choice utility function are statistically significant at a 95% confidence level. The parameters related to shock an inertia effect also tend to be statistically significant, but a few of them have a 90% confidence level. All parameters have the expect sign. The scale factor for wave 2 (during) implies that during that wave there is a variance $1/0.794^2 = 1.59$ times higher, a sign that travellers might be trying metro as an alternative before reaching a steady state once again in wave 3 (after).

Table 4 Model estimation results

Parameter	Estimate	*t*-Value
Membership Model for Latent Class 1: Fully Compensatory		
Regular commuters Regular non-commuters	1.94	19.4
Occasional users	0.713	13.9
Irregular commuters Irregular non-commuters Weekend users	1.38	20.2
Mode Choice Model		
Latent Class 1: Fully Compensatory		
Metro Constant – Wave 1 Before	0.961	11.37
Metro Constant – Wave 2 During	1.12	13.20
Metro Constant – Wave 3 After	1.00	15.88
Combined Constant – Wave 1 Before	0.493	9.56
Combined Constant – Wave 2 During	0.318	8.32
Combined Constant – Wave 3 After	0.469	7.31
In-vehicle time	-0.0601	-2.61
Transfer time	-0.332	-4.89
Wait time	-0.118	-11.23
Transfers	-0.707	-3.01
Latent Class 2: Lexicographic on Transfers		
Metro Constant – Wave 1 Before	4.21	3.51
Metro Constant – Wave 2 During	5.20	3.81
Metro Constant – Wave 3 After	4.88	3.03
Combined Constant – Wave 1 Before	-3.01	-2.56
Combined Constant – Wave 2 During	-2.11	-3.45
Combined Constant – Wave 3 After	-2.95	-2.99
In-vehicle time	-0.345	-17.4
Both Latent Classes		
Shock Effect - Before/During	0.152	2.33
Std. Dev. Shock Effect - Before/During	0.092	2.01
Shock Effect - During/After	0.113	1.78
Std. Dev. Shock Effect - During/After	0.076	2.00
Inertia Effect Bus	-0.598	-1.88
Std. Dev. Inertia Effect Bus	0.474	1.61
Inertia Effect Metro	1.35	3.44
Std. Dev. Inertia Effect Metro	0.84	3.98
Scale Factor Before and After	1	Fixed
Scale Factor During	0.794	11.25

Based on the class membership model parameters, the two latent classes and their predominance withing the sample are shown in Table 5. Most travellers consider all level-of-service characteristics, and hence 85.0% belong to latent class 1. However, the probability of belonging to latent class 2 and strictly minimising the number of transfers before considering only the in-vehicle time decreases with travel frequency. More specifically, 20-33% of the occasional users belong to latent class 2 whereas only 13% of frequent users belong to this class.

Table 5 Distribution of user segments in the two identified latent classes

Cluster name	Probability of Latent Class 1 Fully compensatory	Probability of Latent Class 2 Lexicographic on transfers
Regular commuters Regular non-commuters	87.4%	12.6%
Occasional users	67.1%	32.9%
Irregular commuters Irregular non-commuters Weekend users	79.9%	20.1%

On both latent classes the metro constant is positive, which can be interpreted as a general preference of metro over bus. The metro constant is higher in wave 2 (during the opening of the new metro line), which suggest that travellers have a higher tendency to choose and try metro, which is to be expected. The combined metro/bus constants are positive for latent class 1, which suggest that those travellers prefer having at least one trip leg on metro than travelling exclusively on buses. For latent class 2 the combined metro/bus constants are negative, which is to be expected, as that is the only alternative that necessarily requires transferring.

To better analyse the parameters related to the level of service, Table 6 presents the marginal rates of substitution off the attributes in terms of in-vehicle travel time. All travellers are willing to have larger travel times as long as they are able to travel in metro and not in bus. The same happens in latent class 1 for the combined metro/bus alternative, but in latent class 2 they are willing to have a larger travel time as long as they do not travel in the combined alternative. Latent class 1 values each transfer at a rate of 11.8 minutes of travel time (i.e. they are willing to travel nearly 12 minutes longer to avoid a transfer), while latent class 2 by definition are not willing to compromise having to transfer more than the minimum.

Table 6 Distribution of user segments in the two identified latent classes

Attribute	Latent Class 1 Fully compensatory	Latent Class 2 Lexicographic on transfers
Metro Constant – Wave 1 Before	16.0 min	12.2 min
Metro Constant – Wave 2 During	18.6 min	15.1 min
Metro Constant – Wave 3 After	16.6 min	14.1 min
Combined Constant – Wave 1 Before	8.2 min	-8.7 min
Combined Constant – Wave 2 During	5.3 min	-6.1 min
Combined Constant – Wave 3 After	7.8 min	-8.6 min
In-vehicle time	1.0 (reference)	1.0 (reference)
Transfer time	5.5	n.a.
Wait time	2.0	n.a.
Transfers	11.8 min	n.a.

All mean shock effects parameters are positive, which denotes a tendency from the travellers to switch to alternatives that improve their general utility across waves (see the definition of the shock effect in equation 5). As the shock effect is Normally distributed, given the means and standard deviations 95.1% of travellers have a positive shock effect between waves 1 and 2, and 93.1% between waves 2 and 3. The inertia mean effect of metro is positive, which denotes a tendency of metro users to keep choosing metro across waves. 94.4% of the Normal distribution has a positive sign. The inertia effect of bus is negative, which denotes the opposite: bus users have a tendency to switch to metro across waves. 89.6% of the Normal distribution has a negative sign. These results for the inertia effects are as expected, considering that the change in the system is the opening of a new metro line, which should shift travellers from the bus to the metro.

To evaluate the goodness-of-fit of the estimated heteroskedastic mixed latent class model, we compared the fit with the range of simpler models based on a single class (a traditional logit model) and without inertia and shock effects. The goodness-of-fit of the range of models are shown in Table 7. Two important findings should be highlighted. First, the latent class choice model results in a better fit than if treating all observations as one homogeneous group of users. This suggests that the smart cards indeed represent different users with different travel preferences. Second, the model specifications that explicitly incorporate inertia and shock effects result in better model fit. Thus, these results confirm previous studies in the importance of including inertia effects within transport mode choice. In addition, it is important to include the shock effects when analysing changes to mode choice over time in the context of notable changes to the infrastructure.

Table 7 Goodness-of-fit indicators

Model	Log-likelihood	Adjusted ρ^2	AIC
1 class base model	-43,519	0.423	87,060
1 class + inertia + shock	-43,244	0.426	86,526
2 latent classes	-36,748	0.516	73,004
2 latent classes + inertia	-36,433	0.516	72,922
2 latent classes + shock	-36,427	0.517	72,910
2 latent classes + inertia + shock	-36,314	0.518	72,692

6. CONCLUSIONS

This study has focused on analysing the change in behaviour of public transport passengers over time after the inauguration of a new metro line in Santiago, Chile. The study was based on large-scale RP data from three different periods: before, during and after the opening of the new line. Data shows that, as expected, there is a modal shift towards metro. To properly understand this shift, two modelling tasks were conducted: i) a segmentation analysis based on clustering analysis to identify profiles of travellers that behave different and ii) a latent class mode choice model that incorporates the segmentation as well as inertia and shock effects.

Six segments were found among the travellers, based on their travel patterns along a full week, considering the days and times they travel. These segments are fundamental in explaining the probability of belonging to two different latent classes in the mode choice model. While regular travellers (both commuters and non-commuters) have a higher probability of having a compensatory behaviour and considering all level of service attributes, occasional users have a higher probability of behaving lexicographically and minimising transfers.

Both latent classes differ in their preferences and behaviour. While both latent classes tend to prefer metro over bus, only the fully compensatory travellers tend to prefer the combined metro/bus alternative over bus. On wave 2 (during the opening of the new metro line) there is a higher tendency to choose metro, as would be expected. There is also a higher variance in the decisions, due to travellers trying new ways of travelling before reaching a steady state on wave 3 (five months after the opening of the new metro line).

A significant positive inertia effect was found for metro, as metro users are more likely to keep using metro when its line opens. The inertia effect for bus was negative, which means bus travellers have a tendency to change modes and start using metro. Significant and positive shock effect where also found across all wave changes, a sign that travellers are seeking alternatives that improve their utility as time passes.

The results showcase the important of considering differences across public transport travellers to enhance modelling and forecasting. This study considers differences in terms of segmentation of travellers in terms of their travel patterns and latent classes in terms of their preferences when choosing travel modes.

ACKNOWLEDGMENTS

This research is supported and financed by Independent Research Fund Denmark, grant number 0130-00012B.

REFERENCES

Aftabuzzaman, M., Currie, G., Sarvi, M. (2010). Evaluating the congestion relief impacts of public transport in monetary terms. **Journal of Public Transportation**, 13, 1–24.

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, 221–245.

Axhausen, K.W., Haupt, T., Fell, B., Heidl, U. (2001). Searching for the rail bonus: Results from a panel SP/RP study. **European Journal of Transport and Infrastructure Research**, 1, 353–369.

Batarce, M., Muñoz, J.C., Ortúzar, J. de D., Raveau, S., Mojica, C., Ríos, R.A. (2015). Use of mixed stated and revealed preference data for crowding valuation on public transport in Santiago, Chile. **Transportation Research Record**, 2535, 73–78.

Ben-Akiva, M., Morikawa, T. (1990). Estimation of switching models from revealed preferences and stated intentions. **Transportation Research Part A**, 24, 485–495.

Ben-Akiva, M., Morikawa, T. (2002). Comparing ridership attraction of rail and bus. **Transport Policy**, 9, 107–116.

Bierlaire, M. (2020). A short introduction to PandasBiogeme. **Technical report Transp-OR 200605**. Transport and Mobility Laboratory, ENAC, EPFL.

Briand, A.-S., Côme, E., Trépanier, M., Oukhellou, L. (2017). Analyzing year-to-year changes in public transport passenger behaviour using smart card data. **Transportation Research Part C**, 79, 274–289.

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

Cherchi, E., Cirillo, C. (2014). Understanding variability, habit and the effect of long period activity plan in modal choices: a day to day, week to week analysis on panel data. **Transportation**, 41, 1245–1262.

Cherchi, E., Manca, F. (2011). Accounting for inertia in modal choices: some new evidence using a RP/SP dataset. **Transportation**, 38, 679–695.

Eltved, M., Breyer, N., Ingvardson, J.B., Nielsen, O.A. (2021). Impacts of long-term service disruptions on passenger travel behaviour: A smart card analysis from the greater Copenhagen area. **Transportation Research Part C**, 131, 103198.

Fan, J., Gao, K., Axhausen, K.W., Sun, L. (2018). Existence of psychological inertia in mode shift behavior: New evidence from a comparison study. **18th Swiss Transport Research Conference** (STRC 2018).

Fosgerau, M., Hjorth, K., Lyk-Jensen, S.V. (2007). **The Danish value of time study**. Kgs. Lyngby, Denmark.

Gao, K., Shao, M., Axhausen, K.W., Sun, L., Tu, H., Wang, Y. (2022). 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, 293–303.

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

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

He, L., Agard, B., Trépanier, M. (2020). A classification of public transit users with smart card data based on time series distance metrics and a hierarchical clustering method. **Transportmetrica A**, 16, 56–75.

Johnson, L., Hensher, D. (1982). Application of multinomial probit to a two-period panel data set. **Transportation Research Part** A, 16, 457–464.

La Paix, L., Oakil, A.T., Hofman, F., Geurs, K. (2022). The influence of panel effects and inertia on travel cost elasticities for car use and public transport. **Transportation**, 49, 989–1016.

Morency, C., Trépanier, M., Agard, B. (2007). Measuring transit use variability with smart-card data. **Transport Policy**, 14, 193–203.

Munizaga, M.A., Palma, C. (2012). Estimation of a disaggregate multimodal public transport origin–destination matrix from passive smartcard data from Santiago, Chile. **Transportation Research Part C**, 24, 9–18.

Nielsen, O.A. (2000). A stochastic transit assignment model considering differences in passengers utility functions. **Transportation Research Part B**, 34, 377–402.

Nielsen, O.A., Eltved, M., Anderson, M.K., Prato, C.G. (2021). Relevance of detailed transfer attributes in large-scale multimodal route choice models for metropolitan public transport passengers. **Transportation Research Part A**, 147, 76–92.

Ortúzar, J.D.D., Armoogum, J., Madre, J.-L., Potier, F. (2011). Continuous mobility surveys: the state of practice. **Transport Reviews**, 31, 293–312.

Raveau, S., Muñoz, J.C., De Grange, L. (2011). A topological route choice model for metro. **Transportation Research Part A**, 45, 138–147.

Schlich, R., Axhausen, K.W. (2003). Habitual travel behaviour: evidence from a six-week travel diary. **Transportation**, 30, 13–36.

Şimşekoğlu, Ö., Nordfjærn, T., Rundmo, T. (2017). Predictors of car use habit strength in an urban Norwegian public. **Transportation**, 44, 575–588.

Soza-Parra, J., Raveau, S., Muñoz, J.C. (2021). Travel preferences of public transport users under uneven headways. **Transportation Research Part A**, 147, 61–75.

Soza-Parra, J., Raveau, S., Muñoz, J.C. (2022). Public transport reliability across preferences, modes, and space. **Transportation**, 49, 621–640.

Termida, N.A., Susilo, Y.O., Franklin, J.P. (2016). Observing dynamic behavioural responses due to the extension of a tram line by using panel survey. **Transportation Research Part A**, 86, 78–95.

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**, 133, 272–289.

Tirachini, A., Hurtubia, R., Dekker, T., Daziano, R.A. (2017). Estimation of crowding discomfort in public transport: Results from Santiago de Chile. **Transportation Research Part A**, 103, 311–326.

Tørset, T. (2005). **Kollektivtransportmodellering: Kan eksisterende transportmodeller utvikles slik at de blir mer egnet til analyser av kollektivtransport?** Doctoral Thesis. NTNU, Norway.

Wang, D., He, B.Y., Gao, J., Chow, J.Y., Ozbay, K., Iyer, S. (2021). Impact of covid-19 behavioral inertia on reopening strategies for New York City transit**. International Journal of Transportation Science and Technology**, 10, 197–211.

Yáñez, M.F., Cherchi, E., Ortúzar, J. de D., Heydecker, B.G. (2009). Inertia and shock effects on mode choice panel data: implications of the Transantiago implementation. **12th international conference on travel behaviour research**.

Yáñez, M.F., Raveau, S., Ortúzar, J. de D. (2010). Inclusion of latent variables in mixed logit models: modelling and forecasting. **Transportation Research Part A**, 44, 744–753.