PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

SCHOOL OF ENGINEERING

PUBLIC TRANSPORT RELIABILITY CAUSES AND EFFECTS

JAIME ANTONIO SOZA PARRA

Thesis submitted to the Office of Graduate Studies in partial fulfillment of the requirements for the Degree of Doctor in Engineering Sciences

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Santiago de Chile, April 2020

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Santiago de Chile, April 2020

To my grandma, *Nena*. Every day I try hard to be the person you thought I am.

ACKNOWLEDGMENTS

Instead of extending this section widely enough to avoid leaving someone behind, I will dedicate some lines to those who had a significant impact during this four-year Ph.D. experience.

Firstly, I would like to thank Sebastián Raveau and Juan Carlos Muñoz, who accepted to be part of this dissertation as supervisors. I genuinely hope they don't regret that decision after all these years working together.

On one side, with Sebastián, I had the chance to be supervised by somebody that was first a work-friend and whom I didn't expect to become such an essential part of my day-to-day life. Our productivity rapidly decreased over time, as it was incredibly easy to start talking about complex discrete choice models but ending up watching some random deep-youtube videos, sharing our emotional issues or even going for a 20 minutes walk or eat a mid-morning snack because those things are healthy. I really appreciate our friendship, and probably is the most pleasant outcome of this research. However, every time we decided to actually work, I got astonished by his outstanding capacity to understand newer formulations quickly as well as his "black-box" ability to propose solutions to any issue magically. After all these years, I like to think to myself that I have developed a similar talent. Still, I deeply recognize mine will never be as impressive as his. He is also responsible I attended twelve conferences during my Ph.D. as he encouraged me since day one to send abstracts everywhere I was interested.

On the other side, Juan Carlos is by far the professor who influenced my undergraduate degree the most. I still remember how interesting it seemed anything he was teaching, from logistics, through equilibrium models, to public transportation, his passion. I still feel the same when I see him sharing his (or now, our) work. This passion shifted to my dissertation quickly, pushing me to think in many different directions every time. Even though at the beginning, it was tough for me to understand his sense of humour during our meetings, I feel now I know who he really is, and I happily look those earlier days. Besides, I truly appreciate

how he was able to find a spot in his agenda to have lunch with me whenever I asked. I will never forget his advice, and I hope to continue to have this chance in the future.

Besides, I would like to thank Oded Cats for his support during the second half of my research. Having the opportunity to work with him and his team at TU Delft was the most amazing experience I had during my Ph.D. Even though The Netherlands is not known because of its sunny and warm weather, Oded-s insightful ideas and human quality were more than enough to make this time one that I will never forget.

I am also grateful I had the chance to walk this journey along with Ignacio Tiznado. Even though we knew each other long before the beginning of our theses, I have the feeling our friendship strengthen during these years. At the beginning of this Ph.D., I received many comments about how hard this experience would be, but I never actually took them seriously. However, now I am sure that it would have been times harder if these years were lived without some partner by the side. I greatly appreciate all those moments we shared during this time, all the conferences (and mostly receptions) we attended, all our talks about the impostor syndrome, how each of us compare with each other, and our thoughts about our country's inequality. Ignacio is the most hard-working young researcher I have ever met, I admire him, and I hope we continue working and sharing moments together.

I would like to thank the many friends I have (still don't know how), who have been present personally in every important moment of these recent years. They have supported me when I felt like everything didn't make sense at all, and I won´t ever forget such good friendship and loyalty. I am not naming each of you, as those lists are always unfair. However, if you are reading this, you are likely to be one of them.

As I stated in my candidacy exam, I couldn't have reached so far without my parents' hard work. Francisco and Ximena have always supported me in every decision I have made, even when I decided to continue studying four years ago. Every time they asked what my research was about, even for the hundredth time, I saw their genuine interest to understand and appreciate all I did during these years. More importantly, every time I looked tired, they didn’t bother to ask and treated me softly. I know how unpleasant I can be when things are not going as expected, and most of the time, home was the place I could rest and let those feelings go. I will be in debt to them forever and I hope to have enough time to make it up to them.

Finally, I would like to thank Carolina Contreras for being at my side since 2017 and supported me even during my darkest times. Both of us have grown enormously during these years, and I am happy we have been able to overcome our most significant differences. I appreciate how she had dived into our relationship, even when we had to stay apart for months. The time we spent in The Netherlands was beautiful in every sense, and I hope our next destination will be even better for both of us. She takes good care of me every day, and she always wishes the best for me, even when that might not necessarily be the best for her. Her selfless love is something I never experienced before, and sincerely thank to be such a lucky man.

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PONTIFICIA UNIVERSIDAD CATOLICA DE CHILE

ESCUELA DE INGENIERIA

CAUSAS Y EFECTOS DE LA CONFIABILIDAD EN TRANSPORTE PÚBLICO

Tesis enviada a la Dirección de Postgrado en cumplimiento parcial de los requisitos para el grado de Doctor en Ciencias de la Ingeniería.

JAIME ANTONIO SOZA PARRA

RESUMEN

El comportamiento de las personas al momento de viajar es usualmente modelado a partir de los tiempos promedios de viaje y espera (si corresponde) y el costo monetario de viajar. La confiabilidad del nivel de servicio de cada modo o ruta de transporte es entendida como la certeza que experimenta un viajero sobre su espera, su tiempo de viaje, la hora de llegada a su destino o la comodidad con la que viajará. Esta confiabilidad, aun cuando es considerada por los usuarios, no es incorporada comúnmente en los modelos de comportamiento, especialmente en regiones en desarrollo (como Latinoamérica) donde existe una falta de estudios respecto a la confiabilidad de transporte público.

Esto supone que dos alternativas con igual desempeño promedio pero diferente grado de variabilidad en algún atributo serían percibidas de manera equivalente. Sin embargo, esto no es consistente con la realidad, donde los viajeros desean llegar a un determinado lugar a cierta hora límite para realizar una determinada actividad. No basta que en promedio el usuario experimente un tiempo de viaje que le permita llegar a destino a tiempo; necesita una certeza mayor. Esta situación es aún más relevante para el caso específico del transporte público cuando opera basado en frecuencia. A la variabilidad existente en las condiciones de ruta (producto de congestión o cambios en la demanda) y a la irregularidad en la operación producto del apelotonamiento de buses se suma una baja confiabilidad que es inherente a este tipo de transporte pues no existe una disponibilidad inmediata del vehículo. En otras palabras, el tiempo de viaje total será siempre variable pues al menos el tiempo de espera lo es.

No conocer las causas que generan una baja de confiabilidad, así como los impactos que esta genera en los usuarios tanto en su satisfacción como en su comportamiento nos impide poder generar modelos predictivos que repliquen de mejor forma el uso actual de la red, así como también impide evaluar correctamente proyectos que mejoran la confiabilidad del nivel de servicio sin disminuir necesariamente los valores promedios de sus atributos. De esta forma, el propósito de esta tesis es (i) caracterizar la confiabilidad del transporte público, (ii) comprender cuáles son los elementos que la afectan, (iii) cuantificar los impactos que la falta de confiabilidad genera en la satisfacción y en el comportamiento que tienen los usuarios del

sistema de transporte público, e (iv) identificar qué tipo de beneficios y costos genera un proyecto que mejora la confiabilidad en transporte público.

Para poder llevar a cabo estos cuatro propósitos se propone la siguiente metodología. En primer lugar, para comparar la confiabilidad que actualmente otorgan los servicios de transporte público se realizó un análisis estadístico de los tiempos de viaje efectivamente experimentados por los usuarios en la ciudad. Para ello se contó tanto con información de tipo AVL (Localización Vehicular Automatizada en inglés) como con información de demanda por dichos servicios obtenida a través del sistema de pago electrónico del sistema de transporte público. En segundo lugar, para entender los factores que afectan la regularidad de los intervalos y la variabilidad de tiempo de viaje entre estaciones, se calibró un modelo econométrico que incluya tanto variables temporales como características propias del servicio (demanda, operador, tipo de operación) y de la infraestructura (densidad de semáforos, tramos con vías exclusivas). En tercer lugar, para medir los efectos que genera la falta de confiabilidad se identificó como afecta a la satisfacción y evaluación que hacen los usuarios y a la toma de decisiones respecto a su modo y ruta. Para lograr este propósito realizaron encuestas a usuarios sobre su último viaje realizado y un experimento de preferencias declaradas, el cual incorporó servicios con diferente nivel de confiabilidad en tiempo de espera y hacinamiento. En cuarto lugar, se midieron los beneficios y costos que genera una intervención en un servicio de buses que tenía por objetivo mejorar la regularidad de intervalos.

Esta tesis contribuye en mejorar la comprensión global respecto a la importancia que tiene la confiabilidad del nivel de servicio en un sistema de transporte público. A partir del análisis de los diferentes resultados obtenidos, se observa que la variabilidad de intervalos es un atributo diferenciador entre vehículos de superficie y sistemas de tren subterráneo. Esto se debe principalmente a las diferencias existentes en términos de infraestructura. Estas diferencias generan además cambios en la satisfacción y en el comportamiento de los usuarios. Así, será posible mejorar la manera en la que evaluamos socialmente aquellos proyectos que mejoran la regularidad del sistema, incluyendo los impactos que genera y comprendiendo el comportamiento de los usuarios que es influido por dichos cambios.

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PUBLIC TRANSPORT RELIABILITY CAUSES AND EFFECTS

Thesis submitted to the Office of Graduate Studies in partial fulfillment of the requirements for the Degree of Doctor in Engineering Sciences by

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ABSTRACT

Traveller's behaviour is usually modelled through traditional variables such as monetary cost, expected travel time and planned wait time. Service reliability is understood as the certainty travellers have regarding their travel time, their arrival time, or the comfort level they will experience inside the vehicle. Reliability, although considered by the travellers, is usually neglected from behavioural models, especially in emerging regions (such as Latin America) where there is a lack of studies regarding public transport reliability.

This means that two alternatives with the same average performance but different degrees of variability in some attribute would be perceived equivalently. However, this is not consistent with reality, where travellers want to reach a particular place at a specific time to perform a particular activity. It is not enough that users experience a travel time that allows them to reach their destination on time on average; greater certainty is needed. This situation is even more relevant for the specific case of public transport when it operates based on frequency. To the existing variability in road conditions (product of congestion or changes in demand) and the irregularity in the operation due to bus bunching, there is an inherent unreliability source in this type of transportation, as vehicles are not immediately available. In other words, total travel time will always be variable as at least waiting time is.

Ignoring the causes of unreliability, as well as the impacts it has on travellers, both in their satisfaction and in their behaviour, prevents generating predictive models that better replicate the current use of the network. Besides, it prevents correctly evaluating projects that improve service level reliability without necessarily diminishing the average values of the attributes. Thus, the purpose of this thesis is to (i) characterize public transport reliability, (ii) understand which elements affect it, (iii) quantify the impacts that the lack of reliability generates on public transport users' satisfaction and behaviour, and (iv) identify which type of benefits and costs a public transport reliability improvement project generates.

In order to carry out these four purposes, the following methodology is proposed. Firstly, to compare public transport services reliability currently provided, a statistical analysis of actual travel times experienced by users in the city was conducted. To do so, both AVL (Automated Vehicle Location) information and demand information for these services, obtained through the public transport electronic payment system, were available. Secondly, to understand the factors that affect headway regularity and travel time variability between stations, an econometric model was calibrated that includes both temporary variables and characteristics of the service (demand, operator, type of operation), and infrastructure attributes (traffic light density, sections with segregated roads). Thirdly, in order to measure the effects generated by unreliability, users' satisfaction perception and evaluation, as well as the decision-making process regarding their mode and route, were analysed. To achieve this, passenger surveys about their last trip and a stated preference experiment were conducted, which incorporated services with different reliability levels in waiting time and crowding. Fourthly, the benefits and costs generated by a bus service intervention that aimed to improve headway regularity were measured.

This dissertation contributes to improving the overall understanding regarding the importance of public transport level of service reliability. Based on the analysis of the different results obtained, we conclude that headway variability is a differentiating attribute between surface vehicles and underground train systems. This is mainly due to the differences in terms of infrastructure. These differences also generate changes in users' satisfaction and behaviour. Thus, it will be possible to improve the way how we socially evaluate those projects that improve system regularity, including the impacts generated and understanding better the users' behaviour influenced by these changes.

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1. INTRODUCTION

Reliability, understood as the degree of certainty that travellers have regarding critical elements of their level of service, such as their travel time, their arrival time at the destination or the degree of comfort with which they will experience while travelling inside within the vehicle (van Oort, 2011), is recognized as an important attribute of the level of service. The first empirical evidence was obtained by Prashker (1979), by identifying the impact that different levels of characteristics' variation, such as vehicle travel times or waiting times, have.

Reliability levels are referred to the variability that exists in any level of service attribute across different trips of the same type and characteristics. In this dissertation, reliability will be understood as a mathematical measure of dispersion of any attribute (e.g. standard deviation, coefficient of variation or differences between percentiles) in several repetitions in different days of the same trip. In addition, the variability that exists between the arrival times of consecutive buses of the same service will be called regularity, where a service with identical headways will be called regular and one with random will be called irregular.

Public transport is affected by different types of randomness which impact the reliability they offer. The source of this randomness may come, for example, from disruptions, changes in demand pattern, or changes in operating conditions. However, it is important to distinguish between casual uncertainty sources (such as accidents or protests) from systematic uncertainty, related to service supply (such as dwelling time or travel time between consecutive stops). Unlike specific incidents, the latter type of variability is characteristic of the normal operation of a transport system. Thus, this occasional uncertainty is described by its day-to-day variation (Bates, 2009), and is the object of study in this dissertation.

In addition to these sources of variability, an extra source of uncertainty experienced by users arises due to the public transport vehicle not being immediately available to avoid a wait of uncertain length. In a frequency-based system (without schedules), even under perfect regularity, users are not sure about the next vehicle's time of arrival. By not being able to plan their boarding time, there is a possibility of arriving at the stop at the exact moment that the vehicle does, yielding a null wait, as well as a possibility of arriving exactly when a vehicle leaves the stop, forcing the wait to be maximal. A passenger requiring transfers to reach the destination faces this uncertainty as many times as trip legs in the trip. This uncertainty associated to waiting become more relevant because in public transport system headways are far from regular, and because passengers assign to the waiting stage of their trip a higher value of time.

From a behavioural economic point of view, in the last decades, the level of service reliability has been incorporated into departure time choice models of different transport (Borjesson, 2009; Börjesson, Eliasson, & Franklin, 2012; Engelson & Fosgerau, 2011; Fosgerau, 2009; Fosgerau & Hjorth, 2008; Fosgerau, Hjorth, & Lyk-Jensen, 2010; Hjorth, 2011; Hjorth, Borjesson, Engelson, & Fosgerau, 2015; Lam & Small, 2001; Noland & Small, 1995; Small, 1982; Small, Winston, & Yan, 2005). In general terms, there are three types of these models: central dispersion models, scheduling models and those that represent a combination of both. In the context of urban public transport, these models have been scarcely raised (Benezech & Coulombel, 2013; Engelson & Fosgerau, 2011; Fosgerau & Engelson, 2011; Hjorth et al., 2015). Since public transport vehicles are not immediately available and, in many systems, services' schedules are not offered, travellers must necessarily adapt their departure time to this uncertainty. Thus, the experience of a public transport traveller must recognize not only the in-vehicle travel time, it is necessary to add an access time (which is generally considered fixed) and variable waiting time.

Then, it is necessary to identify and characterize level of service reliability differences between the different modes and routes of public transport in the city, in order to improve our understanding of how travellers take their decisions. Then, it is important to understand how reliability affects their perception of the service received (which we will understand as their level of satisfaction) as well as to understand how this attribute impacts their mode-route choice behaviour.

To make cities more sustainable, public transport needs to become a preferred transport mode. Thus, transport planners should be very sensitive to public transport traveller's experience. In a headway-based operational context, reliability is strongly explained by headway regularity. Regular headways not only enhance wait time but also comfort, travel time and operational costs. Thus, a better understanding of its causes and effects could push agencies' focus towards improving reliability. This is essential to make public transport a more attractive travel alternative, and therefore a critical step in the path towards urban sustainability.

1.1 General Objective and Hypothesis

Public transport's reliability has a high impact on travel decisions by users. In particular, headway regularity can be explained by different infrastructure and operational attributes and produces significant differences in the level of service perceived by users.

To demonstrate this, the purpose of this dissertation is to perform a statistical analysis of the appropriate sources of information and thus be able to generate both explanatory models, regarding the causes that cause different public transport reliability levels in transport routes, as well as behavioural and satisfaction models to understand the effects over users.

1.2 Specific Objectives

In order to understand the characteristics, causes, and implications of service reliability, the research proposed answers four research questions, which correspond to the four specific objectives of this thesis project:

i) What level of reliability do different transport modes offer in our city?

ii) What factors determine the variability of the level of service being offered?

iii) What effects does reliability have on public transport user's satisfaction?

iv) How does the level of service reliability affect user's mode/route choice?

v) Are the benefits from the improvement of service reliability significant?

1.3 Specific Hypotheses

The set of hypotheses raised to answer the specific objectives questions are:

i) Different public transportation modes present different reliability levels. These disparities are perceivable by users and vary across the city. Specifically, buses' level of service variability is higher than subways', mostly by its lack of dedicated infrastructure.

ii) For the case of public transport services which headways aren't controlled, both infrastructure and operational characteristics influences headway variability. In particular, off-board payment stops, segregated corridors and passengers demand have a strong effect. Besides, headway variability naturally increases downstream and it is possible to econometrically model the impact of infrastructure, operational and service characteristics on headway regularity.

iii) Headway regularity has indirect effects over passengers' satisfaction. This means excess waiting time and the increase in average crowding deteriorate passengers' evaluation of the service. Besides, there is a fixed and measurable modal effect, which accounts for rail modes preference.

iv) Headway variability affect passengers' choices through varying day-to-day experiences, specifically over waiting time and passenger density average values and their variability. Besides, there are latent attitudes which explain differences in the perception of public transport attributes.

v) The benefits from improving service reliability benefits are significant, and they might yield to significant annual savings in a Cost Benefit Analysis. Besides, these benefits come not only from the reduction in excess waiting time but also from the improvement of travel comfort.

1.4 Methodology

This dissertation uses both available data from third parties and collects data for addressing its research questions. The description of each of this data sources is presented below. Most data sources involve the fare-integrated public transportation system of Santiago, Transantiago, considering all buses and metro in the city.

1.4.1 Existing data

i) Smartcard information: each smartcard validation in a public transport service is recorded involving the moment and place in which the traveller boards the vehicle for the case of buses or enters the station for the case of metro. Alighting point and moment of each trip leg is inferred based on the next transactions of the same smartcard.

ii) Buses' arrival at bus stops: based on GPS information delivered by the vehicles every 30 seconds, the arrival at each bus stop by each bus in the system is estimated. This information was provided by the metropolitan transit agency in Santiago, Dirección de Transporte Público Metropolitano, DTPM. For the case of Washington D.C., the information was provided by the Washington Metropolitan Area Transportation Authority, which also comprises automatic passenger count information.

iii) Metro trains schedules: arrival and departure times for every train at every station. This information was provided by Metro de Santiago.

iv) Geographical information: geo-referenced route for every bus service, geo-referenced route for every metro line and the geographical position of every bus stop and metro station in the city. Besides, the location of off-board payment stops, segregated corridors and traffic lights was also available.

1.4.2 Collected data

i) Satisfaction Survey: the survey asked public transport users regarding their satisfaction with the wait time and travel comfort experienced during their last trip leg. This survey was conducted during four days in the third week of July 2017 during the extended morning peak hour, from 07:00 am until 12:00 pm. The goal was to characterize the effect that comfort and wait have on travellers' satisfaction. A total of 1,161 responses were obtained.

ii) Stated preferences survey involving level of service reliability: to measure the impact of service reliability has into travellers' behaviour and choices, a stated preference experiment was conducted. Each alternative has three main attributes: waiting time, travel time and crowding inside the vehicle. However, the main particularity of the survey is that each of these attributes are characterised by five random extractions from a probability distribution, which represent an average week experience. This way, variability is presented indirectly, based on the observed daily difference for each alternative. The survey was applied during the first week of October 2019 in 10 different Public Notary Offices. A total of 1,314 people completed the survey, which corresponds to 10,512 choice scenarios.

This dissertation is based on quantitative methods. Several graphical analyses were performed to visualize the differences between modes, alternatives or even between scenarios with different reliability levels. In terms of modelling the causes of headway variability, Multiple Linear Regression as well as Dynamic Panel models were estimated. When modelling the effects of public transport reliability, different Logit models were formulated. Firstly, for the aggregate effects, a Cross-Nested Logit was estimated. Secondly, for satisfaction modelling a Latent Class Ordered Logit model was estimated. Thirdly, a Hybrid Latent Variable Multinomial Logit which considers attributes' variability was estimated. Finally, policy implications are discussed for every modelling formulation.

1.5 Contents and Contribution

This dissertation describes the most important results and conclusions obtained. These results are comprised in six different articles, presented from Chapter 2 to Chapter 7. Chapter 8 finalizes with overall conclusions and learnings. Each article chapter is briefly described below, in terms of their contents and contributions.

1.5.1 Chapter 2 – Full Cost of Headway Regularity

In this article, we provide a review of a full range of impacts of an unreliable public transport service. We show how regularising headway could improve level of service beyond the gains of simply increasing the operational speed. Regular headways positively affect comfort, reliability, travel and wait time, operational costs, and even some urban impacts of bus services. Thus, the focus for public transport agencies and operators should bend into reliability's direction. This is fundamental for making public transport an attractive travel alternative, and therefore must become a core goal for urban sustainability.

This chapter sustain objectives i), ii), and iii) in a general way. Thus, an introductory framework is presented, which will enhance the deeper contributions of the forthcoming chapters.

1.5.2 Chapter 3 – Public Transport Reliability Causes

This article explores on new methods for regression models to explain the evolution of headway irregularity among service lines. Coefficient of variation of headways was selected as the independent variable to study because its direct relationship with extra waiting time. In Santiago, Chile, lack of travel time reliability (mostly on waiting time) is one of the main complaints about the public transport system (called Transantiago). Despite some direct incentives, limited noticeable improvements are observed.

The independent variables considered in the model are grouped in three categories: street, route and bus characteristics. Results show that, as expected, upstream disturbances have a significant effect on the service regularity at downstream bus stops. The results should be useful to orient the interventions in the system's operations, infrastructure and contracts that will improve reliability the most. This chapter deals objective ii) completely.

1.5.3 Chapter 4 – Aggregate Public Transport Reliability Effects

This article presents the estimation of an aggregate demand model based only on real public transportation data, which may be one of the first of its kind. This model showed a negative and significant impact for the coefficient of variation of waiting times over the total demand per origin-destination pair. This fact bears out that reliability, understood through headway variability, is an important attribute and shouldn't be neglected.

This chapter attends to both objectives i) and iv). For the former, the graphical analysis of big data sources presents visually a good representation of public transport reliability in the city of analysis. For the latter, the aggregate choice model estimated presents insightful ideas regarding how different public transport attributes may affect alternative choices at an individual level.

1.5.4 Chapter 5 – Public Transport Users' Satisfaction

In this article, we investigate the existence of non-linearity in users' satisfaction caused by both the crowding level and the number of denied boardings through a post-service satisfaction survey of bus and metro users. An Ordered Logit Model was estimated, accounting for sample heteroscedasticity and preference heterogeneity. Overall, there is a significant and negative perception of the bus mode, keeping all other attributes equal.

The relationship between crowding and satisfaction might bias service planning and delivery if performance indicators associated to service are not properly weighted by the number of passengers served. Improving level of service indicators in this direction might provide public transport agencies a clearer and more accurate perception of the actual users' experience. This chapter deals exclusively with objective iii), providing a complete analysis of passengers' satisfaction perception.

1.5.5 Chapter 6 – Public Transport Choice Modelling

This article describes the survey and modelling considerations to find the impact that reliability has on travellers' public transport choices. An experiment of stated preferences was carried out, where the design characteristics were four operational attributes: speed, frequency, headway regularity and average demand. Every scenario was constructed randomly, based on the operational characteristics of the specific scenario. This way, reliability is not presented as an attribute by itself but as a result of several repetitions of the same trip.

The results prove the importance of headway regularity in terms of passenger choices. Not only the indirect effects were found highly significant, as excess waiting time and over-crowding, but also unreliability per se. As noticed, this chapter bears out exclusively objective iv).

1.5.6 Chapter 7 – Cost Benefit Analysis

In this article, a headway control experiment was conducted and evaluated for Washington Metropolitan Area Transit Authority (WMATA) routes 70 and 79 in Washington D.C. This was conducted as it is understood that headway management can potentially reduce passenger waiting time and on-board crowding on high-frequency services. The field experiment is evaluated by performing a before-after empirical evaluation. The organizational process and challenges involved with the implementation are discussed as well.

Overall, a reduction of 26% in passenger excess waiting time was attained which implies annual time savings that translate into $1 million USD. Even though the field experiment implementation was far from ideal, the benefits obtained so far might pave the road to a long-term commitment to shift into a fully controlled headway-based management. Thus, this final chapter is directly related with the fifth specific objectives, providing a proper study case with enough evidence to demonstrate the importance in benefits evaluation of headway regularity analysis.

2. A COMPREHENSIVE PERSPECTIVE OF UNRELIABLE PUBLIC TRANSPORT SERVICES' COSTS

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2.1 Introduction

High levels in under-priced private car use has brought increasing negative externalities and resource consumption. This has prompted cities around the world to seek ways of encouraging more sustainable mobility alternatives. The New Urban Agenda adopted by the United Nations at the Habitat III conference in 2016 explicitly promotes the significant expansion of "accessible, safe, efficient, affordable and sustainable" public transport systems, which are recognized as essential to the sustainability of large cities (United Nations, 2017; paragraph 114). In urban contexts a combination of buses, minibuses, trams and metros is the main alternative to private cars, particularly for longer trips.

Among the various existing modes of high-frequency mass transit, metro systems play a structuring role (Glaeser, Kahn, & Rappaport, 2008). Transport authorities and users alike tend to favour investment in this mode over surface alternatives such as buses or trams. Thus, when demand is sufficient and the resources are available, many cities opt for building metro. This way, we will focus on the main attributes that travellers value of a metro experience as those that any public transport service should aim for. Four fundamental characteristics of metro systems make them particularly attractive to riders: i) fast, ii) short waits, iii) comfortable (high passenger capacity), and iv) reliable.

Nevertheless, in recent years many cities have implemented systems known as Bus Rapid Transit (BRT) with a view to offering service levels similar to a metro using buses running over the surface road network. To achieve metro-type service levels in this or any other type of surface system, actions would have to be taken in relation to each of the four above-mentioned metro characteristics that would: i) increase speed, ii) increase frequency, iii) increase capacity, and iv) regularize headways (see Figure 2.1).

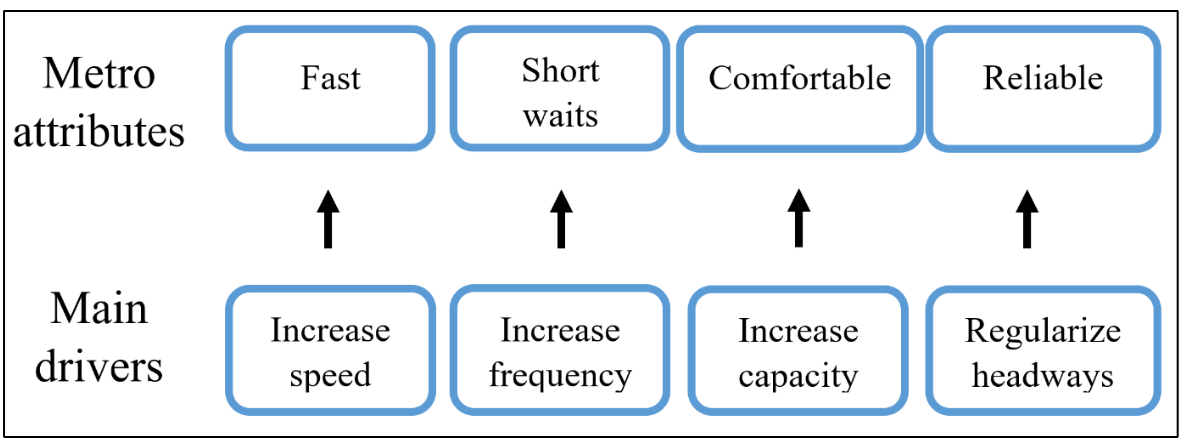


Figure 2.1 Key metro attributes and their drivers.

Increasing speed alone, however, has a series of desirable effects. Not only are trips completed in less time, but the operating cycle time of the vehicles in the system is also reduced. This in turn enables the provision of higher service frequencies and greater delivered passenger capacity for a given vehicle fleet size. In other words, higher speeds mean shorter wait and travel times as well as greater passenger comfort, assuming that this capacity increment exceeds the extra demand that the more attractive service should capture. Furthermore, shorter cycle times reduce operating costs per kilometre and raise each vehicle's productivity in systems operating below their optimal speed. All of which suggests that efforts to improve surface systems should focus on speed as the central driver in improving service levels.

But this concern for speed ignores reliability, the fourth key metro attribute named above. By reliability is meant a level of service experienced by users regularly travelling on a public transport line that does not significantly vary under similar conditions (van Oort, 2011). Both for rail-based and bus systems, wait time is one of the aspects of a trip most subject to service variability (van Oort, Brands, De Romph, & Aceves Flores, 2015). And since waiting is inevitable in every stage of a trip on public transport, variability is inherent in wait time, especially for services with no set timetable designed rather to meet frequency targets. The latter is usual in regions such as Latin America, Africa and Asia, precisely those where public transport is the dominant mode of motorized travel (Muñoz and Paget-Seekins, 2015).

The intrinsic variability of wait times is exacerbated when headways are highly irregular. This is particularly negative for users given that waiting is one of the factors that most effects their trip experience (Ortúzar and Willumsen, 2011; Raveau et al., 2014). Offering a more reliable service for riders thus requires that headways be as regular as possible.

But headway irregularity strongly impacts public transport in multiple ways, and the purpose of this article is precisely to identify those other effects as they impinge on operating costs as well as service levels. By reviewing the literature, we gather different impacts from headway irregularity, providing a novel comprehensive picture and improving our understanding of the consequences of this phenomenon. Our intention is to support the consensus among transport system authorities and operators of the importance of addressing this key attribute of public transport systems, which heretofore has not been given the consideration it deserves and only recently has received significant attention in the academic literature. In what follows, Section 2 discusses the source of headway irregularity, Section 3 describes the impacts it has on service levels and Section 4 outlines its effects on system operating characteristics. Section 5 then examines other consequences of irregular headways and Section 6 concludes with a look at available mechanisms for meeting the challenge of regularity in public transport service.

2.2 The source of headway irregularity

If headway irregularity has such a negative effect on bus systems, why does it occur? Can it not be eliminated simply by ensuring vehicles are dispatched from route terminals at regular intervals? Unfortunately, not. Various disturbances inevitably arise that upset buses' regularity as they proceed along their routes. And once the irregularity sets in it tends to get progressively worse, ending up with buses travelling in platoons from stop to stop. This phenomenon, known as bunching, is the natural evolution of uncontrolled and unscheduled public transport services.

To understand the root causes of this phenomenon, imagine an unscheduled service that is running stably with perfectly regular headways. Furthermore, for the sake of simplicity, we will assume that it offers constant travel times between bus stops and that passengers arrive at a constant rate at every bus stop. So, what happens if one of the vehicles on the line is then held up briefly? The headway to the vehicle immediately preceding will now be slightly longer than normal, while the headway to the vehicle immediately following will be a little shorter than normal. When the vehicle that was held up arrives at the next stop, there will be more than the usual number of passengers waiting, which in turn means its departure from that stop will be somewhat delayed. Furthermore, its passenger load will now be greater than usual so that dwell times at later stops while passengers alight will be longer. Thus, the vehicle will get increasingly slower as it advances along its route.

While all of this is happening, the effect on the vehicle behind is just the opposite. Since its headway to the vehicle in front (the one that was originally held up) is shorter than normal, fewer passengers are waiting at the upcoming stops so boarding times there are also shorter, its passenger load is smaller and the following stop requests are therefore fewer. This vehicle will thus get increasingly faster until it catches up with the ever-slower vehicle just ahead of it. In this sense, regular headways between consecutive vehicles in such a system may be considered as a textbook example of an inherently unstable equilibrium (Daganzo, 2009).

Note that the possibility of buses to overtake each other, which depends on traffic regulations and infrastructure, would still not solve the bunching problem. This is so because once the faster bus passes the slower one it will encounter higher than normal numbers of waiting passengers, which will immediately reduce its speed.

The frequent disturbances that affect public transport vehicles' relative positions along a route can be attributed to two sources. The first one is the variations in the number of passengers to be picked up at stops. The arrival of passengers at a given stop is determined by exogenous phenomena relating to their activities immediately previous plus users transferring at the stop from arriving vehicles serving intersecting routes. The second source of disturbances is the variations in vehicle trip times between successive stops. These may be caused by a number of factors such as traffic signals, congestion or simply differences in drivers' driving styles. Such variations are, of course, much less pronounced in the case of rail-based services that run on dedicated lines and are often driverless. With buses, there is evidence that segregated infrastructure not only boosts speeds but also reduces variability (Durán-Hormazábal and Tirachini, 2016).

Although we have argued here that regular dispatching from route terminals does not prevent vehicle bunching, it does help delay its occurrence. What the evidence suggests is that headway variability tends to increase as vehicles advance along their routes (Newell and Potts, 1964; Johnson et al., 2015). This is illustrated by Figure 2.2, a typical space-time plot of the evolution of bus positions on an unscheduled public transport route. The trajectories of the vehicles show dramatic bunching up happening gradually along the route. This process seems fed by a careless dispatching operation at the terminal (0 km position in Figure 2.2).

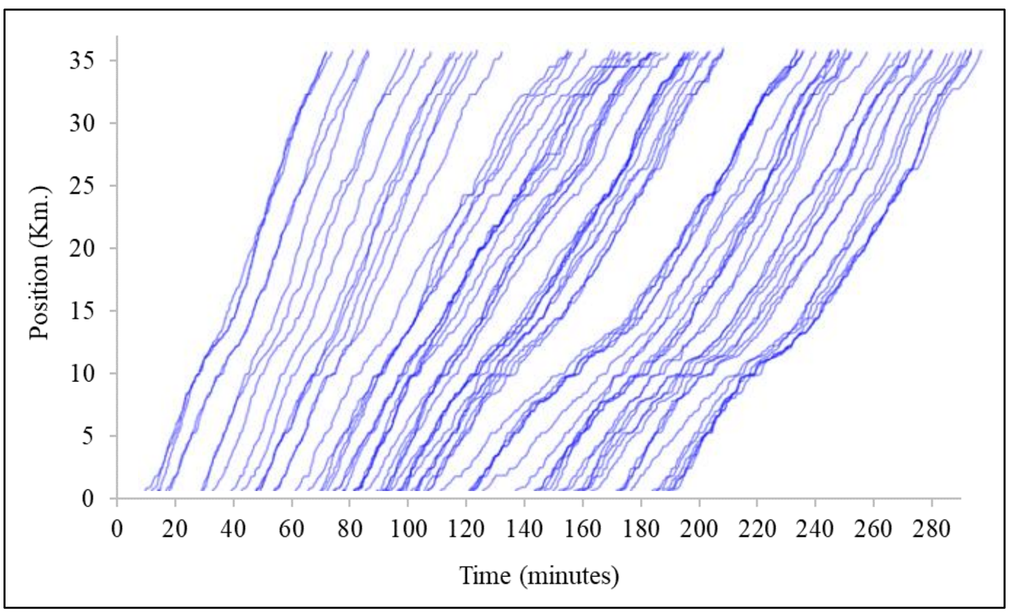


Figure 2.2 Evolution of bus service trajectories in space-time.

The importance of dispatch regularity becomes clear when a headway regularity indicator is calculated for a public transportation agency, as in Figure 2.3. Figure 2.3 displays the evolution of the average headway variability indicator used by Transantiago, the public transport agency in Santiago, Chile, for the seven bus companies operating in the city. The scale is normalized to the lowest (i.e. best) dispatch value for any company. Each service is checked at three points along the route, and Figure 2.3 displays the average indicator of the three points across the routes of each company versus the average distance from the dispatch point across all routes of the company. Figure 2.3 shows that in absence of headway control strategies, headway variability increases quite similarly along the routes across companies, leaving the dispatch regularity as the key performance difference between them. The multiple negative impacts of this phenomenon on both user service levels and system operating variables are taken up in what follows.

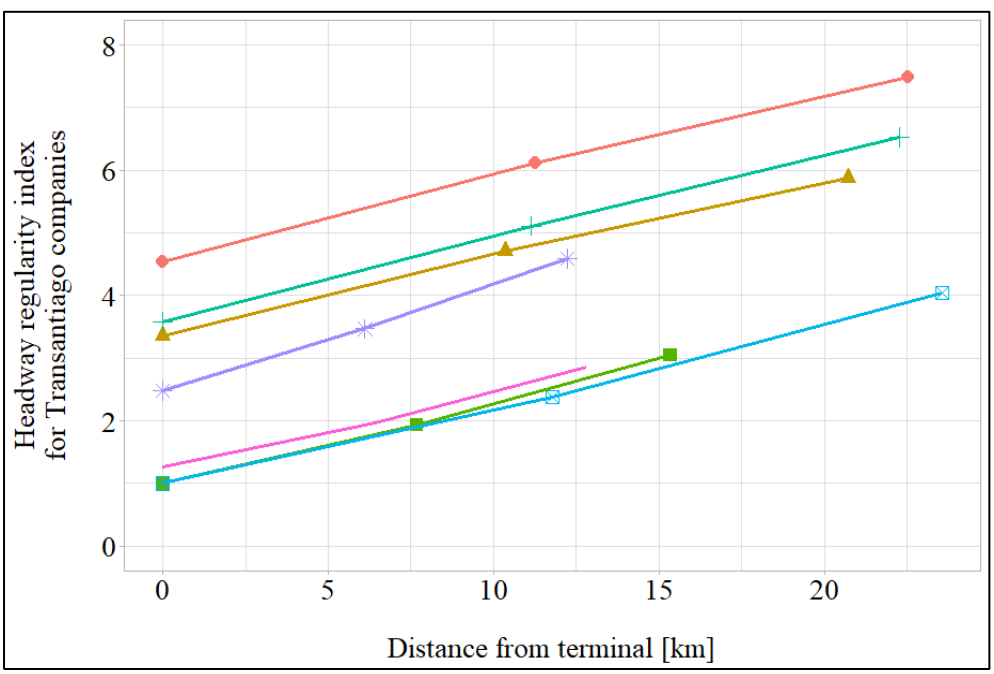


Figure 2.3 Headway regularity indicators for Transantiago bus companies.

2.3 Impacts on user service levels

The immediate impact on users of irregular headways is the lack of system reliability as it becomes more difficult to predict, upon starting a trip, when they will arrive at their destinations (van Oort et al., 2015). But there are other impacts as well. The one most extensively studied is the increase in average wait time. Consider a service that visits a given stop at intervals (i.e. headways) averaging μ_h with a standard deviation of σ_h. Following Osuna and Newell (1972), the average wait before the first vehicle appears for a user arriving at the stop at a given moment (assuming no published timetable or transfer point coordination) is given by the following formula.

$$\mu_w = \frac{\mu_h}{2}\left(1 + \frac{\sigma_h^2}{\mu_h^2}\right) \tag{1}$$

The first term on the right-hand-side is one-half of the average interval and would equal the average wait time if headways were perfectly regular. But wait times increase as headways grow even if average service frequency remains constant. Besides, this extra time cost increases if transfer synchronization at common stops is considered (Gavriilidou & Cats, 2018; Ibarra-Rojas & Muñoz, 2016).

Headway irregularity also generates variability in the number of users boarding each vehicle given that the longer are the intervals, the more passengers will be waiting at the stops. Thus, there is an evident positive correlation between wait times and vehicle passenger loads experienced by riders. By causing passenger load variability, headway irregularity also produces uncertainty in users regarding the level of service they will experience. It also impacts seat availability, making it less likely to travel seated (Babaei, Schmöcker, &

Shariat-Mohaymany, 2014). This situation deteriorates further when passenger loads approach vehicle capacity as some users may not be able to board the first arriving vehicle and thus their wait times will be further prolonged. This issue affects the more vulnerable public transport users, as elders, pregnant women or people with constant or momentary physical disabilities the most.

It follows from the foregoing that only knowing service frequency and average vehicle load masks the fact that for some users, wait times will be considerably longer than the norm and the vehicle that finally arrives will be running very full. Magnifying the gravity of the problem is that the marginal disutility attributed by users to wait times and on-board comfort increases nonlinearly with their magnitudes. In other words, the marginal impact of wait time tends to increase as waiting increases while the marginal impact of on-board trip time tends to grow as passenger density in the vehicle grows (Fan, Guthrie, & Levinson, 2016).

Numerous declared preferences and revealed preference studies of public transport users have determined the existence of a "crowding multiplier" equal to the marginal rate of substitution between in-vehicle trip time under crowded conditions and the same variable under non-crowded conditions, that is, with low passenger loads. This concept has been applied to improve understanding of user behaviour and set criteria for evaluating projects aimed at adjusting vehicle passenger densities (Batarce, Muñoz, & Ortúzar, 2016; Björklund & Swärdh, 2015; Wardman, 2014). Values of the multiplier for a density of 6 passengers per square metre, where travelling seated is the baseline, are found to vary between 1.3 and 2.4 for standing passengers depending closely on the city and transport mode studied (London: Wardman, 2014; Chile: Batarce et al., 2015; Chile: Tirachini et al., 2017, Australia: Wallis et al., 2013; Paris: Haywood and Koning, 2013; Japan: Kato, 2014; Guangzhou: Liu, et al.,2016; Hong Kong: Hörcher, et al. 2017), as shown in Figure 2.4.

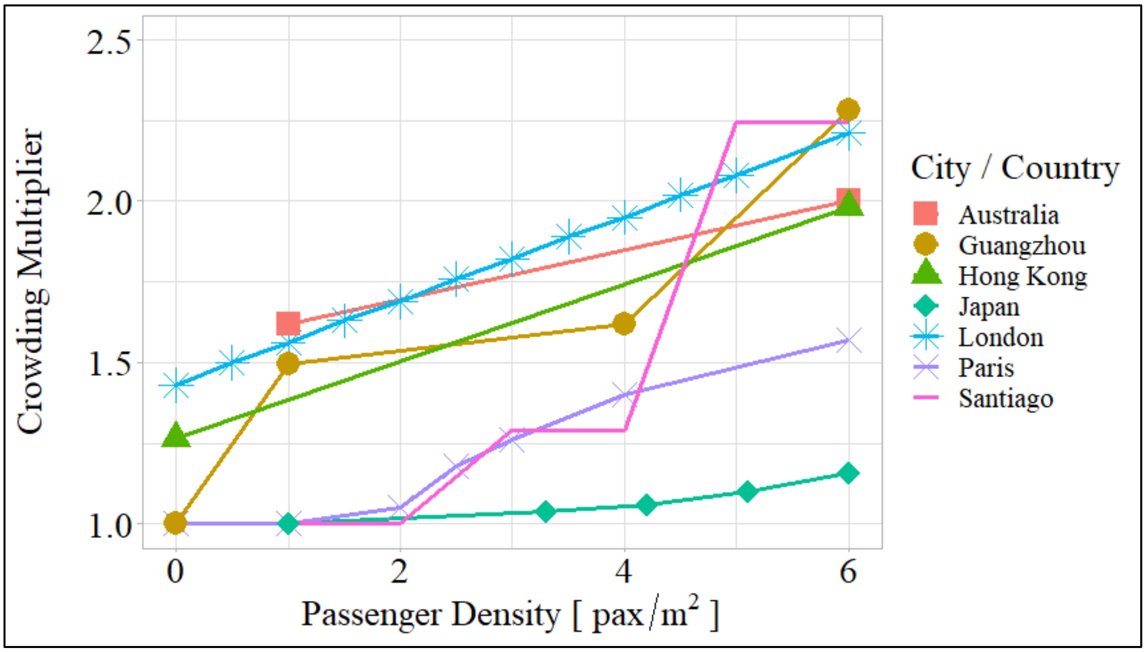


Figure 2.4 Crowding multipliers for various cities and countries.

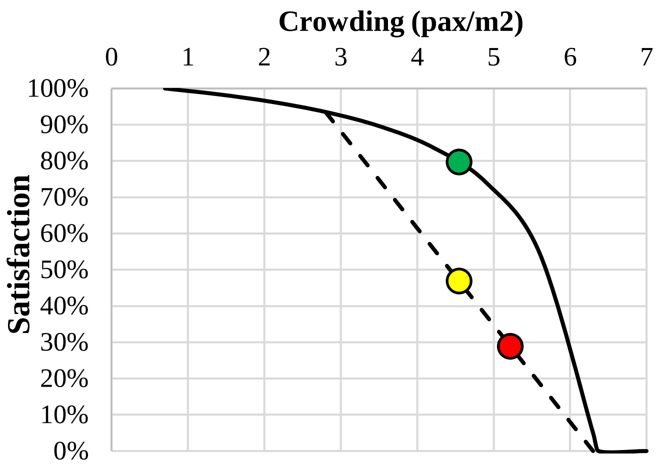
The relationship between passenger load and rider satisfaction has been measured in various user surveys. As expected, users' satisfaction impacts their behaviour, which is of vital importance for public transport agencies (de Oña, de Oña, Eboli, Forciniti, & Mazzulla, 2016; del Castillo & Benitez, 2013). Intuitively, we would expect that satisfaction would not fall linearly as load increased given that up to some saturation point the marginal impact of an additional passenger is increasing.

To illustrate the enormous damage done by headway irregularity to user perceptions of service quality, consider the following example (Soza-Parra et al., 2019b), which is not based on any specific data, but is consistent with our current knowledge regarding attributes perception. A bus line has a scheduled frequency such that service intervals average 6.5

minutes, with the result that in conditions of perfect headway regularity, passenger density in each vehicle is 65% of its capacity. According to the satisfaction curve (Figure 2.5), if those intervals are maintained and the load for each vehicle remains identical, the user satisfaction level will be 79.6% (green dot in figure).

Suppose now that due to poor operational control, the intervals between successive buses alternate between 4 minutes and 9 minutes (the average remaining at 6.5 minutes as originally assumed). The expected loads for the buses at the two different headways will then be 40% and 90% of vehicle capacity, respectively, and users will evaluate their satisfaction very differently depending on the load level the buses they are on is carrying. Those in vehicles at 40% of capacity will report a satisfaction level of 94% while those in vehicles at 90% of capacity will indicate a satisfaction level of 0%. The average figure, combining the satisfaction results for the two vehicle load levels, falls to 47.0% as shown by the yellow dot in Figure 2.5.

What is obscured by this average calculation, however, is that since the passenger loads differ greatly depending on the buses' headway, then so necessarily do the numbers of passengers they carry. Since the indicator of interest is normally the average satisfaction per passenger rather than per vehicle, recalculating on this basis yields an average load of 75% and an average satisfaction of just 47.0% (the red dot in Figure 2.4). In other words, due to headway irregularity the average satisfaction level has fallen from 79.6% to 28.9%, or more than half. This is a direct consequence of Jensen's inequality given the assumed concavity of the satisfaction-occupancy curve.



	Average load	Average satisfaction
Optimal	65%	79.6%
Per vehicle	65%	47.0%
Per user	75%	28.9%

Figure 2.5 Impact of variability on passenger satisfaction.

This situation, already very undesirable, is even more serious considering that users tend to remember bad experiences better than good ones (Kahneman & Tversky, 1979). Service level variability thus biases the public’s rating of the system towards a more negative image of long waits and uncomfortable rides. For a case such as the example in Figure 2.5, it would not be surprising if surveyed users reported lower levels of satisfaction than those predicted by the model.

The arrival pattern of vehicles in this example may seem extreme, but it is not. High headway variability is quite common in many public transport services worldwide. In the example, the coefficient of variation of the headways is approximately 0.38. This means that the average waiting time of a passenger is around 14% higher than in a perfectly regular scenario. For example in Boston (Paget-seekins & Tribone, 2016) this additional waiting time is around 11% for rail-based services and around 43% for bus services. Similar values were observed in 2012 in different Latin American cities (BRT, 2012). We have shown that its effect can be devastating for user satisfaction. It is quite impressive that most public transport agencies annual reports and performance indicators neglect this as if it did not happen. Many agencies do not even report any kind of headway variability based indicator. A partial exception is the broadly used Transit Capacity and Quality of Service Manual (KFH Group, 2013) which addresses reliability, in a high frequency context, with two performance metrics: the coefficient of variation of headways to measure headway adherence, and the excess wait time to measure the extra waiting time for users due to an irregular operation. Even though, these indicators address the impact of headway variability in waiting times, the impact in comfort is neglected. Indeed, the Manual provides as comfort-related performance metrics the load factor (average amount of passengers per seat) for vehicles designed specifically for a mostly seated operation and the average standing passenger space (average free space in square feet or metres per passenger) for vehicles designed specifically for a mostly standing operation. However, as explained before, average measures of comfort across vehicles overestimate the actual level of service experienced by users.

2.4 Impacts on operations

Headway irregularity also negatively affects the operating characteristics of a public transport system (Ceder, 2007; Vuchic, 2017). Generally speaking, public transport services are designed to offer a certain level of capacity in passengers per hour (K, in pax/h), given by the product of the maximum reasonable number of passengers that can be carried by a vehicle (k, in pax/veh) and the frequency of the service (f, in veh/h). Thus, $K=k\cdot f$. The maximum frequency that can be provided with a given fleet is the ratio of the fleet size (n, in veh) to the vehicle time cycle (t_c, in h), that is, $f = n/t_c$. It then follows that the longer time cycle, the greater the fleet size required to maintain the desired level of capacity. We have already seen that vehicle bunching caused by headway irregularity reduces average speed below that achieved with regular headways. This in turn will lengthen the vehicle time cycle and therefore require a larger fleet size to maintain the desired capacity, with a consequential rise in costs per kilometre for the additional vehicles and drivers to operate them.

A reserve of vehicles and drivers will also be required to maintain regular dispatches from route terminals. This is due to the negative effect of the greater time cycle variability caused by bunching on the arrival times at the terminals of returning vehicles completing a cycle.

Another effect of bunching is the simultaneous arrival of more than one vehicle at a stop. In the case of buses, this delays the beginning of the boarding-alighting process at stops, which also affects buses on other lines using the corridor where the bunching occurs (Gibson, et. al., 1989). These delays are further extended for the buses at the head of the bunch, for two reasons. First, they face a higher-than-normal demand due to the long headways ahead of them and therefore longer dwell times; and second, boarding and alighting times are longer due to the greater friction between the abnormally large numbers of passengers getting on and getting off. Both for buses (Milkovits, 2008) and metro trains (Suazo-Vecino et al., 2017), dwell times have been observed to increase non-linearly with vehicle passenger load for a given vehicle size. The line of buses waiting to use the stop also lengthens trip time between stops for all the other lines on the corridor. This necessarily implies that the speed of all these other vehicles will be reduced as well.

Note that a similar phenomenon occurs with high-frequency trains. Although the control systems maintain a minimum spacing to prevent actual bunching, headways frequently do shorten so that the progress of a given train is conditioned by that of the one ahead. And when a train headway becomes longer than the average, it tends to grow along the route for the same reasons explained before.

2.5 Other impacts

So far, we have analysed in depth the effects of headway irregularity in public transport on user satisfaction and service levels and certain operating characteristics. There are, however, other impacts experienced by the community that also deserve mention.

One of these is the simple indignity of having to wait amid crowds of frustrated users at bus stops, a situation people have come to associate with bus services (Tirachini, Hensher, & Rose, 2013). Also, the sight of long lines of buses creates an image of inefficiency even though it is the natural result of this type of system and tends to damage the general perception of buses as a mode.

Another negative impact stems from the systems existing in many cities of the world where drivers are paid as a function of the number of passengers they capture (Johnson, Reiley, & Muñoz, 2015). This arrangement creates a highly destructive rivalry between the drivers, who naturally see the buses in front of them as competitors for users at stops up ahead and therefore a threat to their pocketbook. The result is serious frictions between vehicles that inevitably lead to accidents as well as poor service levels for users. The problem is accentuated by irregular headways, but it could be eliminated if the route operator worked to maintain regular intervals between their buses.

Finally, it has already been noted that variable headways mean passenger loads will be irregularly distributed between buses on the same line. In an empirical study performed in November 29, 2012 in bus line 210 in Santiago, where significant crowding and fare evasion is observed, it was shown that headway regularity can help reduce fare evasion. The experiment consisted in applying a holding strategy in all buses of the line at a subset of bus stops (based on the methodology proposed by Delgado et al; 2012). Figure 2.6 shows the number of card validations in each working day during November 2012 in bus line 210 and in every other line operated by the same company. The straight line represents the regression between card validations in line 210 and card validations in the rest of the services operated by the firm. As expected, a positive correlation is observed. The red triangle represents validations on November 29, a clear outlier of the trend observed the rest of the month. According to the company this behaviour was due to a more even distribution of passengers across buses, so less users entered through the rear doors not paying the fare just because the front door was blocked with passengers.

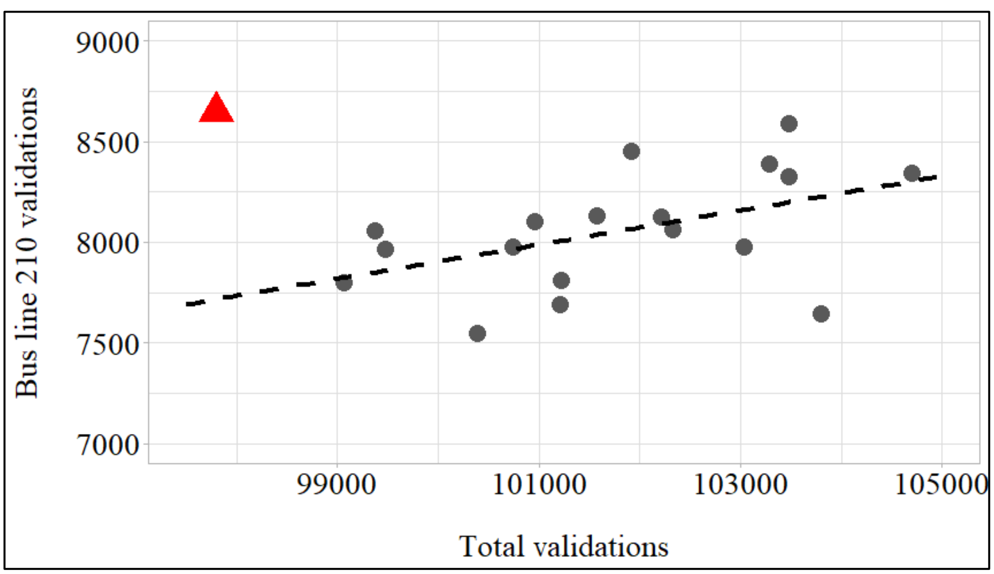


Figure 2.6 Bus line 210 vs total validations during November 2012.

2.6 Achieving regular headways

We have shown that public transport operators should also aim at offering headways as regular as possible at stops along the route. Several actions can be taken to improve this performance: (1) dispatch vehicles under even headways from the route terminals, (2) reduce travel time variability between consecutive stops, and (3) take some control actions along the route.

Dispatching even headways is not always easy since the urban context at the extreme stops of the route may impede to store vehicles. Despite this, very often operators do not pay enough attention to this task and buses are sometimes dispatch in batches. Still, the impact of a smooth dispatch rate is very relevant in the performance of the whole route (Berrebi, Watkins, & Laval, 2015; Ning, Xun, Gao, & Zhang, 2015).

Travel time variability between consecutive stops can be reduced if buses operate segregated from general traffic and if dwell times are speed-up through off-board payment infrastructure (Durán-Hormazábal & Tirachini, 2016; Schmidt, Muñoz, Bucknell, Navarro, & Simonetti, 2016). Also, traffic signals can play an active role extending green phase to delayed buses (Anderson & Daganzo, 2019).

Regarding control actions along the route several studies have proposed different mechanisms based on real-time information about vehicle location and passengers inside vehicles and at stops. The easiest and more frequently studied strategy is vehicle holding (Cats, Larijani, Koutsopoulos, & Burghout, 2012; Muñoz et al., 2013; Xuan, Argote, & Daganzo, 2011), but stop skipping, boarding limits and express operation have also been considered (see Ibarra-Rojas et al., 2015). Bueno-Cadena and Muñoz (2017) present a holding and speed control methodology for a Metro line in which energy consumption is also minimized. More recently, a bus substitution strategy for a scheduled service was proposed by Petit et al. (2018) in which a delayed vehicle turns to not-in-service visiting bus stops to drop passengers only. Morales et al. (2019) propose a bus injection mechanism in which some buses are left at an intermediate stop ready to be injected in service when a long enough headway occurs.

These papers argue that the potential impact of these tools in terms of user time only is highly significant. For example, Delgado et. al. (2012) show that in high passenger demand scenarios holding and boarding limits' savings can reach up to 77% of the excess waiting time, and Cats et.al (2012) show a reduction of 43% in the coefficient of variation of headways and a 73% reduction of bus bunching occurrence with similar holding strategies. A concern with vehicle holding is that deciding how much to hold a bus based on local conditions only has shown to over hold vehicles (a bus is held only because the previous one was held) delivering a costlier operation for the user than no holding at all (Delgado, Munoz, & Giesen, 2012; Muñoz et al., 2013). Also, holding decisions must be taken when buses start to get closer, since separating already bunched buses would take holding the trailing bus for an unbearable amount of time for the users on board. Commercial software to assist each driver on how much to hold a bus at each stop based on real time information is starting to be implemented (Lizana et al, 2014; Berrebi et al, 2018). This should become more common when operators receive a stronger incentive to keep headways as regular as possible. Headway control strategies have shown to provide substantial benefits not only for users but also for providers (Fadaei & Cats, 2016; Soza-Parra et al., 2019a).

Finally, where frequencies are relatively low (5 or fewer buses per hour), timetables are typically defined for each stop. While this helps in solving the reliability problem, it requires extending the cycle time by incorporating large enough buffer travel times in the timetable to guarantee its adherence. But extending the cycle time harms in-vehicle user travel times, the frequency to be offered, and transport capacity. Xuan et al (2011) propose a dynamic holding strategy using bus arrival deviations from a virtual schedule at control points to improve timetable adherence. However, as stated previously, this is not the case for most regions where public transport is the dominant mode of motorized travel. In these regions, high-frequency public transport is the common practice and this trade-off does not exist (Delgado et al., 2012).

The use of mobile apps that provide information in real time on bus positions and stop arrival time estimates reduces passenger anxiety, but of course does nothing for the load levels experienced on vehicles. Another relevant technological advance is the development of autonomous buses. This promises to improve service reliability, first because they will be equipped with automatic control mechanisms, and second because their ability to detect and record the presence of other vehicles will discourage private vehicle drivers from illegally entering bus lanes. The implementation of such buses will also bring benefits such as better driving and pulling in at stops, and fewer accidents.

In conclusion, this article has attempted to show that improving the regularity of public transport vehicle headways will increase service reliability, reduce wait times, enhance user comfort and even cut trip times. Thus, all four attributes associated with good service levels (see Figure 2.7) would be changed for the better. The significant positive impact greater headway regularity would have on both service levels and system operating costs should give cause for reflection on where best to direct the focus of public transport analysis. Typically, the emphasis is placed almost exclusively on maintaining attractive service speeds, and all the more so in the case of Bus Rapid Transit. However, in this paper strengthen through multiple arguments the intuition proposed by Delgado et al (2016), that Bus Rapid and Reliable Transit (BRRT) would perhaps be a better name for the kind of service we should be aspiring to. In this scenario, the focus must be placed in reliability, as much as it has been placed in speed in the previous decades. Faster vehicles bring travellers closer to their desired destination, but these benefits may vanish if unreliability causes people to experience long waits and crowded buses, making their traveling experience miserable. The time has come, to redirect service design and implementation towards reliability.

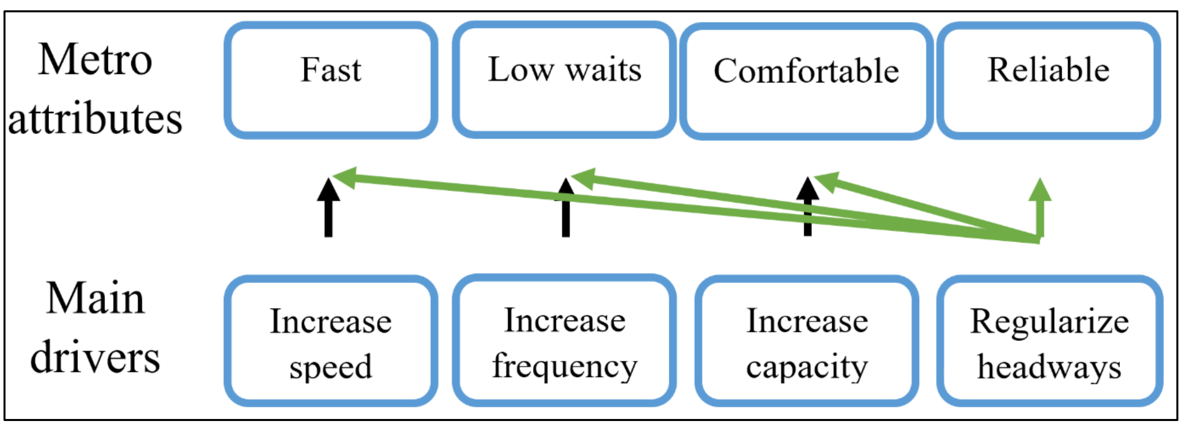


Figure 2.7 Impact of headway regularity on key attributes of public transport.

Acknowledgements

This research was supported by the Centro de Desarrollo Urbano Sustantable, CEDEUS (Conicyt/Fondap 15110020), the Bus Rapid Transit Centre of Excellence funded by the Volvo Research and Educational Foundations (VREF), the FONDECYT project number 1191279 and the scholarship funded by CONICYT for Ph.D. studies (CONICYT-PCHA/Doctorado Nacional/2016). Besides, we would like to thank four "anonymous" reviewers for their insights.

3. WHAT FACTORS DETERMINE THE VARIABILITY OF THE LEVEL OF SERVICE EXPERIENCED BY TRAVELLERS?

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3.1 Introduction

Understanding how public transport travellers make their decisions (in terms of mode, departure time and route choices) is essential in transport planning. Demand models have been traditionally based on a few relevant variables such as fare and travel time. Although usually omitted from planning models, service reliability has been increasingly identified as a key element of travel behaviour (Engelson & Fosgerau, 2016; Fosgerau, 2016). For example, in The Netherlands, measures of service reliability have been incorporated in public transport planning models, based on the premise that reliability explains the difference between travellers' expectations and experiences (Kouwenhoven et al., 2014).

When analysing travellers' behaviour, the value of waiting time is known to be perceived higher than the value of time spent inside the vehicle (Raveau, Guo, Muñoz, & Wilson, 2014). Headway variability affects not only waiting time variability, but also its expected value. Indeed, given a sequence of bus intervals visiting a bus stop where passengers arrive randomly, the average waiting time can be expressed as:

$$E(W) = \frac{E(h)}{2}\left(1 + CV(h)^2\right) \tag{1}$$

, where E(W) is the expected passenger waiting time, E(h) is the mean bus headway, and CV(h) is the coefficient of variation of headways (Osuna & Newell, 1972). If buses visit the stop at perfectly regular intervals, this last term would be zero and the expected waiting time would take its minimum value, i.e. half of the average headway. The difference between E(W) and this minimum waiting time is denoted as the excess waiting time and it results from the unreliability of a service.

To incorporate reliability in a demand model at least three elements are needed: a monetary value for reliability (VOR), a model that can predict the reliability level of a service based on the context in which it will operate, and a model predicting the marginal impact of reliability indicators on users' decisions (Kouwenhoven, 2015). For the second element, this is, to predict the reliability level offered by a service based on its operational context, it is necessary to understand which are the circumstances and variables that affect the level of variability of a public transport service and how they affect it. Thus, the main objective of this article is to expand our current knowledge regarding this set of conditions.

This article takes as a study case Transantiago, the public transport system of Santiago, Chile. Transantiago offers around 400 bus services who attract around 3 million trips in this mode (or trip legs since the system is fare integrated) every day. The bus system is comprised of seven different Business Units that operate the fleet and services. Lack of travel time reliability (mostly on waiting time) is one of the main complaints about the public transport system. To address it, several reliability performance indicators have been included in the private bus company contracts (Beltrán, Gschwender, & Palma, 2013); if a Business Unit fails to meet the required indicator levels, it receives penalties that reduce their revenues. Despite these direct incentives, limited noticeable improvements have been observed. This can be seen in Figure 3.1, where most of the coefficient of variation of consecutive headways observations are above 0.5. Besides, this variability propagates downstream for every Business Unit except for Unit 5.

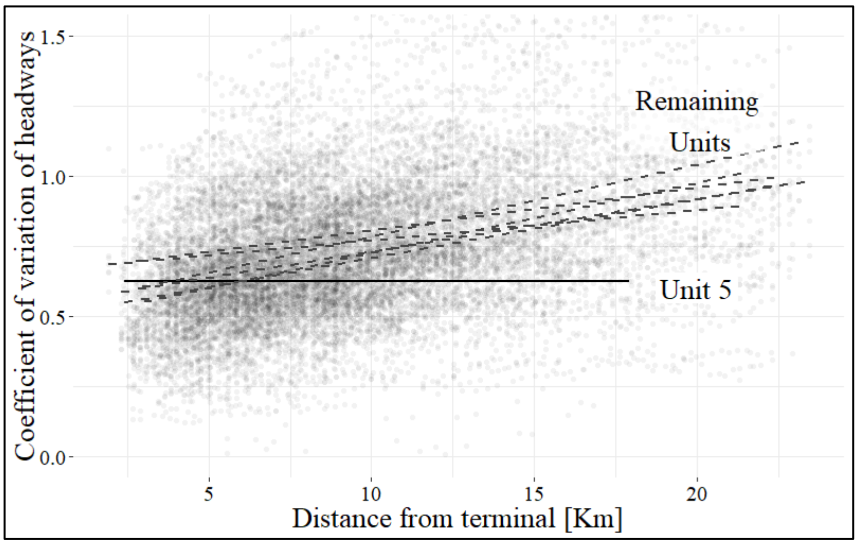

Figure 3.1 Coefficient of variation of headways by distance from the terminal for different business units

Headway variability may be affected by many elements of the context in which a bus service operates. Danés (2016) aimed to explain the propagation of this headway variability between consecutive bus stops in the bus system. This work will expand our current knowledge by identifying several determinants of unreliability for the case of Transantiago. The proposed methodology will allow us to understand some of the main causes of headway variability, both at the dispatching stop, and as it evolves along the route. Given the severe impact of headway variability in the level of service to users, the results of this process are relevant for many reasons. They could orient interventions in the operation, infrastructure and contracts to improve the system's reliability. They can also be used to provide a more fair comparison of the performance of different routes, by distinguishing those elements affecting headway variability that that the operator cannot affect. The article is structured as follows. Section 2 briefly describes the different data sources comprised in this research and describes the methodology used to process the data and the modelling framework. Section 3 shows the main results both for the dispatching and propagation model. Finally, Section 4 presents our main conclusions, their potential implications and provides some guidelines for further research.

3.2 Data and Methodology

Every Transantiago bus is equipped with a GPS system, which sends its position every 30 seconds. During 2012, a project held by Pontificia Universidad Católica de Chile collected, analysed, and processed the GPS information of all Transantiago service. The dataset we will use in this paper consists of the GPS signals for all Transantiago buses for seven days of October during the morning peak hour only. No major disruptions happened to the public transport system during the days of analysis. As these GPS observations are collected every 30 seconds, the exact arrival and departure time at every bus stop is absent.

Each bus route was divided into consecutive inter-stop links. The evolution of headway variability along the route was analysed base on this structure since urban conditions tend to be quite homogeneous within each link. The speed of each bus was then estimated based on the time it takes to reach two consecutive bus-stops. Additional route and stop based information, such as the type of service, the presence of segregated lanes, and the presence of off-board payment stops were obtained from the local public transport metropolitan agency (DTPM). Finally, the location of traffic lights was collected from the local metropolitan traffic control centre (UOCT).

The analysis presented in this article proposes modelling frameworks to explain headway variability for two different contexts: the headway variability at the dispatching stop and its propagation downstream along a route. The dependent variable selected to be explained is the coefficient of variation of headways (CV(h)) since it is a dimensionless variable involving not just headway variability but its relation with the average frequency being offered. It is also directly related with the excess waiting time, which has a strong impact in passengers' level of service. For each bus service operating in Santiago and every stop each of them visits, the CV of the headways observed at the stop over 30-minute periods was computed. Although the specification has considered the CV as the main reliability indicator, it is of course possible to calibrate alternative models for other dependent variables, such as the headway variance, standard deviation, and the difference between a percentile headway value and its mean.

For the case of the dispatching model, a linear regression model is proposed. The coefficient of variation of headways at the first milestone of every bus service run was considered. The independent variables considered in this model are grouped in two categories: attributes at the terminal and along the route. For the former category, the nominal frequency of each specific bus service, the cumulative frequency at the terminal and the direction of the service run were considered. It is expected that the higher the agreed frequency and the cumulative frequency at the terminal, the higher would be the headway variability. Similarly, it is expected that services joining a periphery area with a more central area of the city should present a more irregular dispatch in its outbound run as they usually lack dedicated infrastructure to regulate the incoming sequence of buses into even headways.

To explain the evolution of CV along the route, the cumulative boarding rate, the total distance of the bus service, and traffic light density and segregated corridor proportion along the route were considered. Finally, dummy variables associated to each of the seven companies operating in Santiago were added to identify how their management strategies may affect headway variability.

For the case of the propagation model, there is a strong autocorrelation between independent observations, as the CV at a specific bus stop is strongly correlated with the CV at nearby upstream stops (Abkowitz & Engelstein, 1981; Loo, 1981; Abkowitz & Engelstein, 1983). To solve this issue, the headway variability index measured at an upstream stop was also included as an independent variable. This was expected to allow the model to explain only the headway variability induced between both stops, since the *CV* at the upstream stop would capture the variability occurring elsewhere upstream in the route. However, when performing a linear regression to obtain the parameters, a unit root was found on the upstream coefficient of variation of headways. Situations like the one described here occurs frequently in transportation modelling. An example is the work performed by Lin & Bertini (2002), where they aim to predict bus arrival time by formulating a Markov chain model.

In this work, however, a different approach is proposed to explain headway variability in terms of a set of attributes of the service. The headway variability propagation specification has the following form:

$$CV_{ik} = \phi \cdot CV_{i(k-1)} + \overline{\beta} \cdot x_{ik} + \eta_k + \varepsilon_{ik} \tag{2}$$

Here, CV_{ik} is the coefficient of variation of headways in bus service i at bus stop k, x_{ik} contains a set of explanatory variables occurring between stops k and k-1, and $\bar{\beta}$, η_k and ε_{ik} are the set of parameters, the set of fixed but unobservable service specific effects, and the error term respectively.

Panel data econometrics has demonstrated to be a practical tool to solve typical problems associated with data quality and characteristics, such as unobserved heterogeneity by exploiting the multi-dimensionality of the information (Croissant & Millo, 2008). In order to obtain unbiased parameters, we follow the Arellano-Bond method (Arellano & Bond, 1991). This method is a generalized method of moments which solves endogeneity in the dependent variables without trading off the sample size.

The independent variables considered in the propagation model are grouped in three categories: street, route and service characteristics. Regarding street characteristics along the route, the impact of segregated lanes, as well as the number of traffic lights between two consecutive bus stops, were considered. Dedicated infrastructure is expected to decrease CV while the number of traffic lights to increase it. For the case of segregated corridors, for example, a variable was created which takes the value from 0 to 1, which represent the percentage of segregated corridor between the two bus stops considered.

Route characteristics are those related to the service design, considering traveller's trip length, frequency, distance and number of stops from the head of the service to the stop, bus operator, type of service (express or all-stop), time period, passenger demand, off-board payment stop and route congestion.

As in a high-frequency uncontrolled bus system, disturbances spread downstream, it is expected that the distance from the terminal should have a significant impact on headway regularity propagation. However, when buses bunch, in theory irregularity should not worsen at the same rate. This means that it might be important to test whether the marginal effect of distance is constant.

Off-board payment stops accelerate boarding time (Milkovits, 2008). As buses' detention is one of the key factors which promotes the bunching phenomenon, it is expected that the presence of this type of bus-stops improves regularity (or at least slows down its deterioration rate). However, including this variable might cause a modelling issue, as it might be a source of endogeneity. Off-board payment zones are not placed at random stops, instead they are placed at stops where the demand and traffic conditions impact bus performance the most. To avoid this issue, the probability of the presence of an off-board payment stop was previously calculated and used instead of the actual presence of this type of stop. A Multinomial Logit model is considered, with the boarding rate at the stop, the added frequency at the stop, and a dummy variable if the bus stop is located in a segregated corridor as explanatory variables.

Finally, speed variability should have a significant and negative impact on headway regularity since the source of bus bunching is precisely the variability in travel time between consecutive buses. Thus, the average speed and its standard deviation were considered in the model.

3.3 Results

On one side, for the dispatching model, a Linear Regression Model was estimated by the Ordinary Least Squares method. The linear function proposed is as follows:

$$CV_{i,1} = \alpha + \beta_{contFq} \cdot \text{contFq}_i + \beta_{cumFq} \cdot \text{cumFq}_i + \beta_{return} \cdot \text{return}_i + \beta_{bRate} \cdot \text{bRate}_i + \beta_{dist} \cdot \text{dist}_i + \beta_{bRate,dist} \cdot \text{bRate}_i \cdot \text{dist}_i + \beta_{tlight} \cdot \text{tlight}_i + \beta_{seg} \cdot \text{seg}_i + \sum_{k \in \{\text{Business Units}\}} \delta_k \cdot \text{BUnit}_{i,k} \quad (3)$$

The notation of the variables and the estimated parameters for this model are presented in Table 3.1.

Table 3.3.1 Dispatch model estimated parameters

Attribute	Parameter	Estimated	t-test
Intercept	α	$2.48 \cdot 10^{-1}$	13.44
Contracted frequency	β_{contFq}	$1.78 \cdot 10^{-2}$	12.51
Cumulative frequency	β_{cumFq}	$9.24 \cdot 10^{-4}$	6.95
Returning service	β_{return}	$3.21 \cdot 10^{-2}$	4.31
Cumulative boarding rate	β_{bRate}	$-1.52 \cdot 10^{-4}$	-3.15
Service's total length	β_{dist}	$-9.16 \cdot 10^{-6}$	-6.25
Interaction between boarding rate and total length	$\beta_{bRate,dist}$	$1.15 \cdot 10^{-8}$	3.04
Traffic lights density	β_{tlight}	$-9.06 \cdot 10^{0}$	-2.85
Segregated corridor proportion	β_{seg}	$6.54 \cdot 10^{-2}$	2.38
Business Unit 1 effect	δ_1	$1.17 \cdot 10^{-1}$	6.30
Business Unit 2 effect	δ_2	$1.95 \cdot 10^{-1}$	12.61
Business Unit 3 effect	δ_3	$1.19 \cdot 10^{-2}$	0.88
Business Unit 4 effect	δ_4	$2.24 \cdot 10^{-1}$	15.12
Business Unit 5 effect	δ_5	0	fixed
Business Unit 6 effect	δ_6	$7.87 \cdot 10^{-2}$	5.45
Business Unit 7 effect	δ_7	$5.43 \cdot 10^{-2}$	3.40
Multiple R-squared		18.75%	

In terms of the effect of the attributes at the terminal, we observe a significant and increasing effect in dispatch headway variability for the contracted frequency, the cumulative frequency, and returning services. Both contracted and cumulative frequency were expected to have an increasing effect, as it is expected that headway variability will be higher for those services with high frequency as well as for those terminals with a big number of vehicles to dispatch. In addition, the initial headway variability in returning bus services was found to be higher in average. This is explained by the lack of infrastructure and operational features at the return.

The attributes along the route reflect operational characteristics. Firstly, longer and more demanded bus services show smaller average dispatch variability, which might indicate there is an effort to provide better regularity for those type of services. Traffic light density has also a negative effect in dispatch variability, which might be a proxy of services running through central areas. Finally, the proportion of segregated corridors along bus routes has an increasing effect in dispatch variability.

In order to understand the degree of importance of each of these effects, we measure the average impact for each of them, by multiplying the estimated parameter by the average value of each attribute in the sample. This is presented in Figure 3.2.

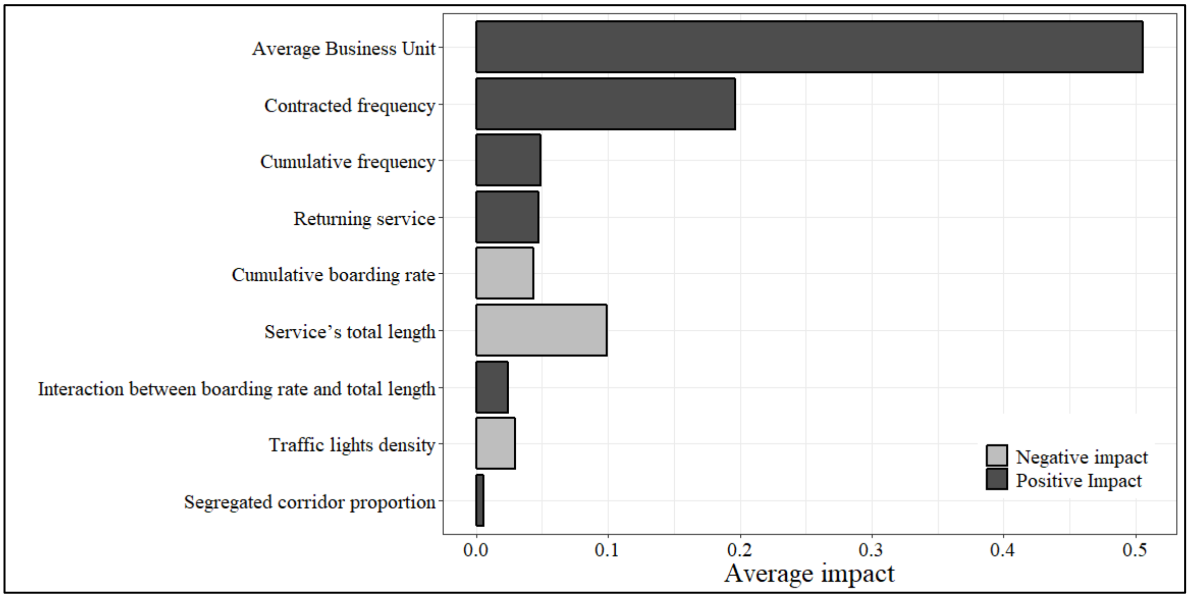

Figure 3.2 Attributes' average impact for the dispatch model

As can be seen, more than 50% of the variation in dispatch variability is explained by the business units' constant effects. The only two significant remaining attributes are the contracted frequency and the service's total length, which account for both terminal and route characteristics.

Finally, we observe a low explanatory power based on the R squared value and the observed v/s fitted scatter plot presented in Figure 3.3. This was expected as most of the average effect is explained by business units' constants.

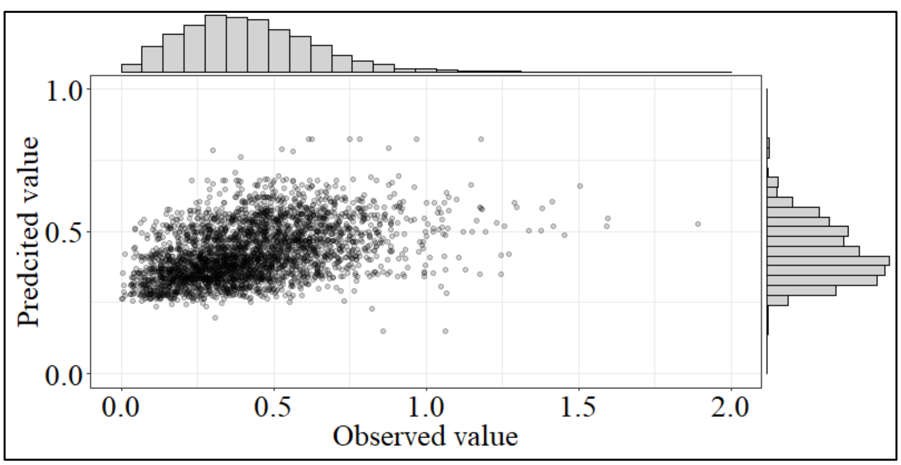

Figure 3.3 Observed vs fitted values for the dispatch model

In terms of the effect of business units, we observe in Table 3.1 that every unit has a significantly higher dispatch variability than Unit 5 except for Unit 3. Based on this fact, we calculated coefficient of variation of headways' distributions for Units 3 and 5 as well as the remaining units. This is presented in Figure 3.4 as follows:

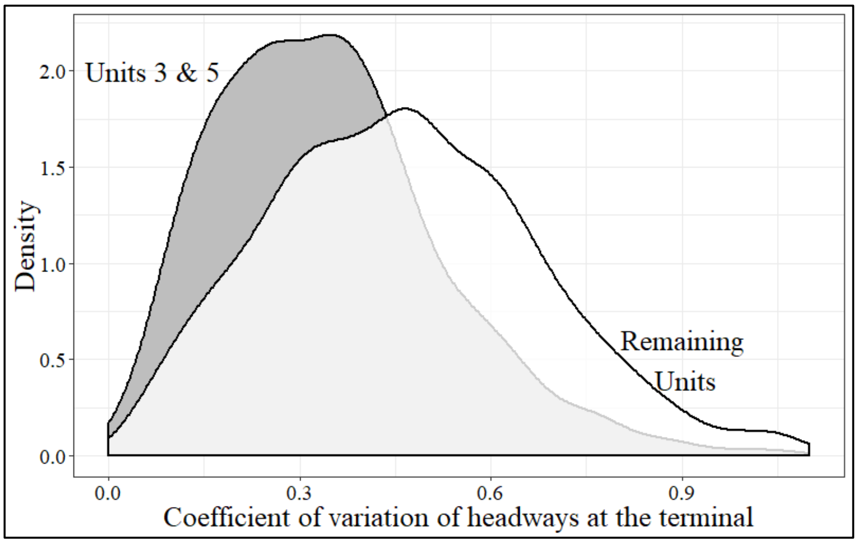

Figure 3.4 Coefficient of variation of headways' distribution for different business units

We observe than even for Units 3 and 5, which have the best performance in the sample, there is a big variability for the dependent variable. All the aforementioned facts prove the strong source of headway variability at the beginning of each bus service. This variability is mostly explained by the lack of headway control management at the time the data was collected.

The propagation model was calibrated using the xtabond2 Stata module (Roodman, 2006). The best model obtained in terms of parameters significance and strict exogeneity of the instrumental variables for the Arellano Bond estimation is the following:

$$CV_{i,j} = \alpha + \phi \cdot CV_{i,j-1} + \beta_{bRate} \cdot \text{bRate} + \beta_{Pops} \cdot \text{Pops} + \beta_{seg} \cdot \text{seg} + \beta_{dist} \cdot \text{dist} + \beta_{seg,dist} \cdot \text{seg} \cdot \text{dist} + \beta_{speed} \cdot \text{speed} + \beta_{SD(speed)} \cdot \text{SD}(\text{speed}) + \beta_{tlight} \cdot \text{tlight} \quad (4)$$

Where *bRate* is the boarding rate (in pax per hour), *Pops* is the probability of the presence of an off-board payment stop in the previous segment, *seg* is the percentage of segregated corridor since the last bus-stop, *dist* is the distance from the terminal in metres, *speed* and *SD(speed)* are the average and standard deviation of speed in the last segment and *tlight* is the density of transit lights in the last segment.

There are 85,816 observations, with 3282 groups (services-period), with an average of 26.15 observations per group. The instruments were the first two lags of CVi,j-1, this is CVi,j-2 and CVi,j-3. The total number of instruments is 573, which is significantly less than the number of groups. This ensures the absence of instrumental over fitting.

The parameters obtained are presented in Table 3.2, as follows:

Table 3.2 Propagation model estimated parameters

Attribute	**Parameter**	**Estimated**	**z-value**
CV(h) last stop	ϕ	$9{,}72 \cdot 10^{-1}$	5,236.11
Constant effect	α	$2{,}54 \cdot 10^{-2}$	119.76
Distance from terminal current stop	β_{dist}	$7{,}41 \cdot 10^{-7}$	122.56
Prob. Off-board payment stop	β_{probps}	$-3{,}27 \cdot 10^{-2}$	-3.50
Boarding rate last stop	β_{brate}	$2{,}79 \cdot 10^{-1}$	9.83
Average speed last segment	β_{speed}	$-2{,}14 \cdot 10^{-3}$	-258.42
SD (speed) last segment	$\beta_{SD(speed)}$	$3{,}62 \cdot 10^{-3}$	112.16
Traffic light density last segment	β_{tlight}	$-1{,}73 \cdot 10^{-4}$	-19.50

Proportion of segregated corridor	β_{seg}	$3{,}41 \cdot 10^{-3}$	2.71
Interaction between distance and segregated corridor	$\beta_{seg,dist}$	$-2{,}80 \cdot 10^{-7}$	-3.24
Number of observations		85,816	
Number of groups		3,282	
Average number of obs. per group		26,15	
Arellano-Bond test for AR(1) in first differences:		z = -8.52 Pr > z = 0.000	
Arellano-Bond test for AR(2) in first differences:		z = 0.33 Pr > z = 0.744	

First of all, based on the results of the Arellano-Bond test for AR(1) and AR(2) in first differences, the Dynamic Panel Model hypothesis is satisfied. This means that the fixed and unobservable effect shouldn't be correlated with the second (and more) lags.

Results show that, as expected, upstream disturbances have a significant effect on the service regularity at downstream bus stops. This can be seen both in the significance and sign of the constant parameter, the distance from the terminal parameter, and the lagged observation parameter. Even though f is close to 1, this parameter was unbiasedly estimated by including the instrumental variables in the model. Besides, the proposed formulation enables us to unbiasedly estimate the rest of the parameters, in contrast with simplified formulations as multiple linear regressions by ordinary least squares which are not able to estimate those parameters properly.

The segregated corridor impact is noteworthy of being analysed. By looking to the parameters, it might seem that segregated corridors increase the propagation rate but reduces the impact of the distance in the propagation rate by a 37.79%. However, this type of infrastructure allows buses to significantly increase their speed. Thus, this strong correlation should be considered to address the full impact of segregated corridors in headway variability. Considering typical operational speeds in segregated corridors and in mixed traffic, we observe that the model predicts that this infrastructure tends to reduce the propagation rate of headway variability.

Finally, there is a negative impact of traffic lights in the operation. This was not expected as the number of stops increases the chance of bunching. However, this attribute is also highly correlated with the standard deviation of speed, which has an increasing effect on the propagation of headway variability.

In order to analyse the relative importance of each attribute in the variation of consecutive bus stops headway variability, we measured the average effect similarly as for the dispatch model. This is presented in Figure 3.5 as follows:

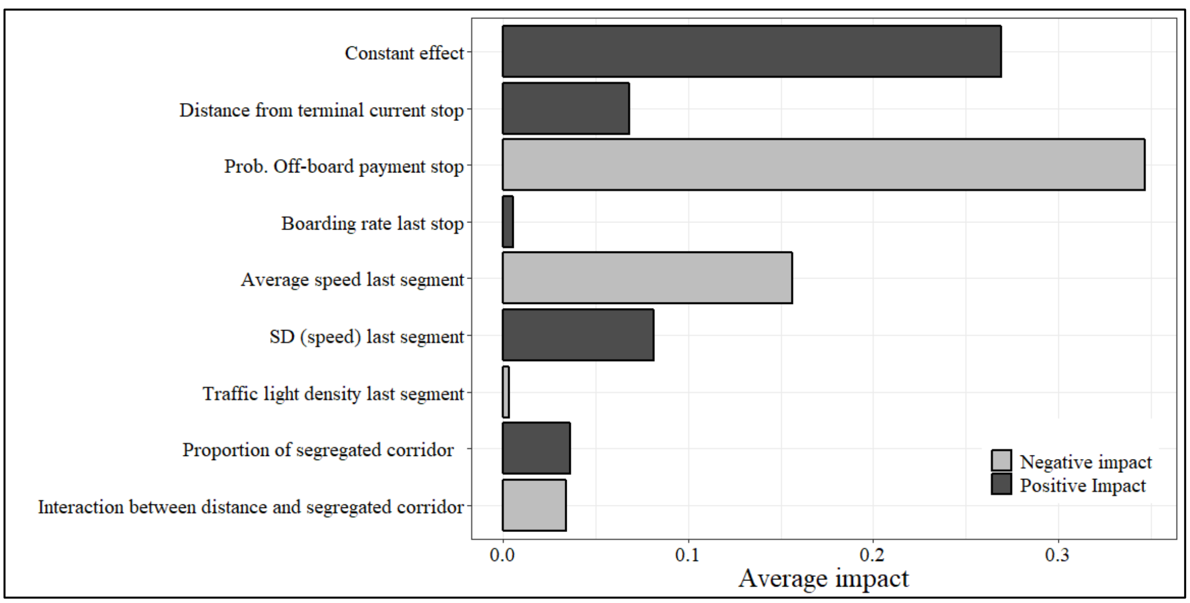

Figure 3.5 Attributes' average impact for the propagation model

We observe that, on one hand, in terms of increasing headway variability, the most important attribute is by far the constant effect, followed by the standard deviation of speeds and the cumulative distance from the origin. On the other hand, in terms of decreasing headway variability, the most important attribute is the presence of off-board payment stops and the average speed in the last segment. These results reinforce the importance of specialized infrastructure to improve bus services' operation and the critical value of the operation at the dispatch.

Finally, the observed and fitted values of the propagation model are plotted in Figure 3.6. We observe that, in opposition to the dispatch model, this one has a significantly better explanatory power. This underpins that the propagation of headway variability, in absence of headway control strategies, is highly more predictable than dispatching.

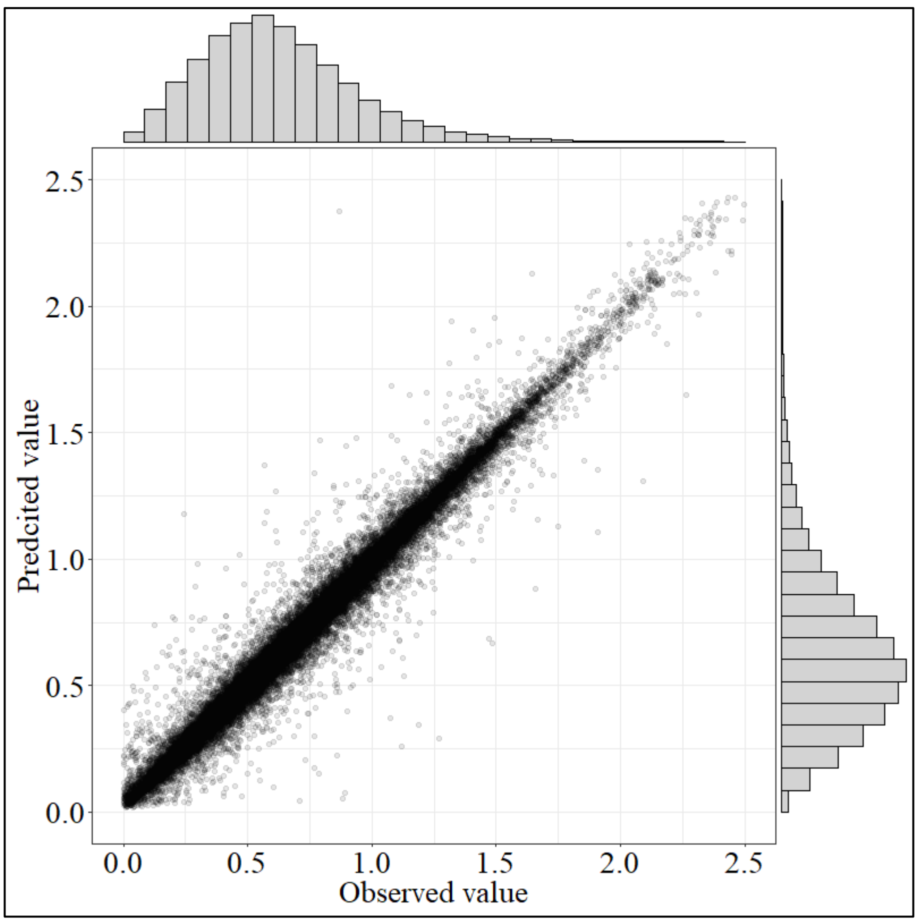

Figure 3.6 Observed vs fitted values for the propagation model

3.4 Conclusions

Overall, it was proven that upstream disturbances have a significant effect on the service regularity at a bus stop. Congestion, given by the mean and standard deviation of velocity and traffic lights density, showed to be significant too. Besides, dedicated infrastructure, such as segregated lanes and off-board payment stops showed a significant impact reducing headway variability. These results indicate that this type of interventions improve the level of service to users and therefore should be encouraged.

In terms of dispatch, we conclude there exists a highly randomized operation. In the absence of headway control strategies at this level, dispatch is operated by rule of thumb principles, as might be dispatching in a First-In-First-Out manner, giving priority to high-demand services, ensuring contracted frequencies, among others. Based on the results of the propagation model, where the most important attribute was related with upstream disturbances, we conclude that the most valuable way to improve headway variability is to improve dispatch regularity, followed by the implementation of specialized infrastructure for bus services, as segregated lanes, and off-board payment zones. It will be interesting to measure in further research to which extent headway control strategies along the route improve headway regularity further.

The contribution of this work is the calibration of a predictive and explanatory model, able to estimate changes in the headway *CV* of a public transport service, under certain interventions. For example, it will be possible to predict the impact of segregating a bus lane or equipping a set of bus stops with off-board payment systems. This way, projects offering a limited impact in improving the average travel time, but reducing headway variability significantly, may justify their implementation. Currently, there is no methodology available for cost-benefit analysis that incorporate the impacts of a transport project in headway variability.

Furthermore, in comparison to the capabilities of Machine Learning models which have strong forecasting capabilities, the proposed methodology not only calibrates a predictive model but also informs regarding the relative importance of different infrastructure attributes as well as the effect of upstream disturbances. Thus, the proposed model is not only novel, but also useful.

Acknowledgements

This research was supported by the Centro de Desarrollo Urbano Sustantable, CEDEUS (Conicyt/Fondap 15110020), the Bus Rapid Transit Centre of Excellence funded by the Volvo Research and Educational Foundations (VREF), and the scholarship funded by CONICYT for Ph.D. studies (CONICYT-PCHA/Doctorado Nacional/2016).

4. PUBLIC TRANSPORT RELIABILITY ACROSS PREFERENCES, MODES, AND SPACE

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4.1 Introduction

Travel time reliability plays an important role in public transport travellers' satisfaction and their perception regarding the level of service, as well as in operational costs (de Jong and Bliemer, 2015). Nevertheless, when planning public transport systems, travellers' behaviour has been usually modelled through traditional variables such as monetary cost, expected travel time and planned waiting time. Other elements such as crowdedness, excess wait time, and mode/service reliability (understood as the certainty travellers have regarding their travel time, their arrival time or the comfort level they will experience inside the vehicle) (van Oort, 2011) are usually neglected from these behavioural models (Petersen and Vovsha, 2006; Raveau et al. 2014). This could lead to erroneous predictions of the demand for public transport alternatives.

In public transport systems, unreliability's main impact is generally the potential delay on the arrival to the destination. Travellers can handle this situation by adjusting their departure time, changing routes or changing modes (Benezech and Coulombel, 2013). In general, users' preferred option is to add a safety margin to the ideal departure time (Bates et al., 2001). Travellers' reaction to unreliability has been widely studied in developed cities among the world, mainly in Europe and North America. However, in developing regions such as Latin America there is a lack of studies regarding public transport reliability. Besides, developing regions are characterized by an accelerated urbanization process and a significant percentage of urban population (Jirón, 2013). This, along with poor urban planning policies, leads to a significant proportion of long trips, from the periphery of the cities to highly concentrated activity centres (García Palomares, 2008; Rodríguez Vignoli, 2008, 2012). These circumstances hinder the operation of public transport services based only on schedules, mainly because of the high frequency needed and the stochastic nature of public transport (Muñoz and Gschwender, 2008). In this context, therefore, public transport reliability needs to be understood and addressed in a different way to what has been done in developed cities.

In terms of planning information, the availability of large volumes of automated data regarding the operation of public transport systems has increased over the recent years. This valuable source of detailed information, properly processed, allows analysing and understanding the system's operation (Birr et al., 2014; Bucknell et al., 2017; Cham, 2006; Fadaei and Cats, 2016; Furth and Muller, 2006; Gschwender et al., 2016) and modelling it in a better way (Cats and Gkioulou, 2017; van Oort et al., 2015; Raveau, 2017). This type of information usually comes from sensors strategically placed within vehicles (such as GPS systems) and smartcard data from passengers boarding and/or alighting the vehicles and allows understanding travel times in a better way.

An application of automated data to characterize public transport level of service is the study by the BRT Center of Excellence (BRT, 2012), which compares the level of service of six Latin American cities: Santiago, Chile; Porto Alegre, Brazil; Guadalajara, Mexico; Mexico City, Mexico; Bogota, Colombia; Lima, Peru. For each city, a socio-economic description of the population was made, as well as a description of the characteristics of the existing public transport system (such as the number of operators, metro lines, operation, fares, payment schemes, infrastructure, vehicles, information systems, quality perception, among others). Level of service indicators of the respective public transport systems were calculated by estimating travel, wait and walk times for 400 representative trips in each city. A relevant indicator within the study relates to travel time variability in the systems. To compute this indicator, the study defined two distinct types of variability: (i) an interpersonal variability, which accounts for the heterogeneity of the existing levels of service within the city, and (ii) an intrapersonal variability, related to how variable the same trip performed repetitively by an individual is (i.e. how reliable is the level of service). This second kind of variability is called day-to-day variability (Hollander, 2006; Jenelius, 2012). However, the travel demand is not adequately considered when measuring the average variability, as the indicators are not weighted by the number of travellers performing each trip. Nor is there an in-depth analysis of the differences between modes and/or operating conditions.

The purpose of this study is to use automated data to perform an in-depth analysis of travel time reliability in a public transport system. That is to say, to characterize this attribute for different modes and infrastructure and to measure the effects of travel time reliability on travellers' mode choice decisions. For this, the case of Santiago, Chile, is considered.

Santiago's public transport system is called Transantiago, where bus and metro services are integrated in fare (Muñoz et al., 2014). There are mainly two types of bus services: regular services, which stop in every bus stop of the route, and express services, which stop only in some of them. There are also five metro lines, where Line 1 is the most crowded one during peak periods, as it runs though the city centre. Line 1 is also the oldest one and has an average distance of 660 metres between stations, the lowest average distance of the network. Furthermore, it is the only line that goes from the west to the east of the city, passing through the most important activity centres. These characteristics make Line 1's performance significantly different and thus it might be needed to study it separately.

In Transantiago, the smartcards only record boardings. Munizaga and Palma (2012) proposed a methodology to estimate a public transport trip matrix (inferring the alightings) using the sequence of validations made with the smartcard and the geographical position of the buses. This trip matrix is used in this study to characterize travel time reliability for public transport routes of similar length in the city during the morning peak period. Additionally, the progressive change of travel time variability as travel length increases is analysed.

So far, the available automated data has not been used in Santiago to understand how travel time variability has an impact (if any) on user's decisions. Furthermore, to the best of the authors knowledge, revealed preferences have not been used to analyse the impact of reliability on public transport travellers' preferences. Based on the available information, this study develops an aggregate mode choice model, in which the explanatory variables are both average level-of-service indicators and indicators of their variability. This analysis further emphasizes the importance of travel time reliability. The analysis and characterization of the travel time reliability and its effects were carried out using only passive data, without the need of any survey. This represents a novel and quite promising approach for choice modelling.

This document is structured in three sections. Section 1 describes the statistical analysis conducted to obtain travel time distributions for bus, express bus, and metro services, as well as the impact of segregated corridors in travel time variability. The results are supported by both statistical and graphical analysis. Section 2 presents the methodology for estimating an aggregate behavioural model as well as its results, which allows to understand the effect reliability has on passenger choices. Finally, Section 3 presents the main conclusions of this study and elaborates on how these results should steer following studies and models for public transport planning.

4.2 Section 1: Characterizing travel time reliability

In this section, the methodology applied for the travel time characterization as well as its graphical analysis are presented. To characterize travel times across the city, a statistical analysis of actual travel times of all travellers on a given week is performed. This analysis is conducted at a trip-leg level.

4.2.1 Travel time distributions and headway regularity

For bus trips, the data comes from smartcard transactions and GPS information. This information was extracted from a trip-leg table constructed with the methodology proposed by Munizaga and Palma (2012). For each smartcard validation, public transport service is recorded as well as the moment and place in which the traveller boards and alights the bus. This information is estimated from the GPS information delivered by the vehicles every 30 seconds, the geo-referenced bus route and the geographical position of the stops along the route.

The resulting database has the boarding and alighting time for every bus trip-leg made by at least one individual. With this information, it is possible to construct travel time distributions for any service between any pair of stops where there are trips within the network. Origin-destinations pairs without any trips are excluded for the analysis. The travel time distributions can be discretised by the in-route distance that separates the pair of stops, in order to obtain travel time histograms for trips of a given length range.

For the case of metro trips, the database of arrival and departure times for every train at every station was provided by Metro de Santiago. Just like in the case of the buses, it is possible to obtain travel time distributions by distance range for every pair of stations that belong to the same line.

In order to analyse headway distributions, a new database was considered for the case of bus trips. This database consists in the estimated arrival time of every bus at every bus stop for the week of analysis. This extensive database was filtered in order to consider the same origin-destination services described above. With this information, for both metro and buses it is possible to calculate consecutive headways for every stop/station in the network. Then, for the time-period of analysis, it is possible to compute any reliability measure. In this case, the coefficient of variation of headways was considered because of its direct relationship with the expected waiting time.

The previously described methodology treats each vehicle alike, regardless of the number of passengers travelling in them. To obtain travel time distributions from a point of view of the user's experience, it is necessary to weight the travel time distributions associated to each origin-destination pair by the travel demand of that pair. To do this, information from smartcard transactions is used. In addition to boarding and alighting stops, and the service boarded, the trip matrix contains expansion factors for each observation. Adding all the expansion factors of those trips that had the same vehicle, boarding and alighting stops, it is possible to obtain the demand for all trips within each service.

However, the smartcard demand database used for the metro services contains information of trips between any two stations within the entire metro network (as no transfers are recorded), while the metro travel times are within lines. For this reason, the available data must be transformed so all information corresponds to metro trip-legs within lines. One way to solve this is to divide each metro trip between any pair of stations (which could use different lines) into its trip-legs. This is not straightforward, as for some pair of stations there is more than one reasonable route. To solve this issue, a choice probability to each of these routes was considered. These probabilities correspond to the travellers' choice proportions, obtained from an appropriate route choice model (Raveau et al., 2011). This model is estimated based on an origin-destination survey conducted within the metro network. As any specific trip-leg that involves a transfer station will be part of multiple origin-destination pairs within the network, the sum of the demand of all those multiple pairs must be computed to have the actual demand of every trip-leg in the metro system.

4.2.2 Graphical analysis

Firstly, we performed a graphical analysis to compare how does the coefficient of variation of headways evolves with the distance from the terminal between buses and metro. This analysis is presented in Figure 4.1. Overall, the average coefficient of headways growth with distance for both modes, as expected. This value remains almost constant for metro, which is mostly explained by its dedicated infrastructure. However, the average coefficient of variation of headways for metro is around 0.5, which is far from a perfectly regular operation. This means on average people wait 25% more even in this ideal scenario in terms of infrastructure and operation.

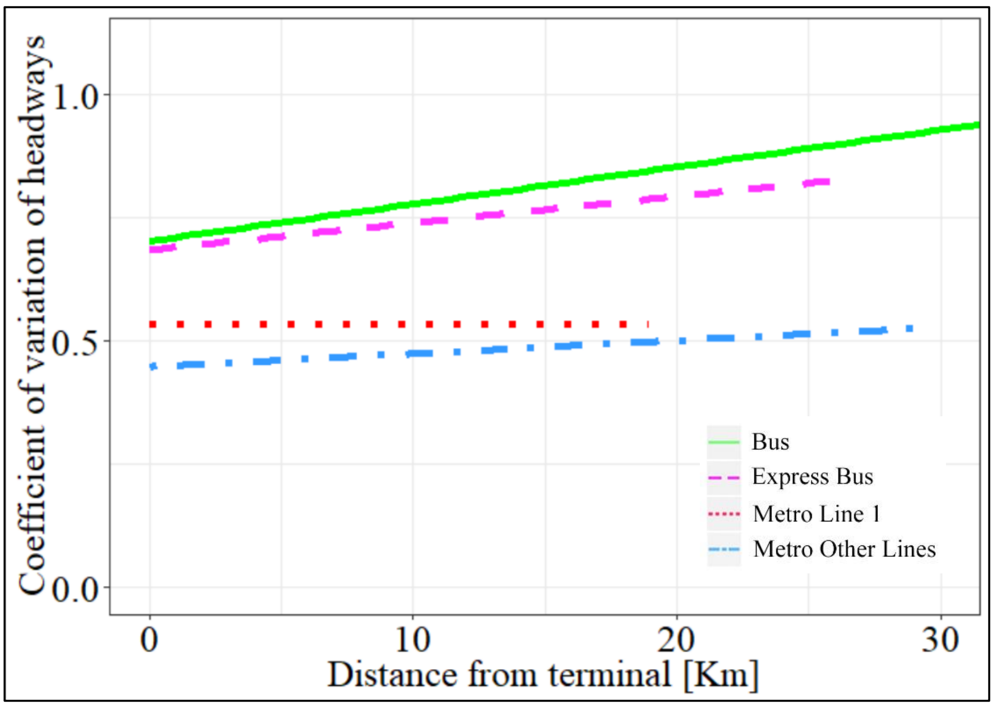

Figure 4.1 Coefficient of variation of headways by distance to the terminal for buses and metro services

We also compared travel times according to distance ranges for the different public transport services of Transantiago. Figure 4.2 shows how travel time increases with travel distance, as expected. However, travel time increases more rapidly for bus-based services than for metro. Within bus-based services, there is a significant difference in the average travel time between bus and express bus services, but there is not enough evidence to suggest a significant difference between their variability, which will be analysed in more detail.

Regarding metro services, there is a significant difference in the speed of metro Line 1 compared to the other lines, and therefore Line 1 is shown separately from the others. There is also a broader dispersion for Line 1 in comparison to the rest of the lines, but, as mentioned in the case of buses, this will be of further analysed. Although the dispersion of the performance of express bus services shows that many of them have a level of service similar to that of regular bus services, there is a portion that resembles both the best lines of metro and Line 1. As future research, it will be important to understand what conditions make these services show such a level of service.

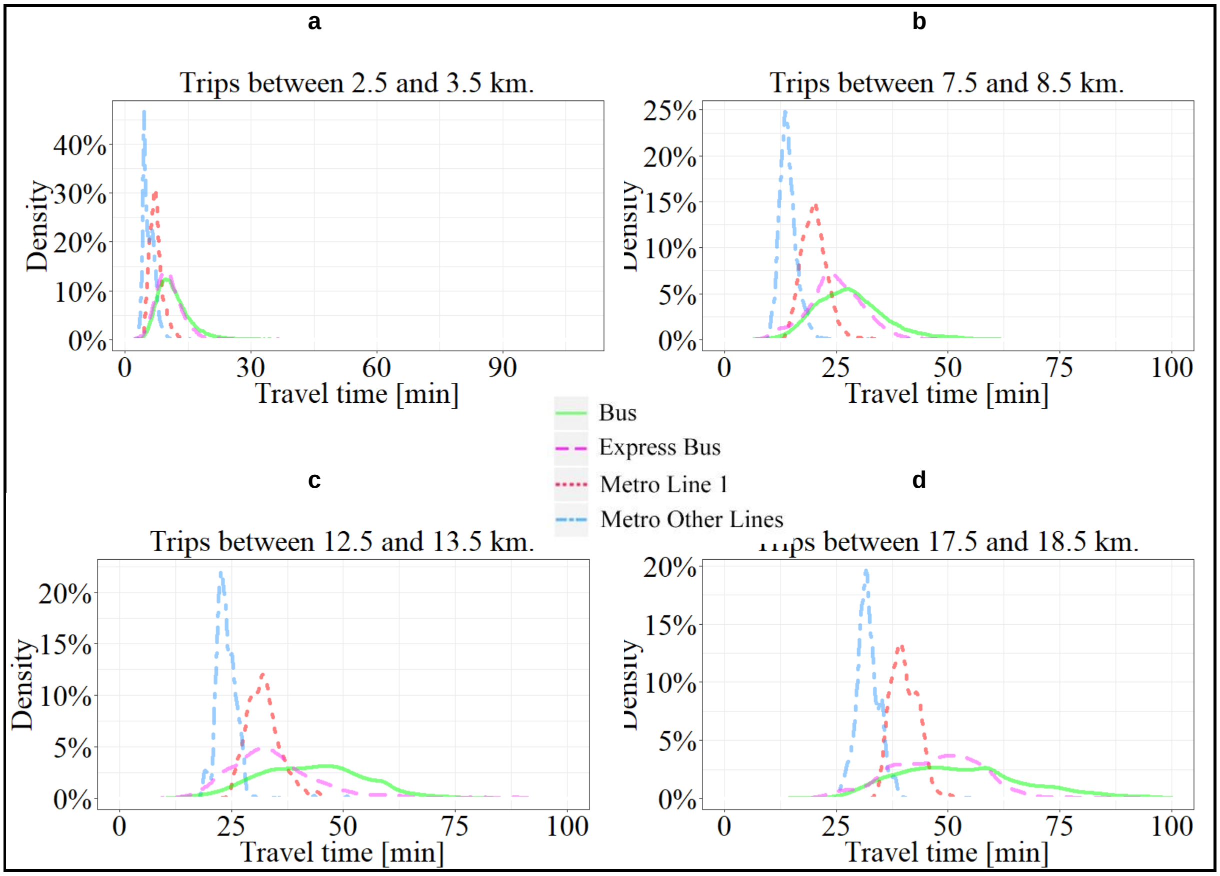

Figure 4.2 Travel time distributions by mode and distance range.
(a) between 2.5 and 3.5 km; (b) between 7.5 and 8.5 km;
(c) between 12.5 and 13.5 km; (d) between 17.5 and 18.5 km.

The relationship between travel time dispersion measures of the histograms and distance can be seen in Figure 4.3. Two dispersion measures are considered for the analysis: the standard deviation of travel time and the difference between the 95th percentile and the average travel time, which in the literature has been called Reliability Buffer Time (Engelson and Fosgerau, 2016). While the standard deviation takes into account travel times shorter and longer than average, the reliability buffer time only measures the difference between the longer travel times and the average.

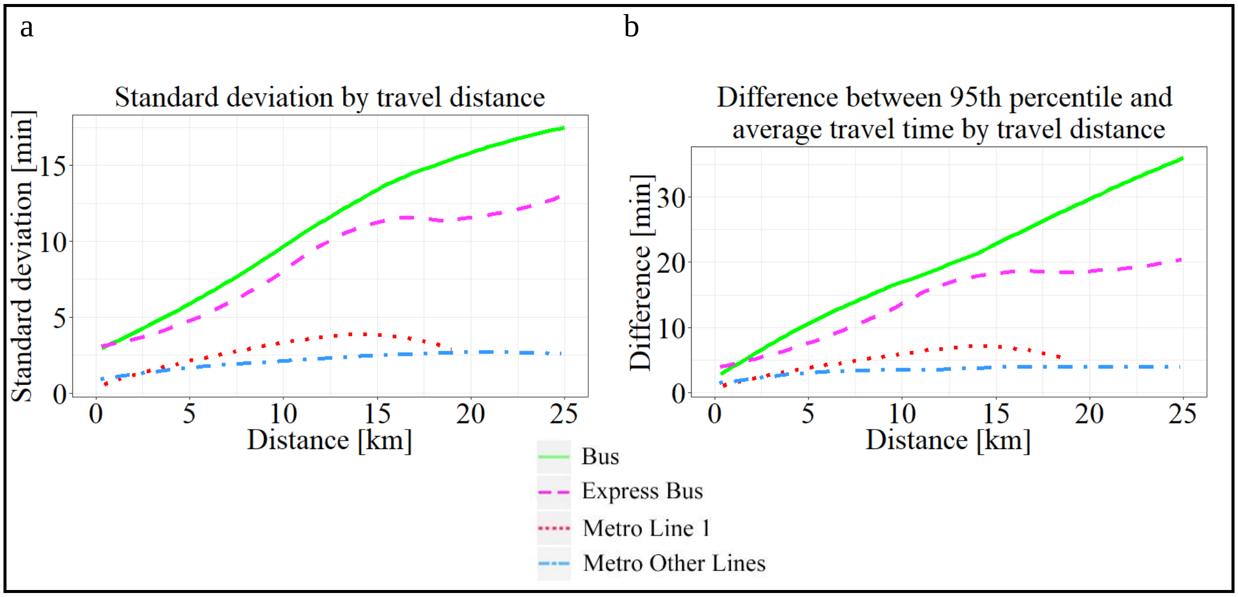

Figure 4.3 Relationship between dispersion measures and travel length.

(a) Standard deviation; (b) Difference between 95th percentile and average travel time.

Overall, both dispersion measures increase with travel length for every mode except for the last segment of Line 1. This happens as the number of origin-destination pairs for every travel distance range decreases as the distance gets longer. For the longest distance range, there is only one origin-destination pair analysed, which is from one end to the other. Thus, the variability is expected to be smaller as there is no variability due to differences in demand on different pairs.

The dispersion is always smaller than 2.5 minutes for metro (except for Line 1, whose maximum is 4 minutes) when the standard deviation is considered as the measure of dispersion, which could hardly be perceived by travellers. Considering the reliability buffer time, the dispersion is almost eight minutes for Line 1 and always smaller than five minutes for the rest of the lines.

4.2.3. The impact of segregated bus corridors on travel time reliability

Over the last decade, to palliate the effect of traffic congestion (mainly due to the increase of private car use) on the performance of public transport systems, there has been a substantial increase in the length of specialized infrastructure for bus services. According to the BRT Centre of Excellence, there are 4.900 kilometres of segregated bus corridors moving 32 million passengers daily in 166 cities worldwide (BRT+ Centre of Excellence & EMBARQ, 2018).

Buses operating in segregated corridors increase their speed in comparison to those operating in mixed traffic. It has also been observed that segregated corridors have a positive impact in avoiding bus bunching by reducing headway variability growth along the route (Danés et al., 2015). However, their impact regarding travel time reliability is less clear.

In this section we provide a graphical comparison between services running on specific segregated corridors and on parallel comparable mixed-traffic lanes based exclusively on passive data. Figure 4.4 shows the considered corridors. The segregated corridors analysed (dashed lines) are Las Industrias and Av. Grecia and their comparable mixed traffic corridors (solid lines) are Vicuña Mackenna and Eduardo Castillo Velazco–Los Orientales–Las Parcelas (ECV-LO-LP), respectively. To isolate the effect of the segregated corridors, only trips that started and finished at bus stops inside the analysed corridors (both segregated and mixed-traffic) were considered.

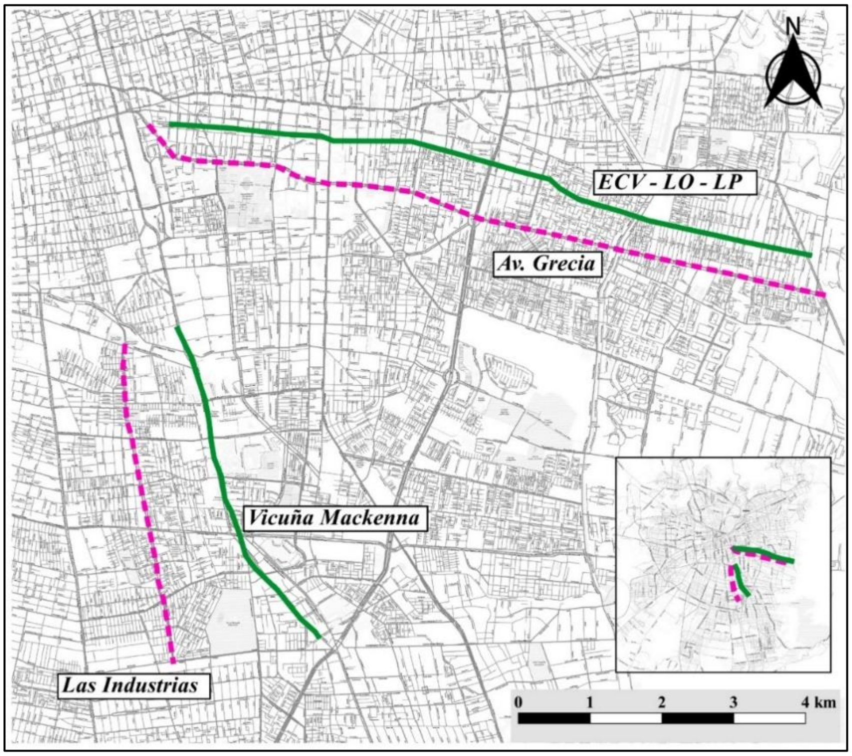

Figure 4.4 Segregated corridors analysed and their comparable mixed traffic corridors.

The evolution of the coefficient of variation of headways from the terminal, as shown in Figure 4.1 is presented in Figure 4.5. It can be seen how, for both comparisons, bus corridors present a lower headway variability value. Remarkably, situations (a) and (b) offer two different situations. On one side, in (a), the value of the coefficient of variation for the comparable services close to the terminal, running in mixed-traffic conditions, is still not close to 1. This means that there is space for this value to grow accordingly with distance. As can be seen, headway variability increases with a higher rate in this mixed-traffic scenario compared with the segregated corridor. On the other side, in (b), the mixed-traffic comparable services have an average coefficient of variation of headways around 1 even close to the terminal. This means that the operation of the services running in these streets is already highly irregular, and therefore is hardly possible to operate even more irregularly. That said, it is expected that headway variability rate of evolution will be lower than in the previous scenario, as can be confirmed in Figure 4.5.

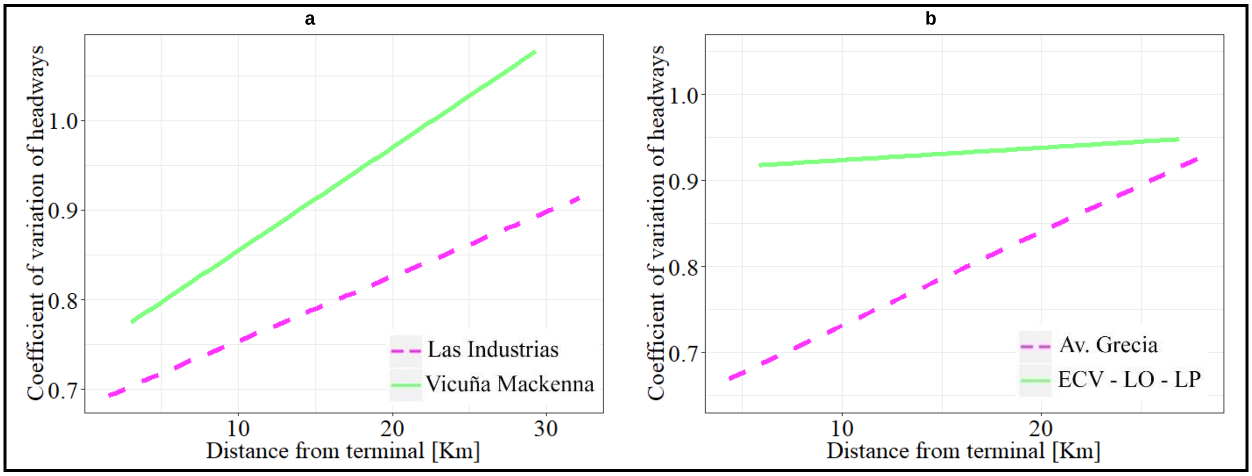

Figure 4.5 Coefficient of variation of headways by distance from terminal.
(a) Las Industrias & Vicuña Mackenna; (b) Av. Grecia & ECV – LO – LP

The speed distribution for both corridor comparisons is presented in Figure 4.6. For both cases the average speed observed in the segregated corridor is higher than in the mixed traffic corridor. This is represented by the difference on the modes of the distributions. However, the difference between speed variability is not clear since the spread of both distributions seems (at least at first sight) rather similar.

As the analysis presented in Section 4.2.1, travel data was grouped in different distance ranges within each corridor. Within each distance range, average travel times and variability measures were computed. The positive impact of segregated corridors on the average speed can be seen in Figure 4.7, which confirms that trips on segregated corridors are, on average, faster (as expected) (Durán-Hormazábal and Tirachini, 2016). Figure 4.7 also shows that the reduction on travel times increases as the trips get longer.

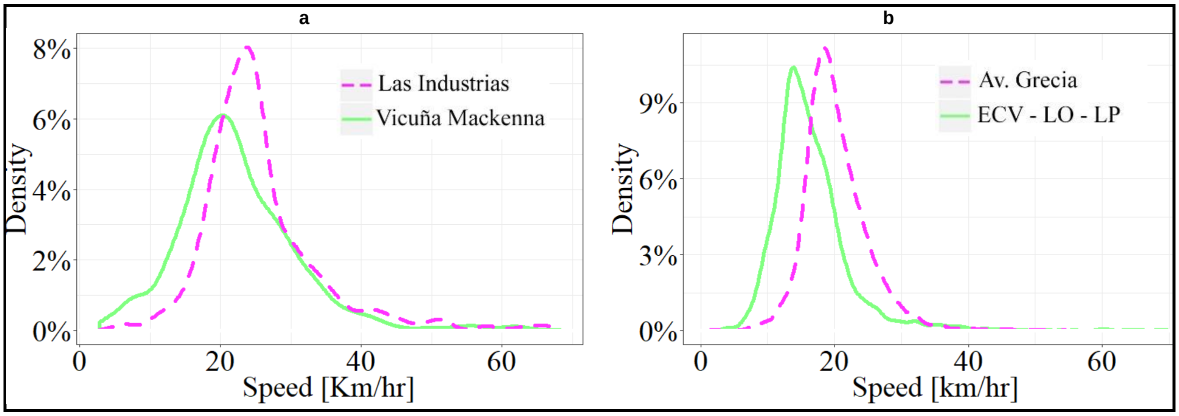

Figure 4.6 Bus services' speed distribution.
(a) Las Industrias & Vicuña Mackenna; (b) Av. Grecia & ECV – LO – LP

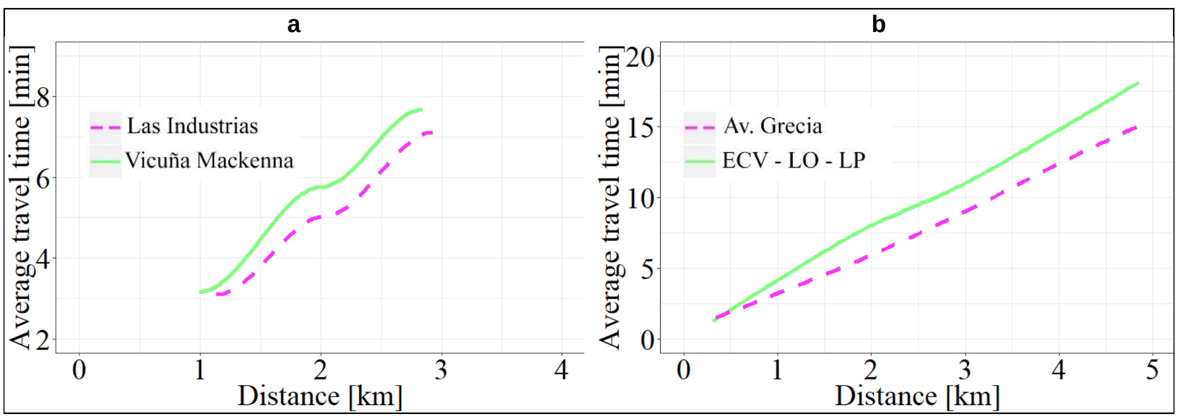

Figure 4.7 Average in-vehicle travel time by travel distance.
(a) Las Industrias & Vicuña Mackenna; (b) Av. Grecia & ECV – LO – LP

However, as it has been argued in this study, characterizing the impact of segregated corridors should include in-vehicle travel time variability. For that purpose, three indicators of travel time variability are computed for every travel distance range: the standard deviation, the coefficient of variation and the reliability buffer time. This analysis is presented in Figure 4.8. Overall, segregated corridors present a better performance in terms of in-vehicle travel time variability. The only exception would be the case of the coefficient of variation in Av. Grecia which is equal to the one of the comparable ways for trips longer than 1.5 kilometres. These figures indicate that there is evidence of a positive impact of dedicated infrastructure, as segregated corridors, not only on the average travel times but for their variability as well.

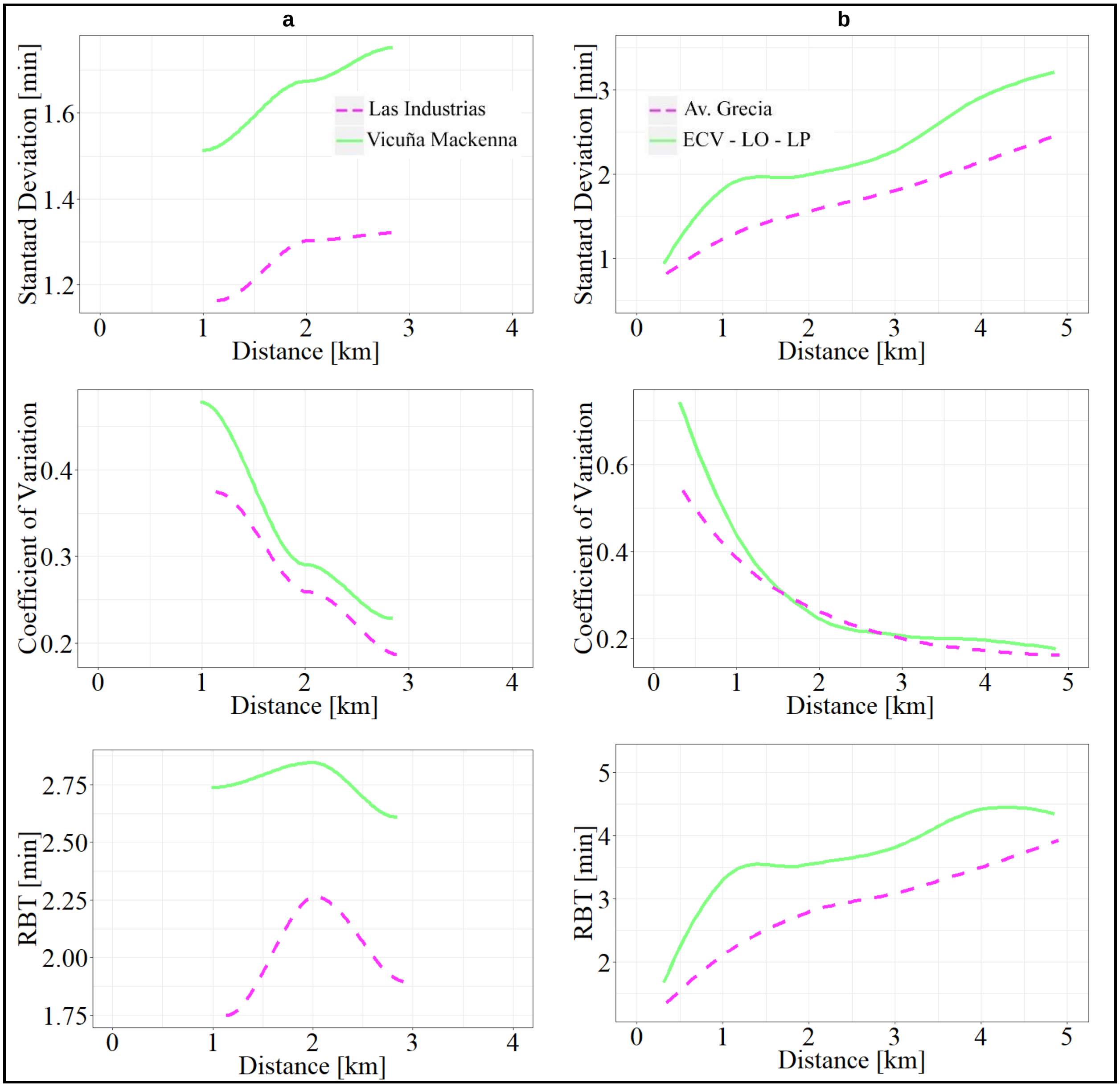

Figure 4.8 Variability measures for in-vehicle travel time by travel distance.
(a) Las Industrias & Vicuña Mackenna; (b) Av. Grecia & ECV – LO – LP

4.3 Section 2 The effect of travel time reliability on mode choice

In this section, the methodology for the aggregate demand model is presented and the results obtained are discussed. This model allows understanding the effect that travel time reliability has on travellers' preferences and on the observed travel structure. To estimate the aggregate public transport mode choice model, it is necessary to build a database for that purpose. The model only considers origin-destination pairs where metro is an alternative to the buses, to analyse individuals' choices between both modes and its combination.

4.3.1 Origin-Destination Pairs

To identify the bus services that are an alternative to metro, buffers (or influence zones) of 750 meters radius were defined around each metro station. All bus stops within the buffer define the origin-destination pairs for bus trips or combined bus-metro trips that could have been done only by metro. For those bus stops with more than one metro station within the range, the closest station was assigned. The 750 meters radius was selected based on the results of Tamblay et al. (2015), which considers the 95% percentile walking distance from people origins to metro stations. The procedure is shown in Figure 4.9, where the left panel shows a general view of the city with while the panel on the right shows, in a more detailed way, the circular buffers created surrounding the metro stations. With this information it is possible to create an aggregate database of public transport trips in bus, metro and bus-metro between selected origin-destination pairs, in order to study travellers' mode choices.

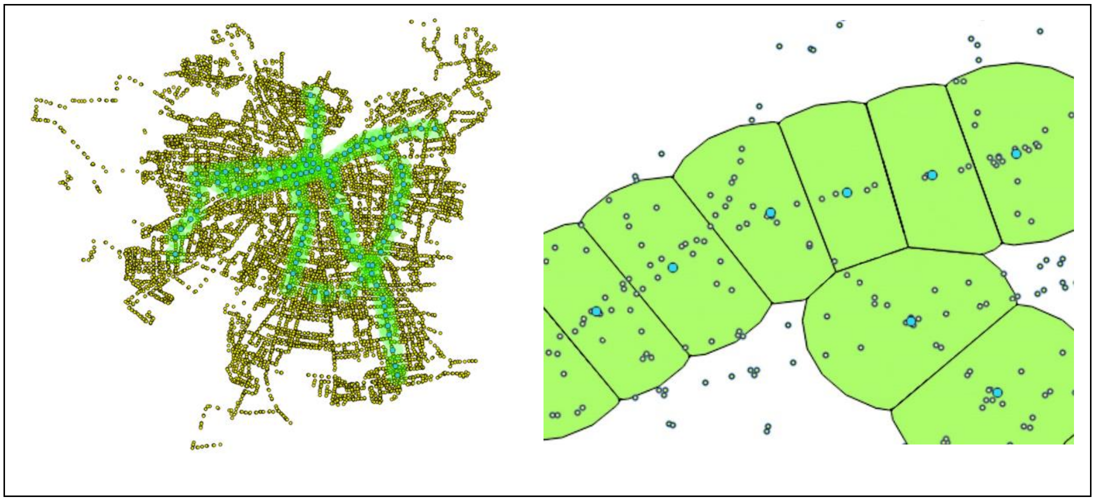

Figure 4.9 Buffers of 750 meters around metro stations.

4.3.2 Database creation

Once the metro stations are matched to their corresponding surrounding bus stops, it is possible to group all trips in the database based on the origin and destination metro station to understand how travel attributes impact the total demand for each mode. The analysis must be conducted at the level of full travel and not at the trip-leg level (as was the case of the analysis presented in Section 1), since only this way it is possible to properly understand and explain travellers' behaviour.

The three considered alternatives are bus, metro, and combined bus-metro. For bus services, the average travel time and its variance were obtained directly from the database used in Section 1, grouping trip-legs into trips. For metro, the information was obtained based on the arrival and departure times provided by Metro de Santiago. As for some origin-destination pairs there is more than one reasonable route, the level of service was computed as a weighted average based on route probabilities calibrated in a previous study for the same network (Raveau et al., 2011). Finally, for the trips made by a combination of metro and bus services, the level of service was obtained as a combination of both procedures. To get a total variance for each trip, it was assumed that every trip-leg was independent and their travel time variances to be additive.

Table 4.1 Number of Origin-Destination Pairs Selected.

Criterion	**Number of origin - destination pairs**	**Morning peak travel demand**	**Percentage of the total (OD pairs/demand)**
At least 1 observation in metro	9,082	1,330,896	100% / 100%
At least 1 observation in bus or bus-metro	7,328	1,289,621	80.69% / 96.90%
At least 6 observations in every alternative	2,315	669,232	25.49% / 50.28%
Presence of headway observations	2,264	662,063	24.93% / 49.75%

The behavioural analysis presented in this study focuses only on the morning peak period. As more than one observation is needed to obtain reliability indicators, origin-destination pairs with five or less trips for any mode were not considered in the analysis. As the estimated bus arrival time database is not exhaustive, it is necessary to filter also those observations without headway information for this mode. This way it is possible to guarantee that every origin-destination pair considered contains enough information to measure variability indicator for both travel and waiting times. The number of origin-destination pairs for every criterion is displayed in Table 4.1.

The number of origin-destination pairs is reduced significantly when the criteria are applied. However, the remaining origin-destination pairs present, as expected, higher demand than the deleted pairs, which represent almost one half of the total demand. Finally, bus observations were corrected by fare evasion (Cantillo, Raveau, Iglesias, Tamblay, & Muñoz, 2018), which is on average 26% for the selected bus stops during the period of analysis. The final number of observations considered is 695,113.

4.3.3 Results

Based on a Random Utility Maximization approach (McFadden, 1974; Ortúzar and Willumsen, 2012) for modelling aggregate mode choice, different specifications were tested to obtain a good fit for the data set. As for the variability of travel and waiting time, the standard deviation, the variance, the coefficient of variation and the reliability buffer time were tested.

As the bus-metro alternative is a combination of the other alternatives, correlation is expected. To address this issue a Cross Nested Logit model (Vovsha, 1997) was calibrated. Two nests are defined, one for the metro alternatives and the other for the bus alternatives. On one side, the pure modal alternatives belong entirely to their respective nest, with each inclusion coefficient (denoted by α) equal to 1. On the other side, the combined metro-bus alternative belongs to both nests, with inclusion coefficients to be estimated. For identifiability purposes the scale parameter at the root was set equal to 1, as well as one of the nests' scale parameters (denoted by λ). The scale parameter estimated was the associated with the metro alternative. The model structure, scale parameters and inclusion parameters can be seen in Figure 4.10.

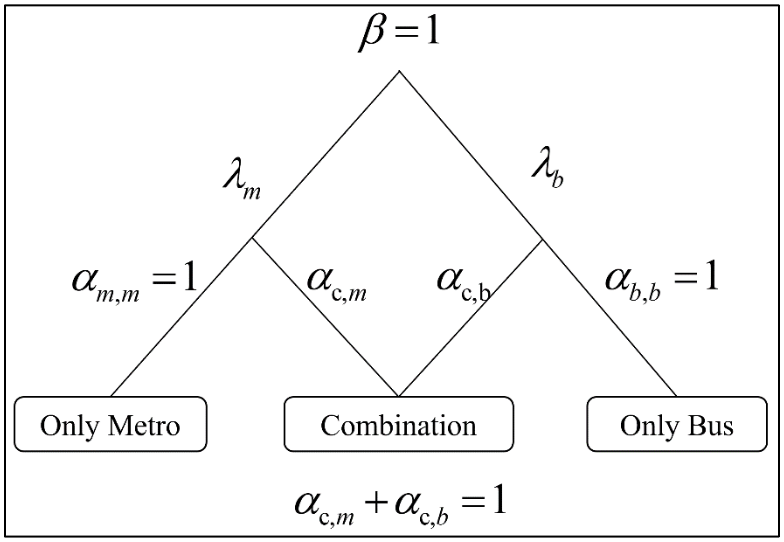

Figure 4.10 Cross Nested Logit model structure.

The best specification was found by the Likelihood-ratio test. Regarding travel attributes' variability, only the variability of headways had a significant effect. From all the different variability measures, the coefficient of variation performed the best. Non-linearity was tested for both travel and waiting time. However, no significant improvement was found in this sense. The selected utility specification V_i considered is:

$$V_i = ASC + \theta_{TT} \cdot \left(1+\delta_{CV(h)} \cdot CV(h)_i\right) \cdot TT_i + \theta_{WT} \cdot E\left(W\right)_i + \theta_{CV(h)} \cdot CV(h)_i + \theta_{TrT} \cdot TrT_i + \theta_{\#Tr(\mathrm{A}\rightarrow B)} \cdot \#\mathrm{Tr}\left(A \rightarrow B\right)_i$$

Where:

TT_i	Average travel time for alternative *i*
$E\left(W\right)_i$	Expected waiting time for alternative *i*
$CV\left(h\right)_i$	Coefficient of variation of headways for alternative *i*
TrT_i	Average transfer time for alternative *i*
$\#\mathrm{Tr}\left(A \rightarrow B\right)_i$	Average number of transfers from mode A to mode B for alternative *i*

Before the results analysis, there are three important modelling considerations to highlight. Firstly, the combined alternative has both specific and common parameters. For example, the average in-vehicle travel time is split by mode and share the parameters for both metro and bus. The same happens with the number of transfers, sharing bus-to-bus and metro-to-metro parameters. The coefficient of variation and the average waiting time is the same parameter than for buses.

Secondly, there is a strong correlation between ASC_{Comb} and $\#\mathrm{Tr}\begin{pmatrix} M \to B \\ B \to M \end{pmatrix}$ as the combined alternative is the only one with transfers between metro and bus (and vice-versa) and the average value is close to 1. Therefore, both parameters associated cannot be estimated at the same time. As our major objective is to understand travellers' behaviour, we decided to define the combined alternative specific constant conveniently, in order to estimate the parameter associated with the number of transfers. The specific constant is defined as follows, proportionally to the amount of in vehicle time spent in bus for the combined alternative:

$$ASC_{Comb} = ASC_{Bus} \cdot \frac{TTbus_{Comb}}{TTbus_{Comb} + TTmetro_{Comb}}$$

Finally, the database consists in 5,429 observations which represent 695,113 revealed choices. As these choices are grouped by origin-destination pairs, every observation has a weight parameter associated, equivalent to the total value of choices for each pair. However, the common practice is to multiply this value so that the total sum of them is equal to the total number of observations. This is done to correctly estimate the standard deviation of the estimated parameters.

The results of the model are shown in Table 4.2. The parameters part of the different alternative utility functions are denoted with B, M, and C for bus, metro and combined respectively. This parameters were obtained using PythonBiogeme (Bierlaire, 2016). All parameters associated with travel attributes have the expected sign and are statistically significant at a 91% confidence level. Also, the combined inclusion parameters $\left(\alpha_{c,m}\text{ and }\alpha_{c,m}\right)$ and the scale parameter for metro $\left(\lambda_m\right)$ were found to be significantly different from 1, which confirms the Cross-Nested Logit structure. Besides, the higher value of $\alpha_{c,m}$ means the combined alternative relates more with metro. This is mostly explained as in bus-metro trips, bus is mostly used as an access/egress mode, meaning that the bigger portion of the trip is done in metro.

Table 4.2 Calibrated Parameters Values

Attribute	**Alternative**	**Parameter**	**Estimate**	**p-value**
Average travel time	B, M, C	θ_{TT}	-0.087	0.00
Marginal effect of Coefficient of variation of headways in the perception of Travel time	B, M, C	$\delta_{CV(h)}$	-0.269	0.00
Average waiting time	B, C	θ_{WT}	-0.086	0.00
	M	θ_{WT}	-0.203	0.00
Coefficient of variation headways	B, C	$\theta_{CV(h)}$	-0.424	0.09
Average transfer time	B, M	θ_{TrT}	-0.078	0.00
	C	θ_{TrT}	-0.026	0.00
Number of transfers	B, C	$\theta_{\#Tr(B\to B)}$	-1.050	0.00
	M, C	$\theta_{\#Tr(M\to M)}$	-0.455	0.00

	C	$\theta_{\#Tr\left(\substack{M\to B\\B\to M}\right)}$	-1.140	0.00
Alternative specific constant	B, C	ASC_{Bus}	-0.159	0.45
	M, C	ASC_{Metro}	0	fixed
Combined inclusion coefficient – metro		$\alpha_{c,m}$	0.854	0.00
Combined inclusion coefficient – bus		$\alpha_{c,\mathrm{b}}$	0.146	0.00
Scale parameter – metro		λ_m	1.780	0.00
Scale parameter – bus		λ_b	1.000	fixed
Number of observations			5,429	
Log-likelihood			-2,763.56	

In order to understand better the impact of each attribute, we calculated the marginal rate of substitution of them with in-vehicle travel time. As in-vehicle travel time perception depends on headway regularity, we define two scenarios to analyse: perfect headway regularity, where CV(h) equals 0 and an irregular scenario, such as arrivals follow a Poisson process, where CV(h) equals 1.

In terms of average waiting time, in a regular scenario we see it is considered higher than in-vehicle travel time only for the cases of metro trips. For this case, the MRS between this attribute and in-vehicle travel time is 2.33. In an irregular scenario, the MRS rises to 1.35 for buses. If we consider the average values of CV(h) for both modes, MRS equals 1.26 for buses and 2.39 for metro. This might be explained as during morning peak hours, waiting for metro might be considered worse as in some stations the amount of people waiting reach an uncomfortable level.

In relation to transfers, we observe that transfer times are lower than in-vehicle travel time under regular headways. Considering the average coefficient of variation on headways, the MRS is 1.15 for buses, 0.92 for metro and 0.38 for the combined alternative. One possible explanation considers that transfer time for the combined alternative are related with access or egress to the metro network, which might be perceived better than travelling itself.

On the other side, the worst perceived transfer is Bus-to-Metro/Metro-to-Bus, followed by Bus-to-Bus, and lastly Metro-to-Metro. This is also in line with our current knowledge, where Metro transfers are not perceived as bad as bus transfers. Based on the MRS, people would travel on average around 17, 15, and 5 minutes extra to avoid a Bus-to-Metro/Metro-to-Bus, Bus-to-Bus, and Metro-to-Metro transfer respectively.

Regarding the coefficient of variation of headways, there are four different aspects to recall. Firstly, this attribute has three different effects in the utility function. It increases the expected waiting time (Osuna & Newell, 1972), it has a direct impact in the utility function, and it has a marginal impact in the perception of travel time. This allow the model to differentiate between two services with different frequency and headway regularity but with the same expected waiting time.

$$E(W)_i = \frac{E(h)_i}{2} \cdot \left(1 + CV(h)_i^2\right)$$

Secondly, the coefficient of variation of headways by itself only has a significant impact for bus and combined alternatives. The non-significative impact for metro can be explained as the combination of its regularity and frequency level might not be high enough to have a perceivable effect in passengers' experience.

Thirdly, the marginal effect of the coefficient of variation of headways in the perception of in-vehicle travel time, $\delta_{CV(h)}$, was found to be significant and negative. This means than passengers are willing to travel longer in order to travel in a reliable bus service. In an irregular scenario, the perception of in-vehicle travel time is ~27% lower than in a perfectly regular scenario.

Fourthly, the *MRS* between *CV(h)* and TT_{Bus} is calculated as follows:

$$MRS\left(CV\left(h\right),TT_{Bus}\right)=\frac{\theta_{TT}\cdot\delta_{CV(h)}\cdot\partial CV(h)/\partial CV\left(h\right)+\theta_{WT}\cdot\partial E\left(W\right)/\partial CV\left(h\right)+\theta_{CV(h)}\cdot\partial CV\left(h\right)/\partial CV\left(h\right)}{\theta_{TT}\cdot\left(1+\delta_{CV(h)}\cdot CV(h)\right)\cdot\partial TT_{Bus}/\partial TT_{Bus}}$$

$$=\frac{\theta_{TT}\cdot\delta_{CV(h)}+\theta_{WT}\cdot E\left(h\right)\cdot CV\left(h\right)+\theta_{CV(h)}}{\theta_{TT}\cdot\left(1+\delta_{CV(h)}\cdot CV(h)\right)}$$

$$=\frac{-0.27+0.98\cdot E\left(h\right)\cdot CV\left(h\right)+4.89}{1-0.27\cdot CV(h)}\left[\min\right]$$

This means the rate of substitution grows with both the coefficient of variation of headways and the expected value (the inverse of the frequency). If we consider the average value of E(h) and CV(h), 6.85 minutes and 0.81 respectively, we obtain a MRS equals to 12.88 minutes, which is comprised by -0.35 minutes in terms of travel time, 6.97 minutes in terms of excess waiting time and 6.26 minutes in terms of regularity. This means passengers, on average, are willing to increase their in-vehicle travel time in 12.88 minutes to have a service with perfectly regular headways. By multiplying this amount by the Chilean social value of time (MDS, 2016) we obtain a monetary value of ~$344 CLP, which is equivalent to a 53.75% of the fare at that time.

Finally, every time the coefficient of variation of headways was included in the specification function, the alternative specific constant of buses decreased its significance. As this attribute was not found to be significant for metro trips, we consider that headway variability as a key attribute in order to explain modal choices. All these results confirm the idea that public transport reliability has a significant impact on passenger's mode decisions.

4.4 Section 3 Conclusions

This study provides evidence of significant differences among headway regularity and travel time dispersion (measured as the standard deviation or the difference between the 95th percentile and the average travel time) for trips of similar length on different public transport modes. The study also shows that these dispersions also increase with travel length for every mode. However, the dispersion is always smaller than 4 minutes for metro (when the standard deviation is considered), which could hardly be perceived by travellers, particularly on long trips.

The results were displayed allowing a clear visualization of the reliability differences between different modal alternatives. The graphs provide an intuition about why certain services could be used to a lesser extent than what is predicted by conventional models (which ignore the uncertainty in the level of service). The figures presented in this paper considered every service within certain distance range, but the methodology is of course applicable for any subset of services satisfying specific conditions (as with the case of particular corridors presented in this study). This visualization allows identifying opportunities for improvement in the system by recognising similarities in the level of service between some bus-based services and metro. For example, clustering those services whose characteristics mimic in some sense their operation with metro (such as the express services in Transantiago or those operating over a segregated corridor).

The aggregate demand analysis proved the significant impact of public transport reliability (measured as the coefficient of variation of headways) in travellers' choice between buses and metro for origin-destination pairs where both modes are available. However, unreliability is not limited to travel or waiting times, also affecting average crowding and its variability. The effect of variability on these attributes should be also analysed and included in demand models, further increasing the impact of unreliability on passenger's behaviour.

It is important to emphasize that all the analysis in this study was conducted by only using passive-data, without the need of any kind of survey or external information. The data used comprises smartcard validation, buses' GPS position and trains' time schedules. Although the demand model is quite general (as no individual information, such as gender or income, is recorded in the smartcards) to the best of the authors knowledge, revealed preferences have not been used to analyse the impact of reliability on the preferences of public transport travellers. In a world were passive-data collection technologies rapidly gain importance over former techniques, studies similar to the one presented here will help to better understand passive-data capabilities and limitations.

The aggregate demand model suggests that, in a more detailed disaggregated model (at an individual level), variability should also have a significant impact in the travellers' decisions. Such disaggregated model would require a travel survey to gather socio-demographic information, and more detailed travel information to compute reliability indicators for each individual based on their past travel experiences. Such disaggregated revealed preference model could provide further insights regarding the effect of reliability in travel demand and have higher repercussions in public policy.

As public transport time reliability has a relevant impact on travellers' decisions, it is necessary to improve it, enhancing the level of service. This paper shows that this is particularly important for bus services, which lag behind Metro in this dimension. An effective way to improve bus reliability is with segregated corridors. This study shows that segregated corridors not only reduce average travel times, but also reduce travel time variability. The methodology presented in this study could be used to assess the impact that other policies and strategies (such as public transport signal priority or bus holdings at stops) have on reducing travel time variability.

Transport planners and modellers should consider these results to improve project evaluation and decision-making processes by better understanding the effects of travel time reliability on public transport travellers. Extending the behavioural models to include additional level-of-service components (such as wait times and crowding levels) would be an interesting research subject. Further understanding the causes and effects of public transport variability has a significant impact on public policy.

Acknowledgements

This research was supported by the Centro de Desarrollo Urbano Sustantable, CEDEUS (Conicyt/Fondap 15110020), the Bus Rapid Transit Centre of Excellence funded by the Volvo Research and Educational Foundations (VREF), the FONDECYT project number 11170127: Behavioural Modelling of Public Transport Systems, and the scholarship funded by CONICYT for Ph.D. studies (CONICYT-PCHA/Doctorado Nacional/2016).

5. THE UNDERLYING EFFECT OF PUBLIC TRANSPORT RELIABILITY ON USERS' SATISFACTION

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5.1 Introduction

To achieve sustainable development, cities need its citizens to use public transport. This is easier when citizens have a positive feeling about their public transport system, which is understood as satisfaction. Within high-frequency public transport, travellers seek and highly value a trip with four fundamental operational attributes: speed, short waits, high transport capacity and reliability (Delgado, Muñoz, & Giesen, 2016; Redman, Friman, Gärling, & Hartig, 2013). This reliability is related to the variability of the level of service experienced by a user making the same trip in different days. The relation between satisfaction and the first three trip attributes has been widely studied, but the relation with reliability has not. Thus, the objective of this article is to estimate the effect of metro and bus service reliability on passengers' evaluation of the quality of service experienced irrespective of mode.

An element that strongly influences the reliability of a public transport service is its headway variance. This variability has a strong impact on users' satisfaction. For example, some studies have shown in Granada (Spain; de Oña et al., 2016), Calgary (Canada; Habib et al., 2011) and Santiago (Chile; DTPM, 2016) that headway regularity along with sufficient frequency was part of the core of public transport quality attributes. Unfortunately, the inherent variability in demand patterns and travel times causes headway instability leading to the well-known phenomenon of vehicle bunching. Headway variability has several harmful effects on travellers when compared with the same frequency being offered under regular headways. Among the most direct effects are an increase in average waiting time and in its variability, and comfort deterioration, since the demand is not homogeneously distributed among vehicles, causing more travellers to experience crowded vehicles than empty ones (Delgado et al., 2016).

To understand how these effects alter travellers behaviour, several stated and revealed preference studies reported in the literature have provided a direct monetary value for travel and waiting time induced by service unreliability (Ortúzar & Willumsen, 2011). However, it is unclear what is the best methodology for valuing experienced comfort in public transport. Recently, different studies have been conducted in order to understand how overcrowding levels affect travellers' behaviour (Batarce et al., 2015; Cats, West, & Eliasson, 2016; Kim, Hong, Ko, & Kim, 2015; Li & Hensher, 2011; Tirachini et al., 2013; Tirachini, Sun, Erath, & Chakirov, 2016). For instance, Batarce et al. (2016) found that the value of time of a user experiencing an overcrowded situation (i.e. six standing passengers per square metre) is 2.5 times larger than the value of time of empty seats available. The authors identify a non-linear relation between the value of travel time and the level of crowdedness the travellers suffered.

Still, it is unclear how different crowding levels, caused by headway irregularity in a high frequency context, and the uncertainty due to unknown waiting times affect travellers' service satisfaction. In this study, we analyse the relationship between users' satisfaction and both the crowding level experienced and the number of denied boardings, exploring whether these relations exhibit non-linear patterns.

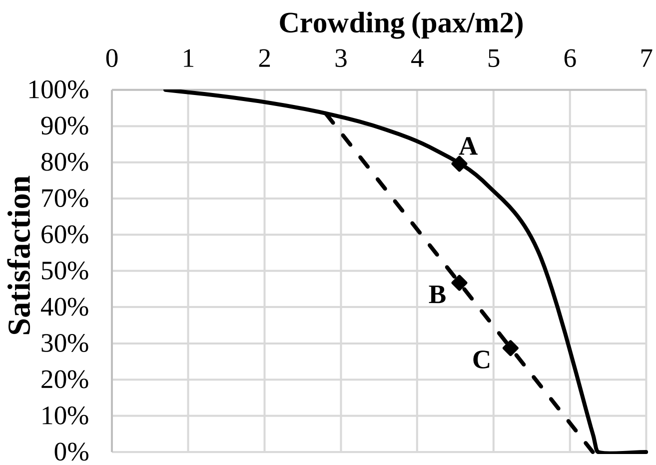
Public transport satisfaction has been studied extensively in the literature, focusing in its definition, , its evolution over time, and its explanatory variables (Abenoza et al., 2017, 2018; Allen et al., 2018; Cats et al., 2015; De Oña & De Oña, 2014; Hensher et al., 2003; Tyrinopoulos & Antoniou, 2008). There is evidence to suggest that users value public transport service reliability the most over any other variable (Allen et al., 2018). Thus, it is especially important to unravel how service attributes caused by poor reliability (e.g. variations in on-board crowding) impact the overall satisfaction.

Instead of explaining the average satisfaction evaluation value by different attributes, we aim in this study to estimate the impact associated with each of the values within the range of satisfaction scores. To this end, we estimate an Ordinal Logit model (McCullagh, 1980). One important characteristic of this model is the possibility to estimate the threshold associated with moving between consecutive scale levels rather than implying that they are all equal.

This study is structured as follows. Section 2 explains the motivation behind the idea of non-linear interaction between travel attributes and passengers' satisfaction. Section 3 describes the survey carried out and the methodology used to process the data. Section 4 shows the main results for the Ordered Logit model while Section 5 shows the satisfaction evaluation analysis. Finally, Section 6 presents our main conclusions, their potential implications and provides some guidelines for further research on public transport satisfaction matters.

5.2 Motivation

Let us assume there is a non-linear relationship between the vehicle load during a trip and the satisfaction of a user experiencing it. It is reasonable to assume that it is expected that the impact of an extra passenger onboard on the rest of the passengers inside the vehicle is not constant as it should depend on the current load level. One well-founded hypothesis is that this curve is concave, as the marginal rate of substitution between crowding and in-vehicle travel time (i.e. crowding multiplier) obtained in different discrete choice experiments (Batarce et al., 2015; Liu & Wen, 2016; Tirachini, Hurtubia, Dekker, & Daziano, 2017; Wardman & Whelan, 2011; Yap, Cats, & van Arem, 2018) increases. It is important to emphasize that this concavity might not hold when analysing the effect of crowding and satisfaction, as there is no evidence suggesting a direct relationship between the value of time and satisfaction. Figure 5.1 illustrates this relation in which service satisfaction drops non-linearly with increasing vehicle occupancy.



	Average crowding	Average satisfaction
Perfectly regular	4.5 pax/m^2	79.6%
Irregular	4.5 pax/m^2	51.8%
Perceived comfort	5.2 pax/m^2	35.7%

Figure 5.1 Satisfaction decline due to headway irregularity.

The impact of this non-linear relation on the level of service perceived by users is not understood completely if the service satisfaction is not analysed. We use Figure 1 to illustrate the underlying damage to public transport service quality perception caused by headway irregularity. Let us consider a bus service that is planned to operate with an average headway of 6.5 minutes and that this implies an average passenger density of 4.5 passengers per square metre over the course of the entire route. The curve of Figure 1 tells us that the expected satisfaction of users of this service should be 79.6% as long as the buses keep regular headways, and therefore, identical loads (letter A in Figure 5.1). However, let´s assume that the headways between buses are 4 and 9 minutes alternately, keeping an average headway of 6.5 minutes. According to this sequence, the expected bus load, considering seated passengers, will be 2.8 and 6.3 passengers per square metre respectively. The satisfaction of users of both types of buses will be quite different; while users of the first type will present a 94% satisfaction, in the second type it will be of only 10%. By averaging both evaluations over vehicles, the average satisfaction evaluation between all buses drops to 51.8%, as illustrated by the letter B in Figure 5.1.

However, this average between average satisfaction of both vehicle types ignores that there are fewer travellers inside the first type of buses than in the second type, and our interest is to obtain the average evaluation perceived across users, not buses. Considering the number of travellers that each type of bus carry, the average crowding perceived by them rises to 5.2 passengers per square metre and the average evaluation drops to 35.7% (letter C in Figure 5.1). Thus, the system was planned for an average evaluation of 79.6%, while it dropped to 35.7% due to the headways' irregularity. In reality, quite often buses actually bunch.

This very worrying impact is aggravated as people tend to assign disproportional weights to their bad experiences over their good ones. Thus, level of service variability affects their appreciation by unbalancing it towards those experiences with long delays and big discomfort. It would not be surprising then that, in the experiment proposed, bad experiences loom over respondents recollection when they are evaluating the system. This fact will be important not only in the methodology design but also in the analysis of the results.

5.3 Methodology

In order to develop a methodology able to identify and model this non-linear effect, a survey was conducted among public transport users in Santiago de Chile who travel with services that are characterized by high headway variability and/or passenger density within the vehicle. The survey collected the perception or satisfaction perceived by users about the waiting time and travel comfort of the trip they just finished. The fact that they are evaluating their just ended experience (i.e. revealed preferences) make this study different and novel in comparison to the literature regarding comfort valuing (mostly based in stated preferences). This survey was conducted between the 17th and 20th of July 2018, during the extended morning peak hour, from 07:00 am until 12:00 pm, to obtain observations in periods when capacity binds and when it does not. Users were asked to report their experience regarding their last trip-leg by metro or bus only (i.e. their most recent experience).

The goal was to characterise the effect that comfort and waiting have on travellers' satisfaction. The survey was carried right outside of four selected metro stations (from west to east: República, Universidad de Chile, Pedro de Valdivia, and Manquehue) and at their surrounding bus stops, approaching alighting travellers to guarantee the randomness of the sample (Figure 5.2). These stations were selected for two different reasons. Firstly, they concentrate a high level of alighting passenger for both metro and bus. Secondly, these passengers represent different origin-destination paths through the city, which means they experience different crowding levels along their trip. This is confirmed in Figure 5.3, which shows the reported crowding distribution for both metro and bus at the four different study zones. Only Manquehue station had a significantly lower crowding for bus and overall reported bus crowding was lower than in metro.

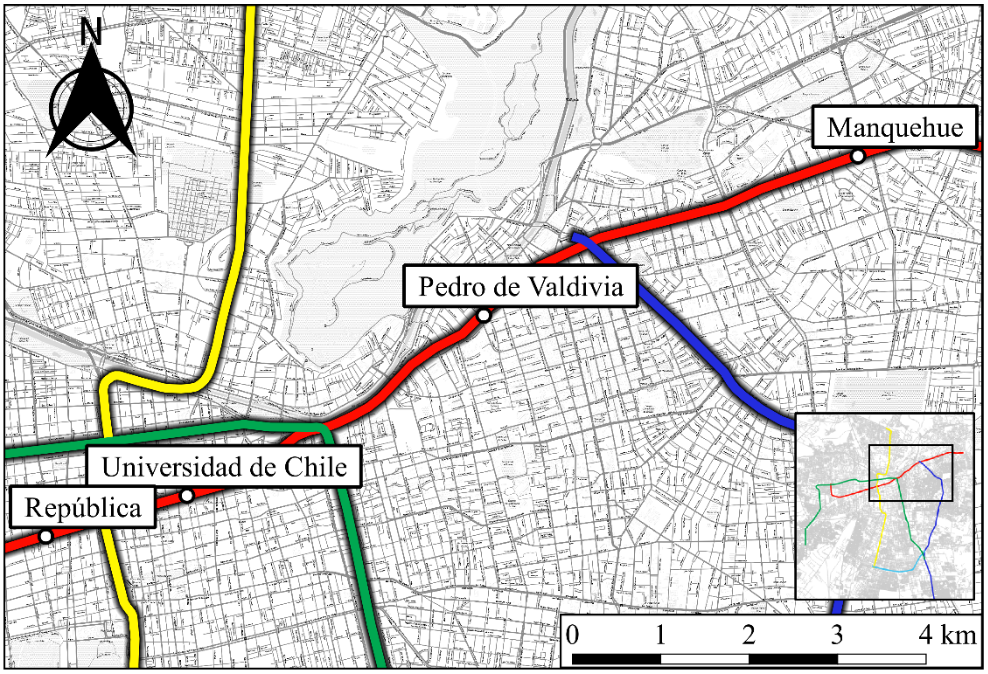


Figure 5.2 Survey area of analysis.

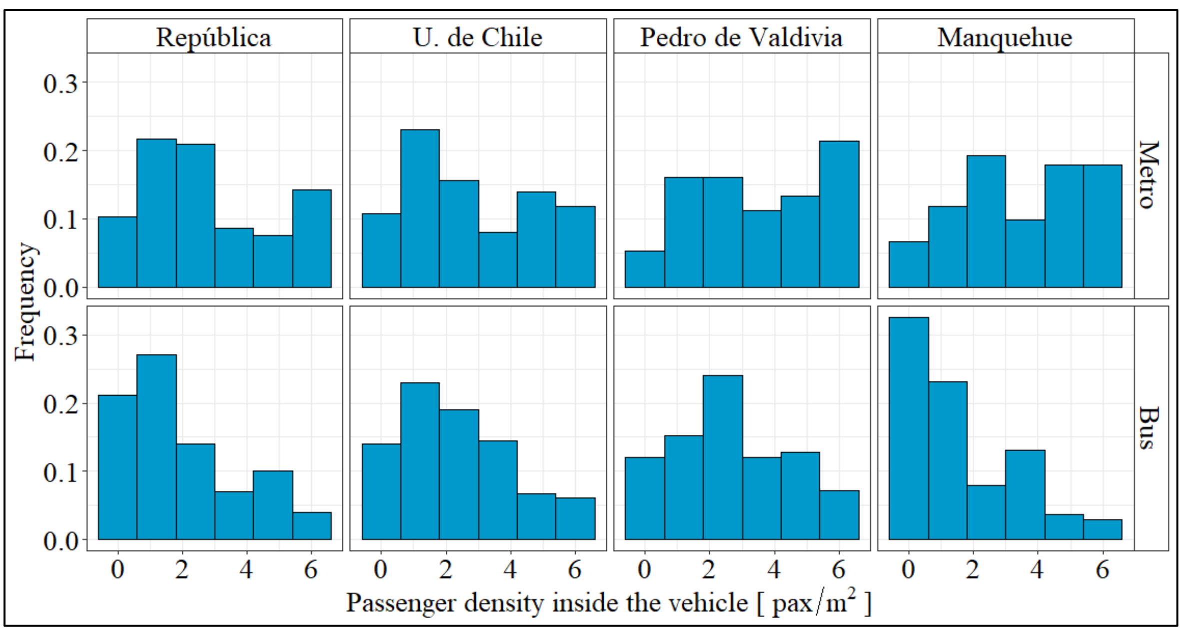


Figure 5.3 Reported crowding distribution for different modes and surveyed areas

Regarding the survey itself, five surveyors worked for five hours each day, obtaining a total of 1,150 responses. The survey was applied for both metro and bus users and gathered information about five aspects, which are detailed below:

1) **Satisfaction**

   Respondents provided a global satisfaction level, using a 1 to 7 scale (traditionally used for grading in the Chilean education system), to evaluate their perceived experience in the travel-leg they have just completed. In Chile 4 is the minimum passing grade.

2) **Number of denied boardings**

   To have a more precise estimation of waiting time, respondents were asked about how many vehicles they could not board due to insufficient capacity before boarding the vehicle they alighted from.

3) **Location during the most heavily loaded section**

   Given the differences in passenger density within the same vehicle, respondents were asked to indicate where (within the vehicle) they were located during the most heavily loaded moment of their travel-leg (Figure 5.4).

4) **Characterisation of the most heavily loaded section**

   Finally, respondents characterised the passenger density experienced at the most heavily loaded moment of their travel-leg by choosing one of six images showing different crowding levels (Figure 5.4).

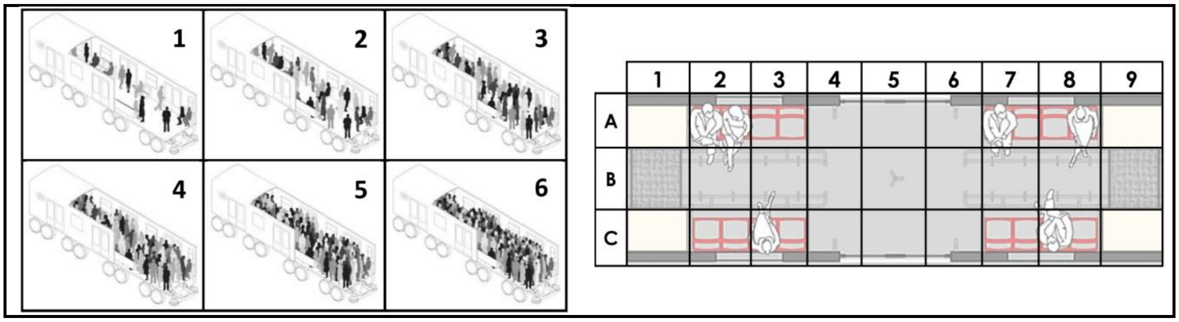


Figure 5.4 Crowding and location inside the vehicle diagrams for metro

Income was not directly asked, but instead, their commune of residence was. In Santiago de Chile, average income is very heterogeneous between the different communes and people living in one of them tend to have a similar income. However, this categorization was not found to be significative in the models.

5.4 Travel satisfaction model with crowding effects

5.4.1 Exploring user categories

To get an idea on how crowding affects different socioeconomical groups' travel satisfaction, scatter plots with a linear trend lines were created (Figure 5.5). Two sets of characteristics were selected, which are sex (men and women) and age (under 35 and over 35) to distinguish between four different groups.

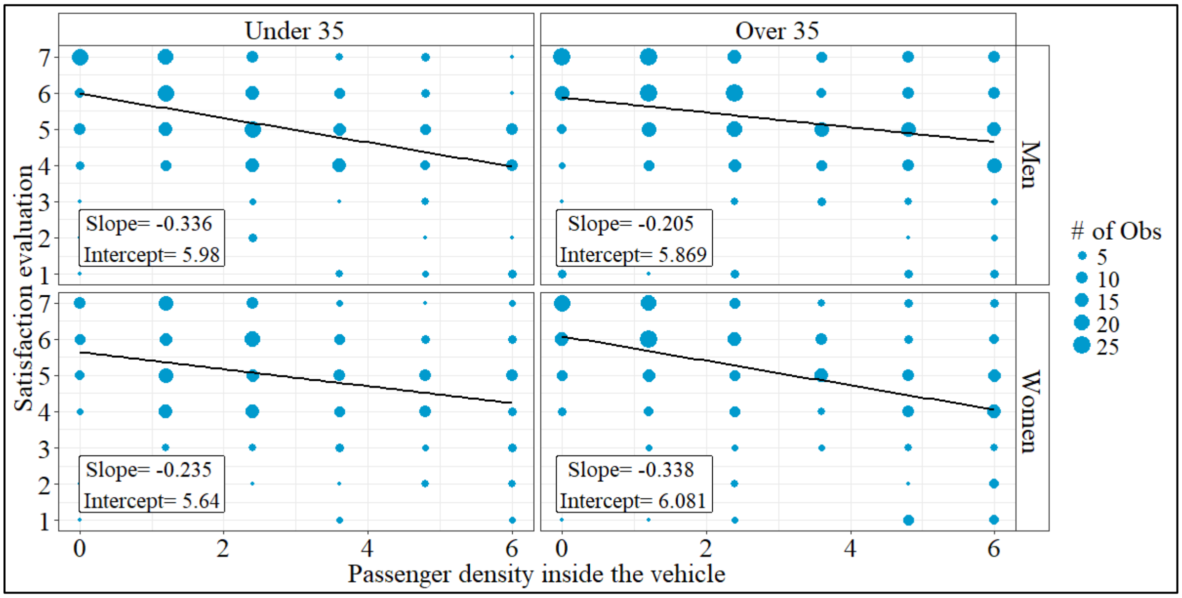


Figure 5.5 Trend lines relationship between satisfaction evaluation and reported passenger density

Overall, men over 35 years old show a lower slope in this linear relationship, which might be interpreted as a smaller sensitivity to crowding. Besides, women over 35 and men under 35 both have a greater slope and intercept, meaning their satisfaction is more influenced by passenger density. Finally, even though the slope is not greater for women under 35, their intercept is lower, implying that people in this category are less satisfied with crowding, everything else being the same.

However, this analysis is not conclusive as these relations are not sufficiently strong and rigid. Instead, latent classes will be analysed.

5.4.2 Latent class Ordered Logit model

Ordered Logit Models are estimated to explain the satisfaction grade given to the just finished trip based on the conditions of the trip and the respondent's socio-economical information. Several models were separately calibrated for metro and bus users, as an initial exploratory approach, in order to analyse potential mode-specific effects. However, to compare the impacts of different variables obtained for bus and metro users, a model considering both modes simultaneously is also calibrated. Finally, to address preference heterogeneity, a Latent Class model is estimated.

Since both databases may have different variances (i.e. heteroscedasticity across samples), a first model with common parameters and a scale factor λ_{Bus} for bus users is estimated. Also, a shift parameter Δ_{Bus} is considered, acting as an alternative specific constant. This parameter will test if, ceteris paribus, there is a difference in the evaluation given by users to the level of service experience inside a bus compared to metro. This parameter is expected to be negative, since bus services are found in the literature to be perceived more negatively than rail-bound services (this is commonly called “rail factor”; Scherer, 2010). This difference may not only stem from psychological factors, but also all those differences related with the operation (i.e. stopping at traffic lights, not constant speed) and the experience (i.e. noise, vibration, cleanliness). Moreover, it has been found that in some scenarios, this strong preference for rail actually hides significant level of service differences (Ben-Akiva & Morikawa, 2002). In the case of Santiago de Chile, both kind of differences are specially noticeably between busses and metro and thus, all the conclusions are specific for this context and can not be generalized to every bus system.

With this model, it is possible to test if there are significant differences between each attribute’s impact between modes. The first impact difference tested is for passenger density. No significant difference between bus and metro parameters is found, suggesting that density is perceived equally bad regardless of the mode when passengers are asked to evaluate their satisfaction. Specific parameters for each mode are tested for the number of denied boardings and the chance to get a seat.

To test the potential existence of a non-linear relation between crowding and satisfaction, two alternative approaches are tested. The first one consists of incorporating an exponent parameter. If this parameter turns out to be significantly different than 1, this means that the relation exercises non-linearity. The second one consists of estimating five different parameters, one for each crowding level, i.e. image (setting the first image as 0). Thus, if the hypothesis that the difference between consecutive parameters is not constant can be statistically rejected, then non-linearity exists. For the sake of readability, all the following models correspond to the first alternative, with an exponent, as it is easier to understand the existence of non-linearity this way and the fit is found not to be significantly better when considering specific crowding parameters for each level.

Finally, to test the existence of preferences heterogeneity, a Latent Class Model (Train, 2009) is calibrated. After trying different alternative specifications, the best resulting model consists of two classes: (i) considering all the attributes (Class 1) and (ii) without considering crowding nor being seated in their satisfaction evaluation (Class 2). Class 1 can be interpreted as being more sensitive to crowding when users evaluate their travel satisfaction because Class 2 lacks any comfort related attribute. This is known in the literature as attribute non-attendance or attribute ignoring (Nguyen, Robinson, Whitty, Kaneko, & Nguyen, 2015). This way, the differences between classes might be interpreted in terms of their comfort sensitivity.

The socio-economic data considered are sex (1 if woman, 0 otherwise), age (1 if under 35 years old, 0 otherwise), and if the respondent was travelling during the morning peak hour. The class membership function is a Multinomial Logit Model, where the Class1 membership systematic utility is:

$$V_{Class1} = \mathrm{ASC}_{Class1} + \beta_{woman} \cdot \mathrm{woman} + \beta_{age} \cdot \mathrm{under35} + \beta_{hour} \cdot \mathrm{peakhour}$$

The systematic utilities for each class and alternative are:

Class 1

$$V_{m,C1} = \theta_{com} \cdot \left(1 + \theta_{com} \cdot \mathrm{Door}_m\right) \cdot \mathrm{Dens}_m^{\gamma_{com,m}} + \theta_{veh,C1} \cdot \mathrm{Veh}_m$$

$$V_{b,C1} = \lambda_{bus} \cdot \left(\Delta_{bus,C1} + \theta_{com} \cdot \mathrm{Dens}_b^{\gamma_{com,b}} + \theta_{seatb} \cdot \mathrm{Seat}_b + \theta_{veh,C1} \cdot \mathrm{Veh}_b\right)$$

Class 2

$$V_{m,C2} = \theta_{veh,C2} \cdot \mathrm{Veh}_m + \theta_{age} \cdot \mathrm{under35}$$

$$V_{b,C2} = \lambda_{bus} \cdot \left(\Delta_{bus,C2} + \theta_{veh,C2} \cdot \mathrm{Veh}_b + \theta_{age} \cdot \mathrm{under35}\right)$$

Where, for mode *k*, Dens_k is the density reported and the remaining are dummy variables: Seat_k equals to 1 if the respondent travelled seated and 0 otherwise, Veh_k equals to the number of denied boardings the respondent experienced, and Door_m equals to 1 if the respondent was located in front of the door in metro and 0 otherwise.

Regarding the class membership model, we observe that, as expected, women are more likely to belong to Class 1, which is in line with previously reported results by research on gender mobility (Allen et al., 2017). This is arguably explained due to other factors related with overcrowding has a larger relative importance for women than for men, such as security and safety.

The same is observed for people under 35 years old as well as with people travelling during the morning peak hour. It is important to emphasise the absence of endogeneity in the latter classification, as there are no significant differences in the distribution of reported densities over time. To complete this analysis, the probabilities of belonging to Class 1 are calculated (Table 5.1).

Table 5.1 Class 1 membership probabilities

		Peak hour	Non-peak hour
Women	**Under 35**	99.6%	98.4%
Men	**Under 35**	98.3%	93.6%
Women	**Over 35**	93.6%	78.6%
Men	**Over 35**	77.6%	46.6%

Overall, people under 35 years old mostly belong to Class 1, regardless of sex and the time of travel. However, when it comes to people over 35 years old, women are significantly more likely to belong to this class, which reinforces that they are more sensitive to crowding. Besides, this was not found in a previous model without classes (tested as taste variations), which confirms the presence of preference heterogeneity in the sample. Finally, based on the socioeconomical distribution in the sample (Table 25.), we compute the average Class 1 membership probability, which is 85.00%.

Table 5.2 Socioeconomical distribution in the sample

		Peak hour	Non-peak hour
Women	**Under 35**	10.9%	10.0%
Men	**Under 35**	12.4%	10.6%
Women	**Over 35**	15.0%	9.8%
Men	**Over 35**	19.1%	12.4%
Average Class 1 membership probability in the sample: 85.0%			

This Latent Class Ordinal Logit Model is estimated using PythonBiogeme (Bierlaire, 2016). The results of this process are summarized in Table 5.3.

Table 5.3 Latent Class calibrated parameters

Attribute		Parameter	Estimate	t-test
Class Membership Model	Alternative specific constant Class 1	ASC_{Class1}	-0.137	-0.32
	Woman	β_{woman}	1.440	1.87
	Under 35 years old	β_{age}	2.820	2.23
	Morning peak hour	β_{hour}	1.380	2.44
Class 1	Reported crowding	θ_{Com}	-1.000	-4.97
	Door impact - metro	θ_{Door}	0.250	2.63
	Reported crowding	γ_{Com}	0.576	6.40
	Travelling seated - bus	$\theta_{seat,b}$	1.050	2.93
	Number of denied boardings	$\theta_{veh,C1}$	-0.316	-4.97
	Shift parameter – bus	$\Delta_{Bus,C1}$	-1.450	-4.69
Class 2	Number of denied boardings	$\theta_{veh,C2}$	-1.270	-4.91
	Under 35 taste variation	θ_{age}	-2.460	-1.83
	Shift parameter – bus	$\Delta_{Bus,C2}$	-2.470	-4.63
Scale factor – bus		λ_{Bus}	0.758	6.62
Number of observations			1150	
Log-likelihood			-1786.836	

Overall, there is a significant and negative shift for bus evaluation ($\Delta_{Bus,Ci}$), which means that users have a more negative perception of the level of service experienced inside a bus than inside metro everything else being the same. Also, the impact of travelling seated is larger for bus users. Class 2 has a more negative perception of buses, as its shift parameter $\Delta_{Bus,C2}$ is approximately 1.70 times larger than Class 1 shift parameter. When considering people under 35, this perception is even worse as Class 2 members have a significant and negative taste variation θ_{age}.

Regarding crowding perception in Class 1, the most interesting result is that this perception is found to be equal for bus and metro. This was tested against three additional models (equal θ_{Com} and different γ_{com}, different θ_{Com} - and equal γ_{com}, different θ_{Com} and different γ_{com}) and none of them turned out to be significantly different to the model presented here. The only exception are the passengers located in front of the door in metro (locations C4, C5 and C6 in Figure 4). These users perceive 25% more negatively this attribute in comparison. Besides, the reported density parameter, θ_{Com}, in Class 1 was found to be larger than the parameters found in previous models without classes. As Class 2 is not sensitive to comfort, these previous models ended up averaging the sensitivities of both classes, which resulted in a lesser estimated parameter. This confirms again the heterogeneity in user preferences.

Respecting the hypothetical non-linearity, γ_{com} is significantly different from 1, which confirms the proposed hypothesis. However, the parameter value is lower than 1, which means that the relationship has the opposite curvature to the one proposed in section 2. An explanation for this finding and its implications will be further discussed in the following sections.

In terms of the possibility of travelling seated, it is found not to be significant for metro users whereas it is positive and significant for bus users. As it is similar with opposite sign to the shift parameter in Class 1, this means traveling seated helps to reduce the breach between buses and metro, showing a more similar level of satisfaction for the same travel conditions.

Finally, the impact of not being able to board a vehicle was found to be linear, same for both modes and significantly different between classes. In terms of denied boardings, Class 2 values approximately four times more the impact of denied boardings. As Class 2 only accounts for this variable in evaluating their satisfaction, it could be expected that they would be more sensitive to this.

5.5 Satisfaction evaluation analysis

With the Latent Class Model calibrated, it is possible to construct the relationship between the crowding level and satisfaction evaluation. As described in the previous section, Class 2 is not sensitive to comfort, and most of the passengers belong to Class 1. Besides, as shown in Table 3, the average membership probability in the sample is 85%. Because of this, the following analysis will focus on Class 1.

First, the probability to evaluate travel satisfaction with a grade from 1 to 7 for densities between 0 and 6 passengers/m2 for non-seated passengers in metro and bus services is calculated based on model estimation results. The results are displayed in Figure 5.6 and Figure 5.7 respectively.

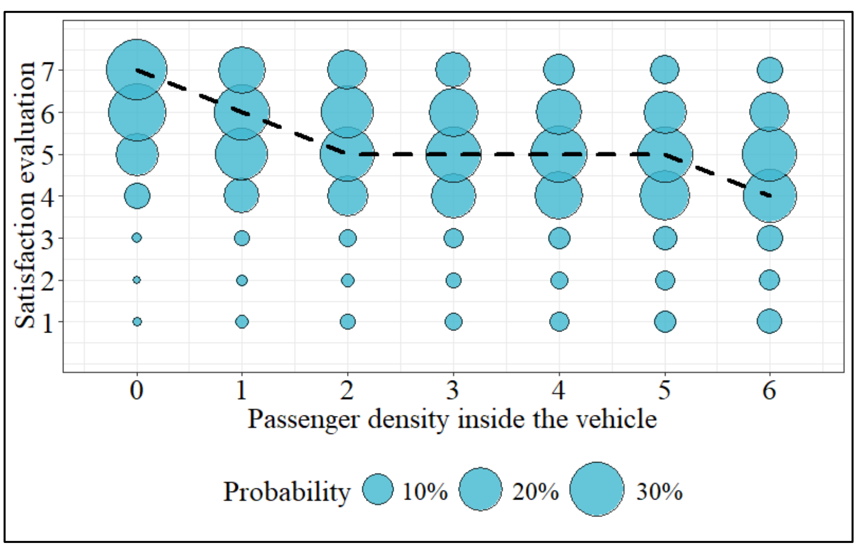


Figure 5.6 Satisfaction evaluation probabilities for bus services.

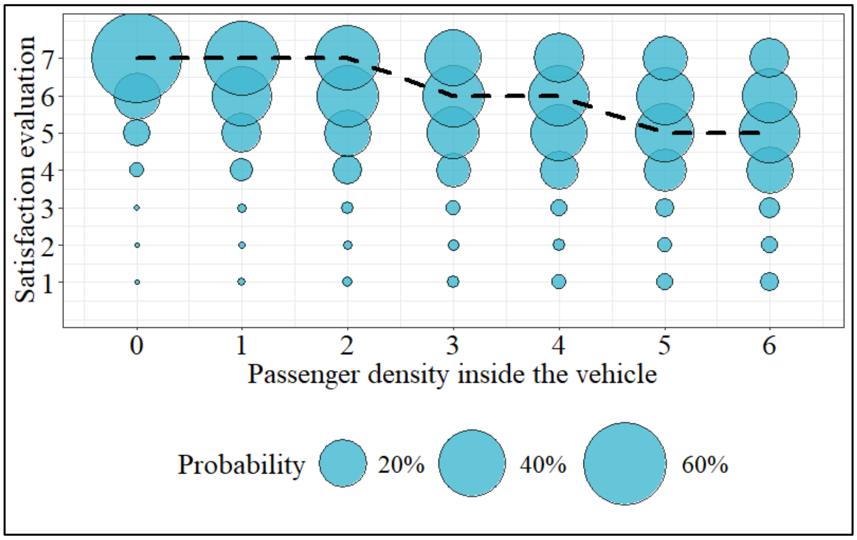


Figure 5.7 Satisfaction evaluation probabilities for metro services.

From the comparison of the two figures, it is noticeable that the distribution of probabilities for metro services is concentrated in the higher part of the satisfaction scale. This means that, on average, people are highly satisfied with this mode even when travelling in overcrowded situations and are more satisfied than when travelling with the bus under the same circumstances. This is explained by the negative shift parameter $\Delta_{Bus,C1}$ described in the previous section.

The share of users indicating low satisfaction rates (i.e. satisfaction levels 1 to 4) increases with passenger density, whereas the share indicating very high satisfaction (i.e. satisfaction level 7) decreases. However, the situation is different for satisfaction levels 5 and 6. Bus service's satisfaction level 5 increases and then remains almost constant, and level 6 is always decreasing, while metro service's satisfaction level 5 is always increasing and level 6 increases and then decreases.

The scale limits may influence the results when people try to give a higher or lesser evaluation. This limitation is referred in the literature as the ceiling effect (Castle & Engberg, 2004). This is not observed in the satisfaction evaluation distributions, even though metro's are mostly in the higher scale limit for densities lesser than two passengers per square metre. As it might be difficult to analyse this probability distributions for every different number of denied boardings, we computed the average value for each reported density value and mode, and plotted one curve for zero, one and two denied boardings. The obtained satisfaction curves are presented in Figure 5.8.

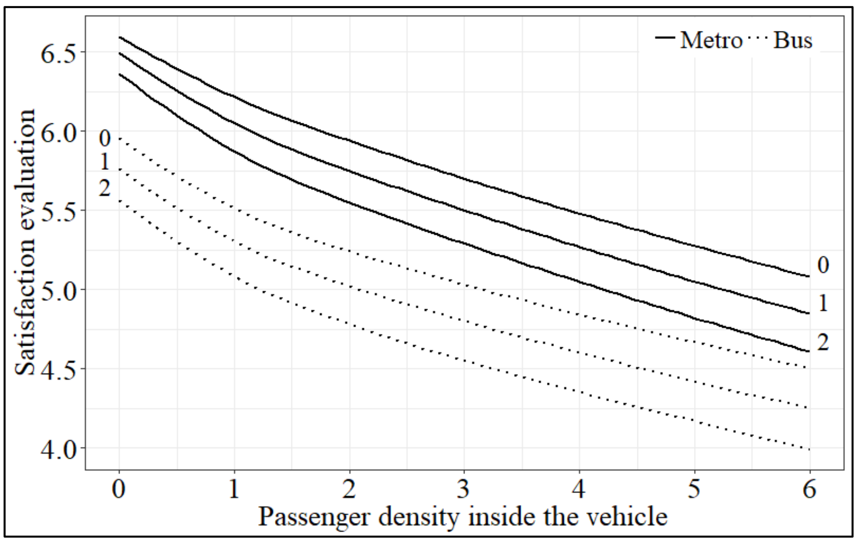
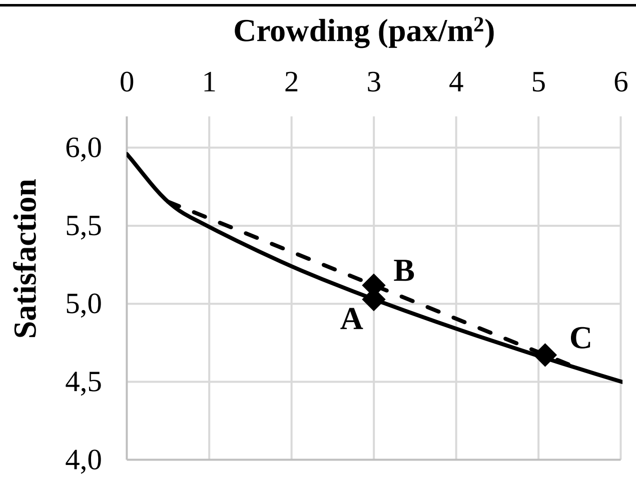


Figure 5.8 Satisfaction rating curves per number of denied boardings and mode.

Metro and bus's curves exhibit some similarities. For example, both modes' curves are decreasing and convex, which is explained by the power parameter in density γ_{Com} and the threshold parameters in the Ordinal Logit Model. Moreover, the difference between denied boardings' curves for each mode has a greater spread with increasing passenger density.

However, the differences between bus and metro curves is more substantial than among curves stemming from the same mode with a different number of denied boarding experiences. There is no single satisfaction evaluation point in bus services in the curves which reflects a higher satisfaction value than the value obtained by the worse situation in metro for identical crowding. Thus, more than two denied boardings in metro are needed to obtain the same predicted evaluation value for bus and metro for a given density level. Furthermore, satisfaction rises 0.25 points on average when passenger density decreases 1 passenger per square metre.

Finally, we perform an analysis similar to the one exposed in section 2. Since each user has a different satisfaction curve, the analysis will focus on non-seated passengers which board the first vehicle for bus services, as can be seen in Figure 5.9. This way, the analysis is centred round the unreliability effects and without compounding it with denied boardings.



	Average crowding	Average satisfaction
Perfectly regular	3.0 pax/m^2	5.03
Irregular	3.0 pax/m^2	5.12
Perceived comfort	5.1 pax/m^2	4.67

Figure 5.9 Satisfaction fall due to headway irregularity.

In this example, if the service maintains a perfectly regular headway, buses would have the same load, which in this case would be of 3.0 passengers per square metre. Under this situation, this model predicts an average satisfaction evaluation of 5.01 based on the estimated model (letter A in Figure 5.9). However, as in the previous example, we will assume that this service operates irregularly with two alternating headways which causes loads of 0.5 and 5.5 passengers per square metre. If we consider the average evaluation per vehicle, we would observe the same average passenger density of 3 passengers per square metre but this time a satisfaction evaluation of 5.11, higher than the one under regular conditions (letter B in Figure 5.9). This occurs because of the convexity of the curve now presented. Nevertheless, when weighting the load in each vehicle, the situation moves in the opposite direction: the average passenger density rises to 5.1 passengers per square metre and the satisfaction evaluation drops to 4.59 (letter C in Figure 5.9).

This situation substantiates the claim that performance indicators must be weighted properly by demand. If it is not the case, public transport agencies might be perceiving they are offering a good service (even better than expected) while passengers are experiencing the opposite, i.e. a deterioration in service satisfaction.

5.6 Conclusions

Providing evidence confirming the relationship proposed between headway reliability and traveller's satisfaction could lead to a change in the perspective public transport systems are planned and operated. This research indicates that waiting time reliability and crowding levels have a very strong impact on users' satisfaction evaluation. Irregular headways generate heterogeneity in vehicles' level of service. An often-ignored problem here is that more travellers experience the more crowded vehicles, reducing the average satisfaction index further than if simply averaging over bus vehicles. A second issue is that crowdedness and waiting time are strongly correlated which should also be incorporated in the model.

The impact of unreliability and crowding on passenger experience is further exacerbated by the non-linear relation between satisfaction and crowding level revealed in this study. Using a Likert-like semantic grade scale, the curve obtained is convex. This curve shape might bias public transport agencies if they do not consider evaluation metrics weighted by the number of users, as gaps between the level of service believed to be offered and perceived by passengers will occur.

The results of this study also confirm that users evaluate, ceteris paribus, worse the level of service in bus than in metro. In addition, regarding socio-economical heterogeneity, people under 35 years old almost always evaluate the service taking into account comfort. However, women over 35 years old are significantly more sensitive to the comfort level, which is in line with our current knowledge of women mobility preferences.

Regarding the methodology employed in this study, we conclude that it is possible to obtain a crowding/satisfaction curve with a simple survey. It would be important to replicate this kind of experiment as the results are limited to the specific Santiago de Chile context. Presumably, since buses and metro offer a very different level of service in the case of the study area, it would be important to analyse how different satisfaction is perceived when buses perform significantly better.

Our results are consistent with other studies that have identified a preference by transit users for metro to the detriment of buses. Understanding how much of this satisfaction or preference is explained by the difference in level of service experienced by users may encourage more affordable and cost-effective alternatives with high level performance, as Bus Rapid Transit (Delgado et al., 2016; Hidalgo & Gutiérrez, 2013).

Future research should pursue at least two new directions of analysis. Firstly, it would be important to characterize respondents by income, to test preferences' differences in the context of satisfaction evaluation. In many cities low income households are located far away the city centre, with poor public transport service. Thus, a better understand of their preferences and needs would enhance public policy application. Secondly, provided with reliable load information for both metro and buses (i.e. weights or APC), the comparison between stated peak passenger density and actual density measures could be analysed. This may expand the current knowledge we have about crowding perception and its relationship with satisfaction.

To make large cities more sustainable public transport should be one of the preferred modes to use. Thus, transport planners should measure, monitor and respond to traveller's satisfaction with their service experience. As we have shown in this study, if transport agencies are evaluated based on performance indicators, these must be properly weighted by the actual number of passengers served to understand the real conditions they face and the perceived quality of the service they deliver.

Acknowledgements

This research was supported by the Centro de Desarrollo Urbano Sustantable, CEDEUS (Conicyt/Fondap 15110020), the Bus Rapid Transit Centre of Excellence funded by the Volvo Research and Educational Foundations (VREF), the FONDECYT project number 1150657 and the scholarship funded by CONICYT for Ph.D. studies (CONICYT-PCHA/Doctorado Nacional/2016).

6. TRAVEL PREFERENCES OF PUBLIC TRANSPORT USERS UNDER UNEVEN HEADWAYS

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6.1 Introduction

Mode choice models, which are used to predict individuals' behaviour regarding the use of different modes of transport, typically consider average attributes such as travel time, waiting time, fare and/or accessibility as explanatory variables (Ortúzar & Willumsen, 2011). However, it is reasonable to think that travellers also consider these attributes' variability, instead of only considering their average values. In the case of unscheduled public transport services (which is common when medium to high-frequency is offered), this variability is strongly affected by headway irregularity between consecutive vehicles. Still, most individual utility models neglect its effect. Its impact is sometimes recognized as part of the expected waiting time, since the average waiting time experienced by a user exceeds half of the average headway because of headway variability. Notice that even if headways were to be completely regular, a user arriving randomly to the stop will face a random waiting time. Thus, in most cities waiting time is of uncertain nature for which its average value provides limited information. Finally, assuming that headway variability only affects the average waiting time fails to incorporate its full effect in users' satisfaction. As Munoz et al (2020) argue, headway regularity also affects comfort, reliability and travel times.

Despite its relevance, service reliability, both for travel time or waiting time, has been scarcely incorporated into choice models. Instead, its effect has been approached through psychological studies that are much more complex than the behavioural assumptions with which the individuals' choices are usually modelled. Examples of this are the Prospect Theory (Kahneman & Tversky, 1979) or Regret aversion (Loomes & Sugden, 1982). This might explain why obtaining a reliability valuation for choice models has been so elusive.

Over the last decades, stated preferences experiments involving service variability have been carried out, in which typically two or more travel alternatives are presented, with average travel times, cost, and some representation of the variability that travel time entails. These representations goes from possible delays or ranges (Batarce et al., 2015; Hjorth et al., 2015; Jackson & Jucker, 1982; Kouwenhoven et al., 2014; Li, Hensher, & Rose, 2010; Small, Noland, Chu, & Lewis, 1999; Small, Noland, & Koskenoja, 1995), circular diagrams (Bates, Polak, Jones, & Cook, 2001), bar diagrams (Devarasetty, Burris, & Douglass Shaw, 2012; D A Hensher, 2001; Hollander, 2006), histograms (Copley, Murphy, & Pearce, 2002; Tilahun & Levinson, 2010) and probabilities (Li et al., 2010). However, almost none of these studies intends to capture a broad impact of service variability in the level of service.

Despite the correlation between headway irregularity and low comfort, only Batarce et al. (2015) incorporates crowding effects and waiting time variability in their study, finding no significant impacts. This could have happened because of the large amount of information presented to each respondent, which may ignore certain information that seems less relevant or important, biasing their responses. Excess of information is a major problem when designing an experiment focused on public transport since to fully characterise an alternative it would be necessary to specify travel times, waiting times, cost, crowding and the variability of those attributes.

Another approach to address reliability is to study travellers' learning. This method recognizes that the variability of travel or waiting times is not understood in the same way as an average cost or time, since it relates to the repetitive realisation of the same trip (Bogers, Bierlaire, & Hoogendoorn, 2008). An example of this method is presented in Avineri and Prashker (2005) for private car routes. They study a network consisting of two different alternatives with different average and variability of travel time, and in which the average fastest route is the more unreliable. However, according to our knowledge, very few studies have carried out this methodology, and none has been applied to a public transport context.

Thus, the purpose of this research is to contribute in the understanding of the impact of service reliability on the choices made by public transport travellers. To do so, an experiment of stated preferences was conducted in Santiago de Chile, with headway regularity as a key design factor. In this experiment, this attribute is presented implicitly, through its impact in different day experiences. In Section 2, the survey design is described. The modelling approach and results are discussed in Section 3. Finally, conclusions and further research are presented in Section 4.

6.2 Survey Design

6.2.1 Variability Representation

Stated preference surveys have been widely used to understand people choices and behaviour in the last decades. However, attributes that are uncertain in nature, it is still unclear how to represent them in these experiments. Different schemes have been tried: regular schedules, circular schedules, probability distributions, vertical bars, among others (Bates et al., 2001; Copley et al., 2002; Hollander, 2006; Small et al., 1999) (Figure 6.1). Among these alternatives, travel time bars had the best performance in terms of people understanding.

In our research, we expect respondents to compare different public transport services operating in a high-frequency context. In principle, each of these services would be subject to variable waiting and travel time. As there is more than one time-attribute to compare (i.e. waiting time and in-vehicle travel time), horizontal bars were selected instead of vertical bars. By doing this, people can compare vertically the length of these horizontal bars between alternatives.

To represent service variability, we represent each alternative by the level of service to be experimented by a user in a sample of five consecutive days, i.e. representing a typical week of service. Each day is characterized by a waiting time, a travel time, and a crowding level inside the vehicle.

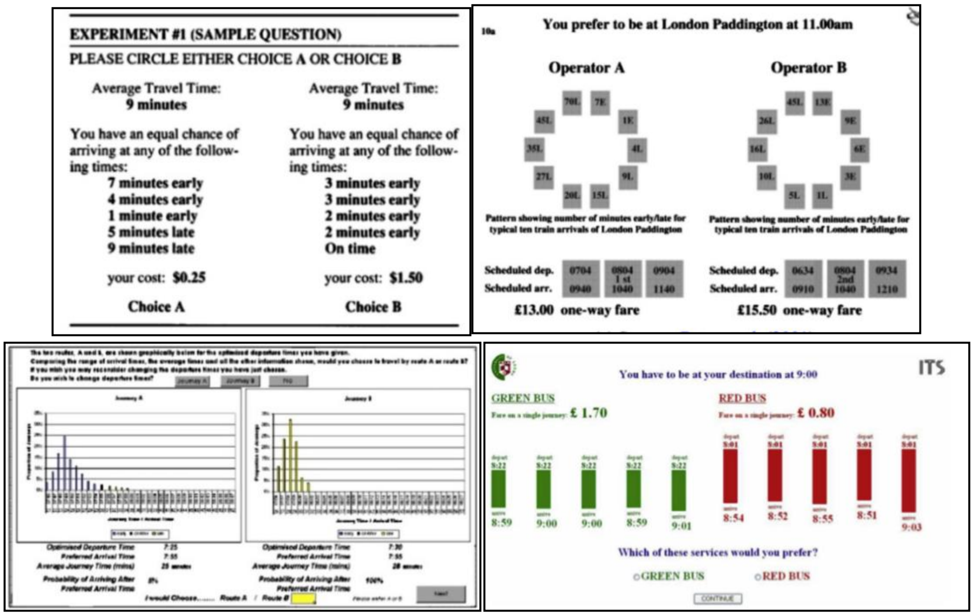

Figure 6.1 Variability representations

During the stated preference survey design, it is important to define the kind of relationship to analyse in advance. This way, scenarios representation will consider these expected results in the way they are framed. We defined a hypothetical utility function to calibrate after the survey is applied as follows:

$$V_j = \beta_{ttime} \cdot \left(1 + \sum_k \beta_k \cdot \delta_{kj}\right) \cdot TT_j + \beta_{wtime} \cdot \overline{WT_j} + \beta_{disp(\mathrm{WT})} \cdot disp\left(WT_j\right) \tag{1}$$

Where, for every alternative j, TT_j represents its travel time, δ_{kj} is a dummy variable indicating the crowding level k, WT_j is the average waiting time and $disp(WT_j)$ stands for a waiting time dispersion indicator. The objective is to identify the impact of service unreliability in people´s preferences. The source of this uncertainty would come from headway variability which we will assume exogenous. Thus, based on a given probability distribution for the headways, representative observations of crowding inside the vehicle and waiting time are obtained. By repeating this process five times we obtain the weekly travel experience that will be included in the survey. It is important to highlight that monetary cost wasn't considered in order to represent better the current public transportation system in the city of study. Besides, the utility function presented in (1) is represent a preliminary intuition; further specifications are tested in this work.

In order to reduce the cognitive load of the survey, we made two design considerations. Firstly, we decided to restrict variability only to crowding and waiting time, leaving travel time constant. Secondly, each crowding level is presented combined with travel time. We have called this combination "crowding bars", which means that a long and crowded experience is represented by a long bar filled with the respective number of passengers (Figure 6.2 represents three different trips of the same duration but with different levels of crowding). This is coherent with the literature, which states that the impact of occupancy in a public transport trip is directly related to its length through crowding multipliers.

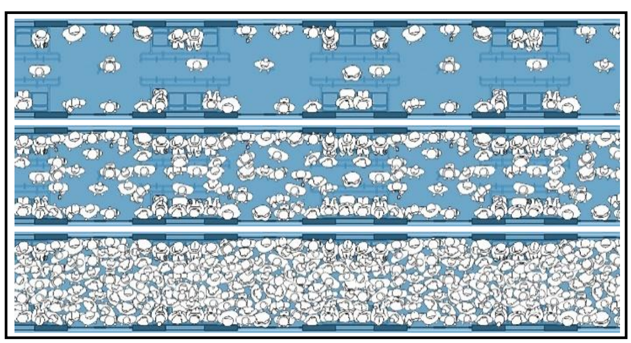

Figure 6.2 Crowding bars for 1, 3, and 6 passengers/m2

6.2.2 Simulated Design

One of the most important objections towards stated preference surveys is their lack of realism. This lack of realism would induce people to act differently in these virtual scenarios than in real life. To avoid this, we identified two potential sources of lack of realism: i) presenting alternatives that could rarely be observed in reality, and ii) neglect the inherent uncertainty of random attributes by presenting them in the alternative as taking a stable fixed value. In order to reduce these problems, we designed the virtual scenarios based on four operational inputs, instead of directly defining the level of service to be experienced by each user. The four inputs are: i) speed, ii) frequency, iii) a headway probability distribution and iv) an average passenger arrival rate. In each choice scenario, the values associated to these four attributes are used to determine five representative and coherent instances. These five instances are used to represent the service experienced by someone during a work week. This service is defined by a constant travel time for all five days and variable waiting times and vehicle crowding across days (Figure 6.3). This type of information, that is, descriptive and experienced, has proven to be the one that best represents users' learning process (Ben-Elia & Avineri, 2015). This way, reliability is not presented as an attribute by itself but as a result of several repetitions of the same trip. As will be described later the sampling process we follow yields five instances that are as representative as possible of the probability distribution, and we present them to the respondent in a random order.

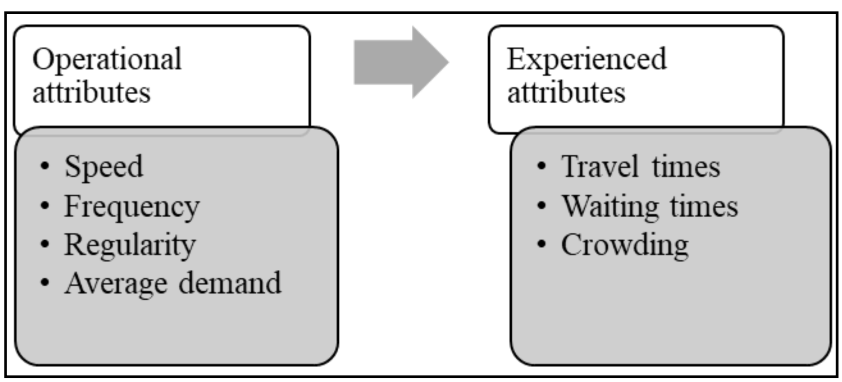

Figure 6.3 Operational and experienced attributes

Within this framework, travel time is obtained directly from speed. However, the waiting time experienced by a user during a week depends on bus headway distribution. And this distribution depends on the frequency being offered and headway variability. The crowding inside the vehicle that a user would experience should be directly dependent of the length of the headway ahead and the passenger arrival rate to the stops. These relations between operational and experienced attributes are summarized in Figure 6.4.

In our experiment we assign different levels to each operational attribute. For speed, we consider two levels, representing travel times 15% shorter and 15% longer than the travel time reported by the user at the beginning of the survey. This allows us to face each respondent with a scenario that mimics the level of service they experience daily. For frequency we also consider two levels, yielding an average headway of 5 and 10 minutes. For passenger demand we consider two levels yielding 1 and 3 passengers/m2 in the case of a bus trailing a headway that matches the average headway. The crowding inside the bus will be higher or lower if the headway that the bus us trailing is longer or shorter than the average one. The actual headway is obtained from the headway distribution as is explained in the next paragraph.

For headway distributions we consider three levels named no variance (identical headways), irregular headways, and bus bunching. For the 5-minutes average headway, the irregular scenario consists of equally likely headways of 2, 5, and 8 minutes while the bunching scenario consists of equally likely headways of 5, 10 and 0 minutes (bunched vehicle). For the 10-minute average headway case, the distributions are identical, but with twice as large headways in each case.

The headway distribution, $f_h(h)$, is used to determine the following waiting time distribution for a user arriving to the stop at any moment with identical probability:

$$f_{w^*}\left(w\right)=\frac{1-F_h\left(w^*\right)}{E\left(h\right)} \quad \rightarrow \quad F_{w^*}\left(w\right)=\int_0^{w^*}\frac{1-F_h\left(w\right)}{E\left(h\right)}dw \tag{2}$$

To present respondents of the survey a set of five representative instances of this distribution, we calculate its 10%, 30%, 50%, 70%, and 90% percentiles. Such a set provides an unbiased sample of the experience of a user of this service. The order in which these five instances is presented to the user is randomized to better represent a typical week. Thus, the methodology to determine the waiting time and the travel time of each weekday in the survey alternative has already been described. The only remaining attribute to generate is the passenger density that the user would experience. It could be imagined that the crowding level should be proportional to the waiting time, but this is not as simple. Although long waiting times always respond to a long headway and therefore to a high crowding level, short waiting times can happen in long or short headways and therefore they are not indicative of the crowding level to be experienced by the user. For example, under an irregular operation consisting of headways of 2, 5, and 8 minutes, a 7-minutes waiting time can only be experienced by a user arriving during an 8-minutes headway, while a 1-minute waiting time could be experienced by users arriving in any of the three possible headways. Thus, given a waiting time, the probability that said wait occurred in a specific headway is the inverse of the amount of headways larger than that wait, K*.

$$P\left(h=h_i \mid w=w*\right)=\frac{1}{K*} \quad \forall h_i \geq w* \tag{3}$$

Thus, based on this distribution, we randomly associate a headway to each waiting time and the crowding experienced by the user corresponds to the demand arrival rate times the headway.

Thus, the entire scenario construction process can be summarized in the following diagram:

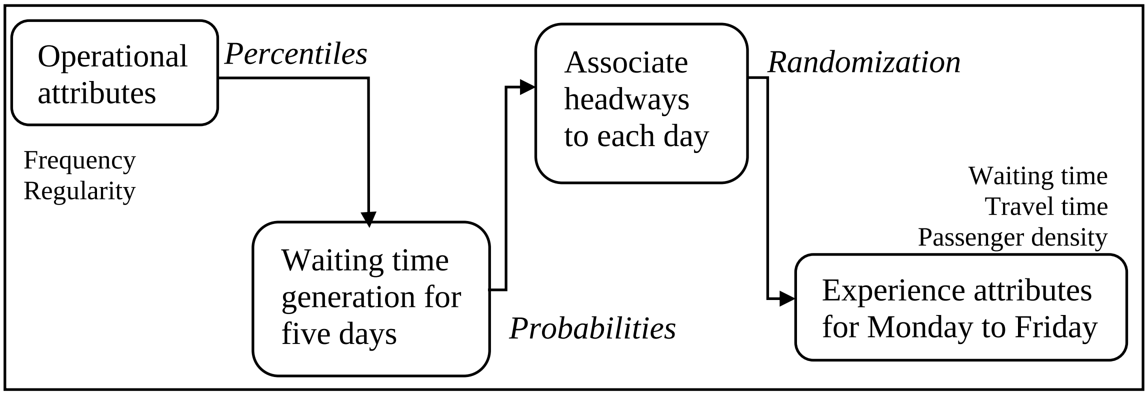

Figure 6.4 Scenario construction diagram.

After all this process, one alternative to be presented in the survey looks like this:

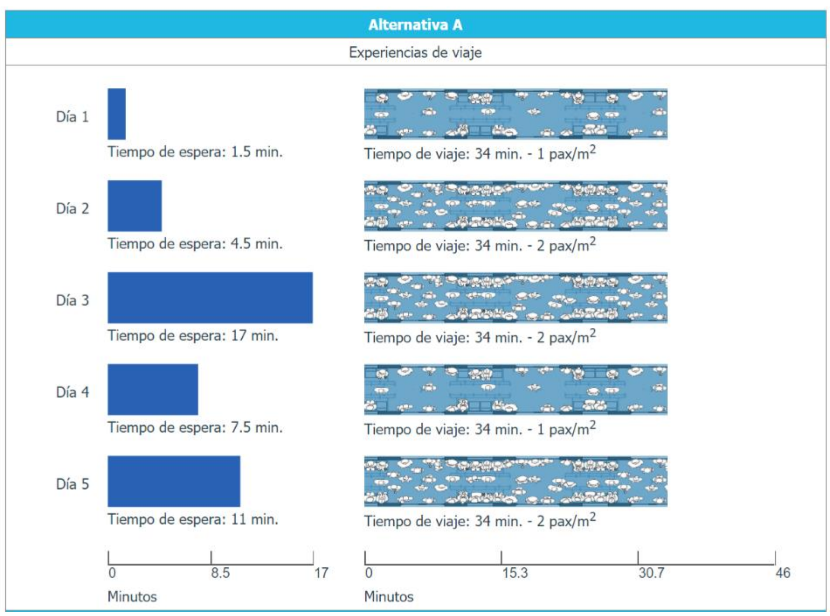

Figure 6.5 Alternative example

6.2.3 Survey Description

The whole survey is structured as follows: typical travel description, discrete choice experiment, attitudinal questions, and socio-economical characterization.

Firstly, respondents described their current travelling characteristics. For their most common trip, they identified the transport mode used in its most part, and its purpose.

Public transportation users were asked for the average in-vehicle travel time for that trip. For the remaining modes, respondents indicated their average in-vehicle travel time as well but also, they were asked for their estimation of the in-vehicle travel time for the same trip but using public transportation. In addition, each respondent indicated the average number of weekly days they travel by public transport.

Secondly, respondents were exposed to eight discrete choice scenarios with two independent public transportation alternatives each. These alternatives were unlabelled and represented generic public transportation services. Based on the results of the pilot survey, in every choice scenario only two out of the four operational attributes (speed, demand frequency and regularity) were different. This allowed us to present scenarios to respondents in which the number of elements changing between alternatives was not that many. The eight scenarios are presented in Table 6.1. They were randomized in the order they were presented in the survey, in order to avoid any cognitive load bias.

Table 6.1 Survey scenarios

Scenario Number	**Trade-off Attributes**	**Alternative**	**Speed**	**Frequency**	**Demand**	**Regularity**
1	Speed & Frequency	Alt A	High	Low	Low	Bunched
		Alt B	Low	High	Low	Bunched
2	Speed & Demand	Alt A	High	High	High	Irregular
		Alt B	Low	High	Low	Irregular
3	Frequency & Demand	Alt A	Low	Low	Low	Regular
		Alt B	Low	High	High	Regular
4	Speed & Regularity	Alt A	Low	Low	Low	Regular
		Alt B	High	Low	Low	Bunched
5		Alt A	Low	High	Low	Regular

	Speed & Regularity	Alt B	High	High	Low	Bunched
6	Frequency & Regularity	Alt A	High	Low	High	Irregular
		Alt B	High	High	High	Irregular
7	Frequency & Regularity	Alt A	Low	Low	High	Irregular
		Alt B	Low	High	High	Irregular
8	Demand & Regularity	Alt A	High	Low	High	Regular
		Alt B	High	Low	Low	Irregular

Thirdly, after the discrete choice experiment, respondents had to evaluate their level of agreement with 12 attitudinal statements on a scale from 1 to 7 (which is the educational grading scale used in Chile). These statements are related to crowding aversion attitudes, public transport easiness, and punctual behaviour. Table 6.2 presents these statements, as well as the designed attitudinal latent variable. The survey ends with a set of socio-economical questions. These questions asked about gender, age, education level, main occupation, household size, and monthly personal income.

Table 6.2 Attitudinal statement

N°	**Statement**	**Crowding aversion**	**Public Transport Easiness**	**Punctual Behaviour**
1	It is hard for me to be punctual			✓
2	Public transport is a solution for environmental issues		✓	
3	It is easy to know how much time my most common trip will take		✓	✓
4	I try to board the first bus or train, no matter how crowded it is	✓		✓
5	Being late causes me an unpleasant feeling			✓

6	I can easily plan a public transport trip		✓	
7	I leave home in advance to ensure I will arrive on time and as comfortable as possible	✓		✓
8	I choose more comfortable travel options even if they take more time	✓		✓
9	Waiting gives me an anxiety level that affects me			✓
10	Wherever I am, I know how to return home by public transport		✓	
11	Being late to my common destination can bring me problems			✓
12	When leaving home, I know how crowded the bus or train will come	✓	✓	

The survey was applied during the first week of October 2019 in 10 different Public Notary Offices in Santiago de Chile. The locations of these offices are displayed in Figure 6.6. These places were selected as they gather people from different areas of the city and long waiting to be attended is common, so these people usually have enough time to respond. A total of 1,314 people completed the survey, which corresponds to 10,512 choice scenarios.

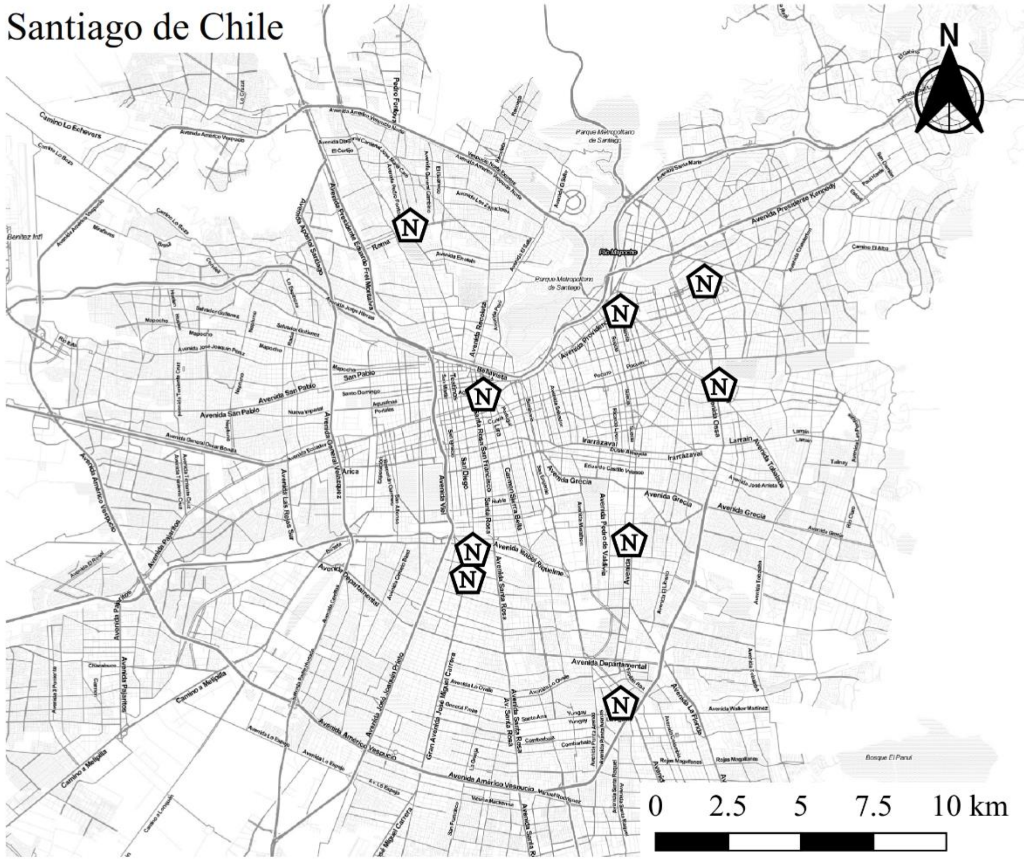

Figure 6.6 Public Notary Offices' location

Regarding the sample, 59% of the respondents are public transport users and 31% are car users. Among car users, 71% of them declared that they know how long it would take to commute by public transport.

6.3 Model Description and Results

A Hybrid Discrete Choice Model was formulated for this study. One of the characteristics of these models is the possibility to include subjective elements, as perceptions or attitudes, in the form of latent variables (Ben-Akiva et al., 2002; Raveau, Álvarez-Daziano, Yáñez, Bolduc, & De Dios Ortúzar, 2010). In general terms, latent variables will be included to indicate random taste variation for different attributes in the discrete choice model. To do so, a Multiple-Indicator Multiple-Cause (MIMIC) model was estimated, where the proposed latent variables are explained by different socio-economical characteristics. Both models were estimated simultaneously, as the latent variable, and therefore its error term, is part of both the measurement equations for the indicator and the utility function of the discrete choice model (Bierlaire, 2018).

The tree latent variables presented in the previous section were found both by a MIMIC model and a Principal Component Analysis (PCA). However, only two of them, crowding aversion and punctual behaviour were found to have a significant impact in the discrete choice model. Our hypothesis is that the remaining latent variable, public transport easiness, has an impact on the evaluation of the system and not in the perception of public transportation level of service. For crowding aversion, the explanatory variables in the MIMIC model were car users, age, income, gender and being a dependent employee. For punctual behaviour, only age and being a dependent employee. The resulting latent variable model relationships in Figure 6.7 and equations 4 and 5.

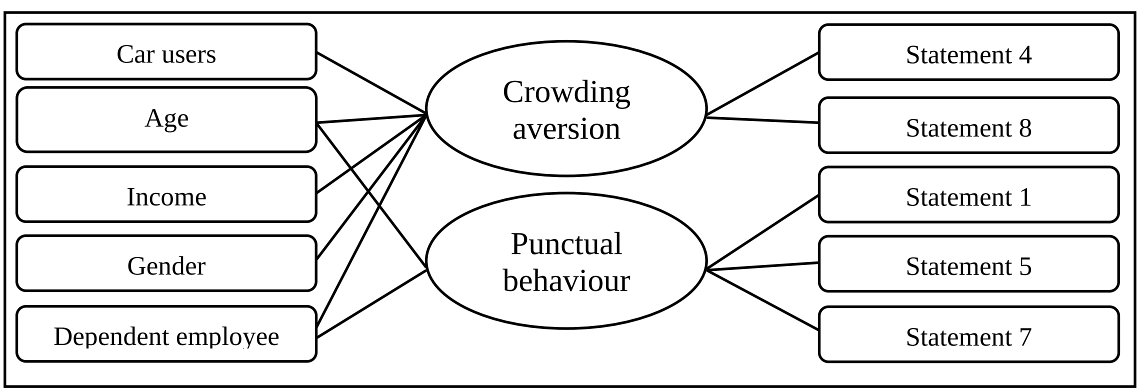

Figure 6.7 Public Notary Offices' location

With measurement equations for statements 4 and 8

$$V_{\text{Statement } i} = \alpha_{\text{Statement } i} + \gamma_{\text{Statement } i} \cdot \text{CrowdingLV} \quad (4)$$

and

$$V_{\text{Statement } i} = \alpha_{\text{Statement } i} + \gamma_{\text{Statement } i} \cdot \text{PunctualLV} \quad (5)$$

for statements 1, 5, and 7.

For the discrete choice model, the systematic utility considered travel time, its interaction with the punctual behaviour latent variable and the interaction with different crowding levels only for high density scenarios (i.e. high density level for both alternatives); the expected waiting time for each alternative; the coefficient of variation of headways; the average passenger density and its interaction with the crowding aversion latent variable; and the possibility of travelling seated. A Multinomial Logit Model was considered, and the best specification was found by the Likelihood-Ratio test and is presented as follows:

$$V_{i,j} = \beta_{TT} \cdot \text{TT}_i + \beta_{Punctual} \cdot \text{PunctualLV}_j \cdot \text{TT}_i + \delta_{CrMultiplier} \cdot \phi_{HighDensityScenario} \cdot \overline{\text{Dens}}_i \cdot \text{TT}_i + \beta_{WT} \cdot \overline{\text{WT}}_i + \beta_{CV(\text{WT})} \cdot CV(\text{WT})_i + \beta_{Dens} \cdot \overline{\text{Dens}}_i + \beta_{Crowding} \cdot \text{CrowdingLV}_j \cdot \overline{\text{Dens}}_i + \beta_{Seat} \cdot \text{Seat}_i \quad (6)$$

Where:

TT_i	Average travel time for alternative *i*
PunctualLV_j	Punctual behaviour latent variable for person *j*
$\phi_{HighDensityScenario}$	Equals 1 for high density level for both alternative scenarios. 0 in any other case.
$\overline{\text{Dens}}_i$	Average passenger density alternative *i*
$\overline{\text{WT}}_i$	Expected waiting time for alternative *i*
CV(WT)_i	Coefficient of variation of waiting times for alternative *i*
Seat_i	Number of days with available seats for alternative *i*

This hybrid model was estimated simultaneously, as stated previously, with 50 Halton draws to simulate the latent variables. The results for the MIMIC model and discrete choice model are presented in Table 6.3 and 6.4 respectively.

Table 6.3 MIMIC model estimated parameters

Attribute			Parameter	Estimated	t-test
Crowding aversion	Statement 4	Constant	$\alpha_{\text{Statement 4}}$	0.586	3.90
		LV Effect	$\gamma_{\text{Statement 4}}$	-0.781	-4.00
	Statement 8	Constant	$\alpha_{\text{Statement 8}}$	-0.161	-0.98
		LV Effect	$\gamma_{\text{Statement 8}}$	-1.000	fixed
	Car users			0.345	7.42
	Age			0.014	5.29
	Income			0.010	1.96
	Gender			0.327	7.28
	Dependent Employee			-0.227	-5.28
Punctual Behaviour	Statement 1	Constant	$\alpha_{\text{Statement 1}}$	0.366	2.03
		LV Effect	$\gamma_{\text{Statement 1}}$	1.000	fixed
	Statement 5	Constant	$\alpha_{\text{Statement 5}}$	1.42	5.16
		LV Effect	$\gamma_{\text{Statement 5}}$	0.978	4.80
	Statement 7	Constant	$\alpha_{\text{Statement 7}}$	0.616	2.68
		LV Effect	$\gamma_{\text{Statement 7}}$	1.27	5.93
	Age			0.037	7.87
	Dependent Employee			0.145	2.35

Table 6.4 Discrete choice model estimated parameters

Attribute	Parameter	Estimated	t-test
Travel time	β_{TT}	0.01400	1.98
Punctual behaviour LV	$\beta_{Punctual}$	-0.01940	-3.95
Crowding multiplier	$\delta_{CrMultiplier}$	-0.00162	-2.18
Average waiting time	β_{WT}	-0.11900	-7.59
CV of waiting time	$\beta_{CV(WT)}$	-2.42000	-5.05
Average passenger density	β_{Dens}	-0.29900	-5.13
Crowding aversion LV	$\beta_{Crowding}$	-0.12800	-2.44
# Days with seats available	β_{Seat}	0.05200	2.83

As there was no cost attribute in the experiment, we compare the marginal rate of substitution (MRS) between the alternatives' attributes through in-vehicle travel time. Besides, as the modelling framework consider random latent variables, this produces both travel time and passenger density parameter distributions.

In-vehicle travel time parameter distribution is presented in Figure 6.8. In this Figure, a 3 passenger per square metre density is considered, as the crowding multiplier affects this distribution. Besides, punctual behaviour latent variable has a significant impact, which translates in a higher perception of time for people who consider punctuality higher. Both being a dependent employee and age have a significant and positive impact in this latent variable. This means that punctuality is valued higher for older and dependent employees. As the punctual behaviour latent variable has a positive value for every observation, we observe negative values for every person of the sample, as expected. Besides, we observe a significant difference between dependent and non-dependent employees. The average parameter for the former is -0.0190 while for the latter is -0.0159, which translates in a 19.5% difference. In addition, the average value of this parameter for 3 passengers per square metre is 37.99% larger than in an empty vehicle scenario and 75.98% larger when the passenger density rises to 6 passengers per square metre.

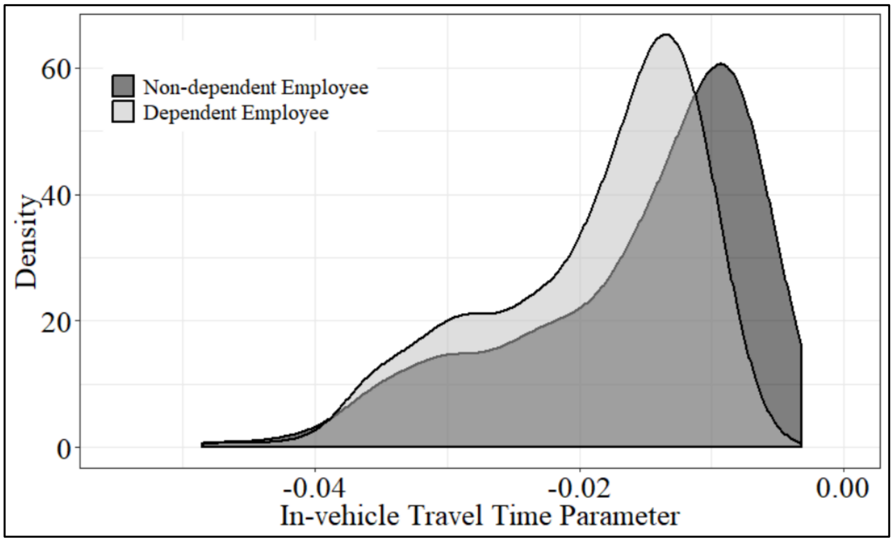

Figure 6.8 In-vehicle Travel Time Parameter distribution

In terms of direct effects, we observe a significant impact of the coefficient of variation of waiting times, which confirms the importance of reliability on people choices. In addition, expected waiting times and the number of days with seats available have also a significant impact with expected sign. If we consider the average in-vehicle travel time for dependent employees and a 3 passenger per square metre density, we obtain a value of 6.26 for expected waiting time and 2.74 min for the number of days with seats available. This means that people, in average, perceive waiting time ~6 times longer than in vehicle travel time and are willing to increase in ~3 minutes of in-vehicle travel time each day, ~15 minutes in total to have an extra day with seats available.

In terms of passenger density, we observe a significant impact of the crowding aversion latent variable. This variable is significantly explained by gender (being women), car as main travel mode, income, age, and being a dependent employee. The distribution of this parameter, differentiated by gender, is presented in Figure 6.9.

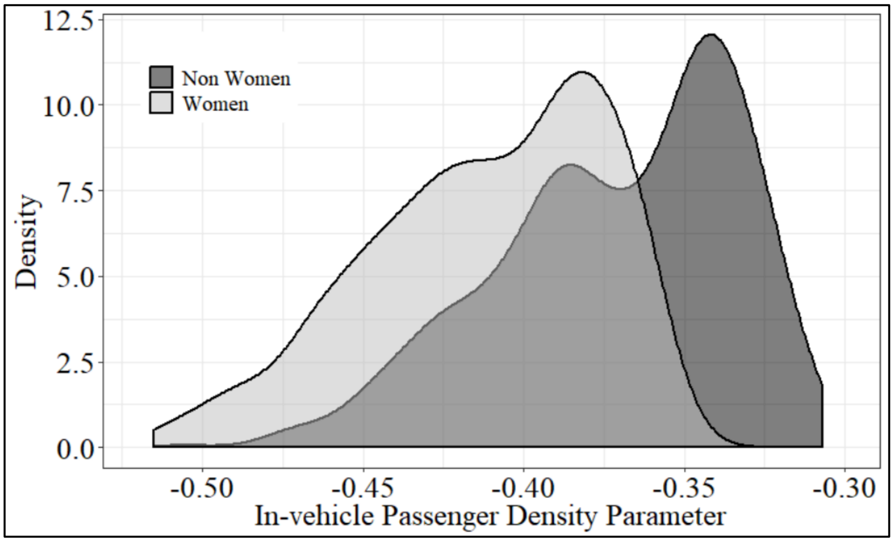

Figure 6.9 In-vehicle Passenger Density Parameter by gender

We observe a negative parameter for every observation in the sample and a significant difference by gender, which is in line with our current knowledge (H. Allen et al., 2017; Soza-Parra, Raveau, Muñoz, & Cats, 2019). Though the average parameter has only a 11% difference, with -0.412 for women and -0.371 for non-women, we observe a 38.7% of non-women with a passenger density parameter shorter and the smallest value of this parameter for women. In other words, around 2 out of 5 non-women perceive passenger density less than every woman.

However, when we measure the marginal rate of substitution between this attribute and in-vehicle travel time, as in Figure 9, we observe no difference between genders. This happens because travel time perception is also affected by passenger density. In sum, this means that regardless the gender, people are willing to exchange the same number of minutes in order to decrease their passenger density, but in terms of final utility, women will be worse.

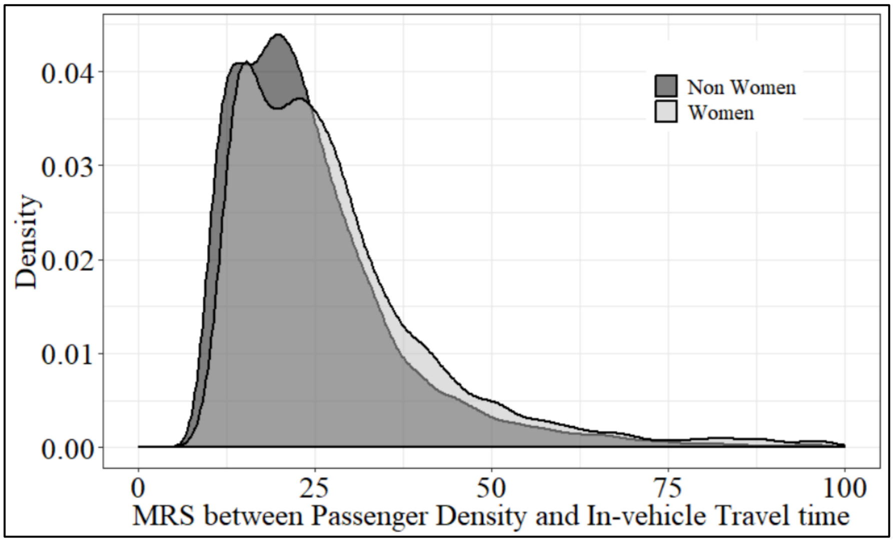

Figure 9.- Marginal Rate of Substitution between Passenger Density and In-vehicle Travel time gender

6.4 Conclusions

This study has proved it is possible to model public transport reliability effects on users through a stated preference survey. The results presented in this article are in line with our current knowledge and confirms the importance of this attribute in people's decisions. Being able to know public transport reliability's impact allows us to improve the understanding we have of the way in which users choose their mode and route.

Besides, we have shown significant evidence of the presence of deep psychological characteristics which influence the perception of different transportation attributes. Crowding aversion has been approximated previously by systematic taste variations. Our proposed approach expands this former modelling by incorporating random latent variables for each respondent part of the study, considering those socio-economical attributes typically considered. Regarding punctual behaviour, our approach only considers differences in the perception of the average in-vehicle travel time attribute. To the best of authors knowledge, this is the first time this latent variable is considered under a public transport discrete choice scenario and a mean-variance approach. This effort should be extended, in order to consider not only travel time but its variability, as well as expected and excess waiting times.

Nowadays, machine learning has proved its strong predictive capabilities. This fact, in addition with the large number of passive information available day after day, is producing better forecasting models every year. Even though this hybrid model does not enhance the predictive strength of an analogue Multinomial Logit significantly to be considerable, this framework expands our current understanding regarding people attitudes and considerations toward public and massive transport mobility. This point is by far the differentiating dimension between statistical and deep learning models. Thus, it would be interesting to analyse how to obtain the most of both modelling methods, with socio-economical characteristics effects on statistical models' side and predictive capabilities on supervised learning models' side.

Combined with previous work related with headway irregularity causes, projects that improve the reliability of the system can be evaluated completely, fully understanding the benefits that this brings and how users respond to these changes. For example, the impact of bus corridors can now be better understood, as it is clearer than the effects are not only in the form of in-vehicle travel time reduction, but also in headway evenness, and the reduction of waiting times and crowding inside vehicles. All these attributes influence significantly passenger behaviour, meaning assignment models should consider them in order to quantify projects benefits.

All of the above mentioned should lead us to a better planning of the public transportation systems of our cities. It becomes clear than headway regularity should be considered as a key attribute in every public transportation operation. Its effects on excess waiting time and crowding variation have been studied in the last years. Through this article, we provide evidence that headway variability not only affects passengers' behaviour indirectly through those attributes, but it also influences their choices by itself. Public transportation reliability, understood through the perspective of headway regularity, is worth studying further.

Acknowledgements

This research was supported by the Centro de Desarrollo Urbano Sustantable, CEDEUS (Conicyt/Fondap 15110020), the Bus Rapid Transit Centre of Excellence funded by the Volvo Research and Educational Foundations (VREF), and the scholarship funded by CONICYT for Ph.D. studies (CONICYT-PCHA/Doctorado Nacional/2016). In addition, we would like to thank

- Mrs. Myriam Amigo
- Mrs. Linda Bosch
- Mr. Fernando Celis
- Mr. Juan Facuse
- Mrs. Mónica Figueroa
- Mr. Sergio Jara
- Mr. Luis Alberto Maldonado
- Mrs. Patricia Manríquez
- Mrs. Lorena Quintanilla
- Mrs. Dora Silva

for their selfless assistance providing their public notary offices to conduct our survey.

7. LESSONS AND EVALUATION OF A HEADWAY CONTROL EXPERIMENT IN WASHINGTON D.C.

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7.1 Introduction

Service reliability, defined in terms of the certainty travellers have regarding their waiting time, their arrival time, or the comfort level they will experience inside the vehicle, is one of the most important attributes of a passenger trip. In a high-frequency context, poor reliability not only increases the risk associated with a travel alternative, but also worsens the experienced outcomes. For example, if the crowding level inside a vehicle is highly variable, the likelihood that a passenger will experience high density crowding increases. This increases the average crowding experienced over time (Tirachini et al., 2013).

This paper focuses on high-frequency services where customers arrive at a stop without consulting a schedule, typically services that come at least every 15 minutes. Both comfort and waiting time averages and variabilities in this high-frequency context are explained mainly by one attribute: headway regularity. A transit service is considered regular, in a frequency-based context, when consecutive headways are evenly distributed. When vehicles operate irregularly, passengers experience an extra amount of waiting, which has been coined excess waiting time. Besides, they experience more crowded vehicles because, as mentioned before, it is more probable that a passenger will arrive during a long headway interval (Cats, 2014). Moreover, additional costs are induced by irregular services. For example, if several bus routes are running along the same corridor, congestion around bus stops might arise. This issue adds extra travel time to the passengers on-board the vehicle and increases the waiting time for the passengers waiting at the bus stop.

In the absence of real-time headway control, bus services have an inherent tendency towards irregular operations as small variations in headways lead to uneven crowding, irregular dwell times, and further widening of gaps in service. The positive feedback loop between service headways, number of boarding passengers, and dwell times results in a deterioration of service regularity. The latter implies longer passenger waiting times, more uneven on-board crowding and a skewed distribution of vehicle travel time, resulting in time losses and inefficient resource utilization.

Headway control strategies require real-time vehicle positioning information. The possibility of using fleet management systems for improving service regularity was already conceived by Osuna and Newell (Osuna & Newell, 1972). With the increasing availability of automatic vehicle location data, a growing number of studies have investigated the prospects of headway control strategies. Analytical and simulation studies have concluded that methods based on the regulation of bus movements in relation to the headways from the proceeding and succeeding buses are most promising (Cats, Larijani, Ólafsdóttir, et al., 2012; Daganzo & Pilachowski, 2011).

In this study, a headway control experiment that was conducted for routes 70 and 79 operated by the Washington Metropolitan Area Transit Agency (WMATA) is described and analysed. These routes connect the northern part of Washington D.C. with the city-centre. Prior to the experiment, the practice was to run these routes as schedule-based services, even though service frequency is 6 buses per hour. A before-after performance evaluation is performed based on data collected six months after the implementation of a headway-based control. In the analysis, we elaborate on the organizational processes and related implementation challenges. We also quantify the impacts on service users and the service provider. This supports an empirical-based evaluation of such experiments and allows future implementations to learn from the experiences gained in this pilot.

This document is structured as follows. Section 2 describes past headway control experiences as well as some state-of-the-art conclusions about this issue. Section 3 details the experimental design and implementation of the specific headway control experience on WMATA routes 70 and 79 in Washington, D.C. Section 4 describes the before and after evaluation. Section 5 presents the benefits quantification, considering both service users and service provider perspectives. Finally, Section 6 concludes and elaborates on the lessons gained and opportunities to move forward.

7.2 Headway Control – The Premise, The Promise and Potential Pitfalls

Even though methods for stabilizing service headways have been proposed for over almost half a century, field experiments have not been documented in the research literature until fairly recently. Moreover, most of the field trials have been very limited and exhibited significant shortcomings in their implementation. Pangilinan (Pangilinan, Wilson, & Moore, 2008) analyses the results of a field trial on a single bus line in Chicago that relied on a dedicated dispatcher in the control room and street supervisors. The critical shortcoming in this implementation was that the dispatcher was the only one with access to real-time vehicle positions. This resulted in a prohibitive workload that did not allow the dispatchers to effectively monitor and respond to discrepancies to achieve the desired service performance. Several studies have attempted to mitigate this shortcoming by providing operators with the means to monitor their relative positioning and instructions. However, technical difficulties were often prevalent and limited pilot execution and performance, resulting in experiments that were shorter and smaller-scale than planned. Lizana et al. (Lizana, Muñoz, Giesen, & Delgado, 2014) analyse the outcomes of a two day pilot on a bus line in Santiago de Chile where instructions were provided via tablets. They concluded that technical failures and operator compliance were persistent challenges. Tablets were also used by terminal personnel in a light rail multi-branch line in Boston to support an even-headway policy in their dispatching strategy (Fabian, Sanchez-Martinez, & Attanucci, 2018). Berrebi et al. (Berrebi, Crudden, & Watkins, 2018) report small scale implementations of headway control on the Atlanta streetcar system and a bus route in San Antonio. The former was operated by three vehicles and the latter lasted for two days. Based on their experiences, the authors conclude that headway control implementation involves technical challenges that may be overlooked in simulation experiments, including the quality and frequency of location data transmission and operators’ response. Cats et al. (Cats, Larijani, Ólafsdóttir, et al., 2012) examined in a transit simulation model the implications of operator compliance and the frequency of vehicle positioning updates on the performance of headway control strategies. This robustness analysis was performed in preparation to a field experiment.

Ideally, bus operators should be directly and frequently informed about the instructions (i.e. speed adjustment between stops, holding at stops) resulting from a headway control strategy. A series of field experiments in Stockholm benefited from the presence of a computer display that is positioned in the bus operator cabin. All buses are equipped with a system that enables projecting to the operator the discrepancy from the desired bus location in minutes (i.e. negative values indicate that the bus is running behind, positive values imply running ahead). Cats (Cats, 2014) found a reduction of 38% in excess waiting times. In addition, he discusses the relevant considerations in extending field experiments into full-scale and long-term implementation of operation geared towards better regularity performance including aspects pertaining to performance monitoring, incentive schemes and business models. A detailed framework for quantifying the impacts of public transport interventions such as headway control strategy is provided by Fadaei and Cats (Fadaei & Cats, 2016). They concluded that the total service user and provider benefits associated with the latest experiment in the abovementioned series amounts to 36.8 million Swedish crowns on an annual basis (approximately $4.5 million USD). Following the field experiments, since 2015 the transport authority and the incumbent bus company agreed that all trunk bus lines in the Stockholm inner city would use a headway control strategy.

7.3 Experimental Design and Implementation

7.3.1 Headway management background

The Washington Metropolitan Area Transit Authority (WMATA, also known as Metro) is the largest transit agency in the Washington, DC region. WMATA operates 6 rail lines and 260 bus routes, with the bus system carrying about 380,000 people on an average weekday. WMATA's bus service has been schedule-based, with on time performance (OTP) measured at several timepoints on each route. A route's on time performance is based on how often the bus arrives at a timepoint within a window of two minutes before to seven minutes after the scheduled arrival time (i.e. [-2,+7]). This schedule-based metric works well on less frequent routes, but has some significant weaknesses on frequent service. When buses are scheduled to come every 10 minutes, for example, most customers simply arrive at the stop and wait without consulting a schedule, so even spacing is more important than schedule adherence. The relatively large window within which a vehicle is considered "on time" is also not well-suited to these more frequent routes. Figure 7.1 illustrates this situation, where all buses are considered on-time under a schedule-based on-time performance, but the average customer wait is approximately 7.99 minutes, instead of the 5 minutes one would expect in the event of a perfectly regular service.

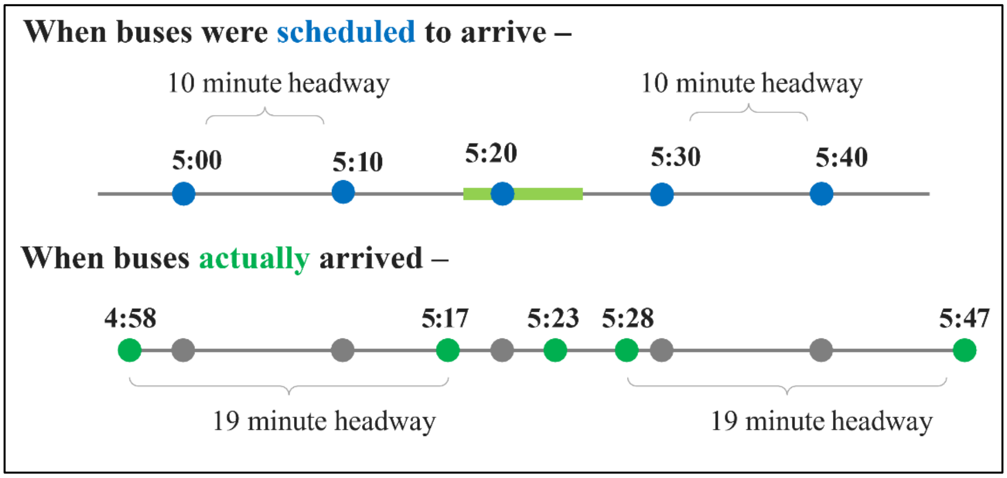

Figure 7.1 WMATA's schedule-based metric records the buses in green as on time

WMATA staff began looking for ways to better manage and measure the service on frequent routes. Beginning in 2012 the agency had experimented with managing some frequent routes on a headway basis using street supervisors. These early efforts were generally successful but resource-intensive, and ultimately were discontinued due to lack of resources. Since that time, several frequent routes have had published timetables that indicate that, for example, "Managers will schedule departures every 10 minutes until 5:30 p.m.," but little active management occurred on these routes. In the beginning of 2017 WMATA staff and management decided to renew efforts to actively manage frequent service on a headway basis.

7.3.2 Experiment set-up

The agency decided to start with one corridor to determine the best approach and demonstrate the benefits of the additional resources required. The corridor selected is known as Georgia Avenue and is served by two routes, the 70 and 79. These routes begin at the Silver Spring Transit Center in Maryland, near a job and population centre, and travel in a mostly straight path down Georgia Avenue and 7th Street NW to the Washington, DC downtown core, with an end-to-end route length of about 7.5 miles (12 km). Traffic is a significant issue in the downtown core, where a major sports and event arena adjacent to the route can cause major disruption to route operations. The location of these lines can be observed in Figure 7.2.

Figure 7.2 Routes 70 and 79 location map

A number of intersections on the corridor have transit signal priority, though the system is still relatively new. The parameters determining when priority is granted are conservative, so the benefits to travel time are modest. There is also a brief segment of dedicated bus lanes on the corridor, extending for four blocks.

Route 70 is a local route with 60 stops carrying nearly 11,000 passengers on an average weekday using both 40-foot and articulated buses. Route 79 is part of the "MetroExtra" set of limited-stop routes, averaging about 6,000 passengers on weekdays and serving 25 stops. The 79 runs from 5 a.m. to 8 p.m. seven days a week, while route 70 offers 24-hour service. Exact frequency varies by the time of day, but during peak periods each route departs at least every 15 minutes.

Unlike many similar corridors in the region, the chosen corridor has a relatively simple service pattern, which made it an excellent candidate for headway management. The corridor is also among the highest ridership in the system, but performance has been relatively poor. On-time performance prior to the implementation of headway management was 65-75%. More details regarding the performance of routes 70 and 79 are shown in Figure 7.3. WMATA's systems report bunching as buses that arrive at less than 50% of the planned headway.

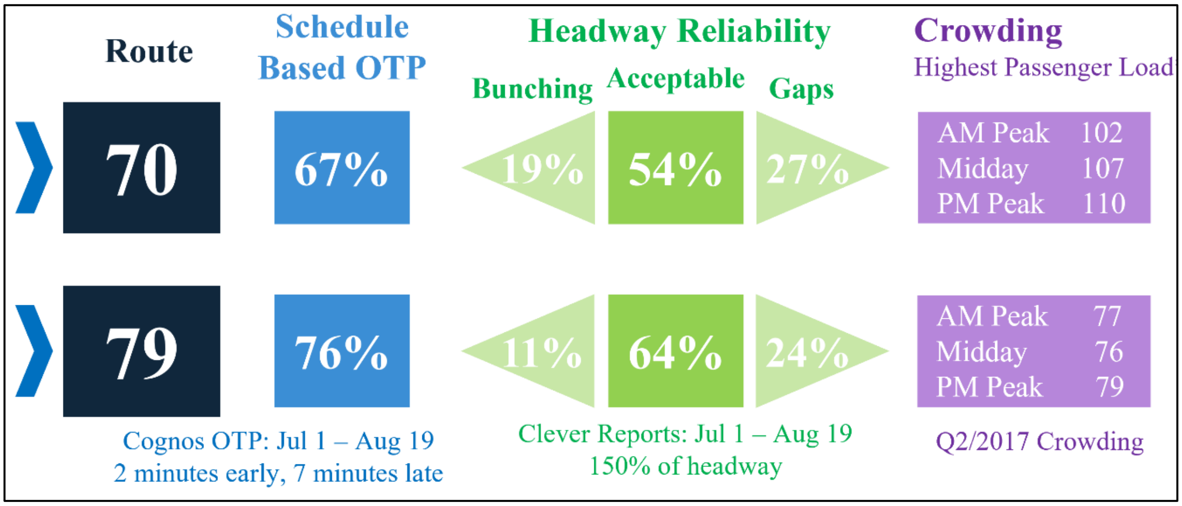

Figure 7.3 Performance indicators for routes 70 and 79

As with many busy, frequent urban bus routes, the service had a lot of short and long gaps. Specialists in the operations communications centre were able to monitor these issues but had limited effectiveness at managing them. Specialists must call the operators on the radio to communicate problems. Since operators are required to stop and secure the bus prior to answering radio calls, these calls were often not answered in a timely manner. Street supervision was limited and focused on accidents, mechanical problems, and other incidents rather than on managing performance.

Managers and planning staff knew that the shift to headway-based operations would be both a logistical and a cultural change. Bus operators and street supervisors who for decades have been expected to adhere to schedules would need to be retrained. Service adjustments like holds would need to become more common to keep service evenly spaced. Passengers who were unaccustomed to these service adjustments might have questions. Performance metrics would need to be adapted to encourage even spacing over schedule adherence. Management decided that training a group of dedicated street supervisors to be stationed along the route would be the most effective way to make this transition.

7.3.3 Pilot implementation

To implement headway management, bus operators and street supervisors were trained on headway management and active service management techniques. A "playbook" of techniques was provided, including information on holding, expressing, short-turning, and other options for restoring even headways when bunching and large gaps occur. A small number of "reserve" buses were also stationed in strategic locations near the route to be inserted as needed to fill gaps in service.

Street supervisors were stationed at key locations along the route, including both terminals, a major transfer point in the middle of the route near a rail station, and other locationsas needed. This required seven full-time positions to ensure adequate coverage on the route across two shifts from the early morning through the early evening hours on weekdays. These supervisors were dedicated to the corridor, with no other duties, and were provided with new tablets equipped with software that displays the location of all vehicles on the route in real time. The communications centre also dedicated specialists to managing the routes full time. These changes began in October 2017, with training for all operators complete in December of that year.

This approach to actively managing headways is resource-intensive. The agency hopes to move to a solution based on in-vehicle technology in the future, such as that in use in Stockholm and Santiago, as headway management is expanded to other frequent routes. This interim approach was adopted to demonstrate the performance improvements of a headway-based approach in order to build support for headway management techniques among bus operators, street supervisors, and other stakeholders. While bus operators might at first be reluctant to change their working routine, Hlotova et al. (2014) found that the headway-based strategy deployed in Stockholm resulted with lower stress levels based on the analysis of heart rate measurements. The on-site staff have also played an important role in communicating with customers about service adjustments, such as holds, that passengers may not be used to.

New performance metrics were defined to go along with the project. In particular, staff began reporting on headway adherence on these routes, defined as the percentage of timepoints where buses arrive within the scheduled headway plus 3 minutes (i.e. [0, h+3]), rather than traditional schedule-based on-time performance. Comprehensive weekly reporting was implemented showing performance and other statistics such as accidents and incidents on the route.

For a more comprehensive performance assessment, automated vehicle location (AVL) data from April 2017 and April 2018 was analysed for a before and after assessment. These months were chosen to capture an "after" period when the program had been fully established, and also because these time periods were relatively free of major disruptions. The AVL data is event-driven, with event records roughly every 15-30 seconds.

7.4 Before and After Performance Analysis

The following section describes and compares the level of service offered before and after the headway control implementation. The data used comprises the arrival time of every bus at every bus stop (even if they are not served) for the entire months of April 2017 and April 2018. Only working days were considered and all the figures refer to data from route 70, the primary line.

The most important outcome to analyse following this headway control experience are the consequences for passenger waiting times. Since headways are expected to be more regular after the implementation, we expect passengers to wait less on average. Assuming random arrival of passengers to bus stops, there is a direct relationship between average headway, $E(\hat{h})$, headways coefficient of variation, $CV(\hat{h})$, and the expected waiting time, $E(\hat{w})$ (Osuna & Newell, 1972):

$$E(\hat{w}) = \frac{E(\hat{h})}{2} \cdot \left(1 + CV(\hat{h})^2\right) \tag{1}$$

Instead of computing the coefficient of variation for the whole period of analysis, it was disaggregated per hour of the day. Figure 7.4 shows the average change observed between the before and after situation per direction and dispatch time between 06:00 and 23:00 hours. Moreover, in the lower right corner of each direction box, the average change per direction is shown. This display shows how the improvements are distributed within the day.

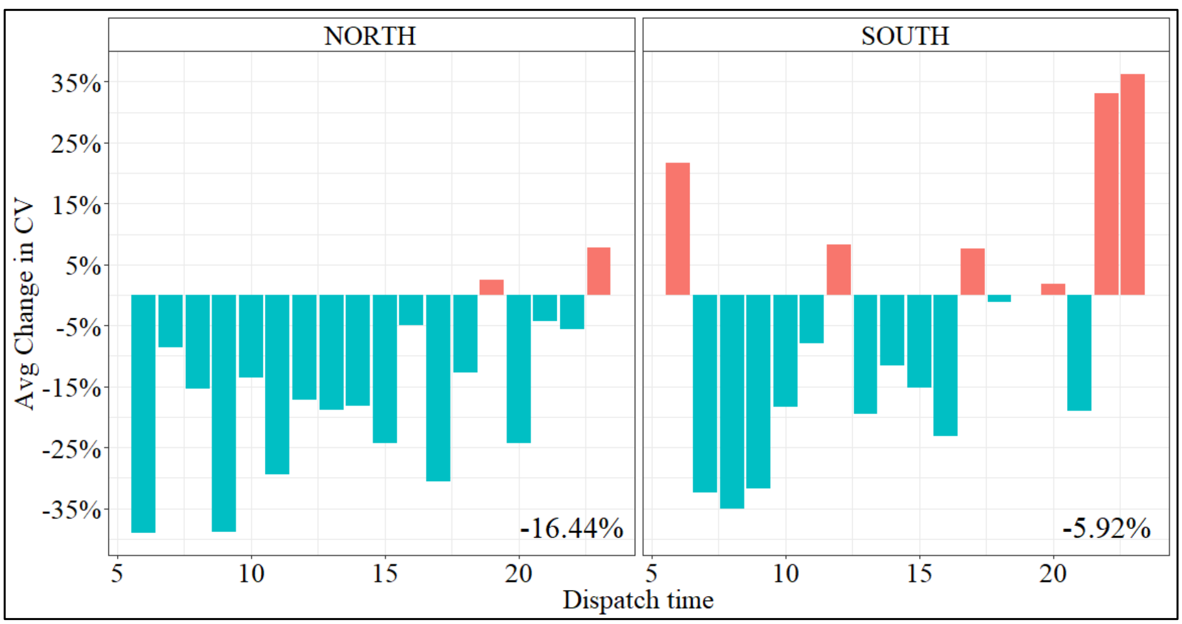

Figure 7.4 Average change of the coefficient of variation of headways per direction and dispatch time

A significant improvement in terms of headway variability is observed, with average reductions of 16.44% and 5.92% for North and South directions, respectively. Headways on the North direction have become almost always more regular, with the exception of 19-20 and 23-24 hours. Active headway management by street supervisors is not in place at these hours.

This improvement can be further analysed to examine how the change in headways is spatially manifested along the route. Figure 7.5 shows the relative change of the coefficient of variation of headways per bus stop, dispatch time and direction.

A visual inspection of this heatmap reveals that the only bus stop where regularity has systematically worsened rather than improved is bus stop number 31 in the Northbound direction (located in the intersection of Georgia Ave. with Shepherd St). Noticeably, regardless of the regularity in the previous bus stops, the coefficient of variation is significantly worse at that specific bus stop compared to the before period. Particular characteristics of the on-street conditions could be causing this performance decline, as signal timing, stop location, on-street parking, etc. Besides, this stop also comes just after a major transfer and supervision point at a rail station. During the time the data for the paper was collected that rail station was a relief location where drivers switched off, which caused occasional long delays. Aside from this Northbound stop, in the Southbound direction a significantly worse situation is observed at the hours of 6-7 and 22-23. Note that street supervisors do not implement headway management control during those hours.

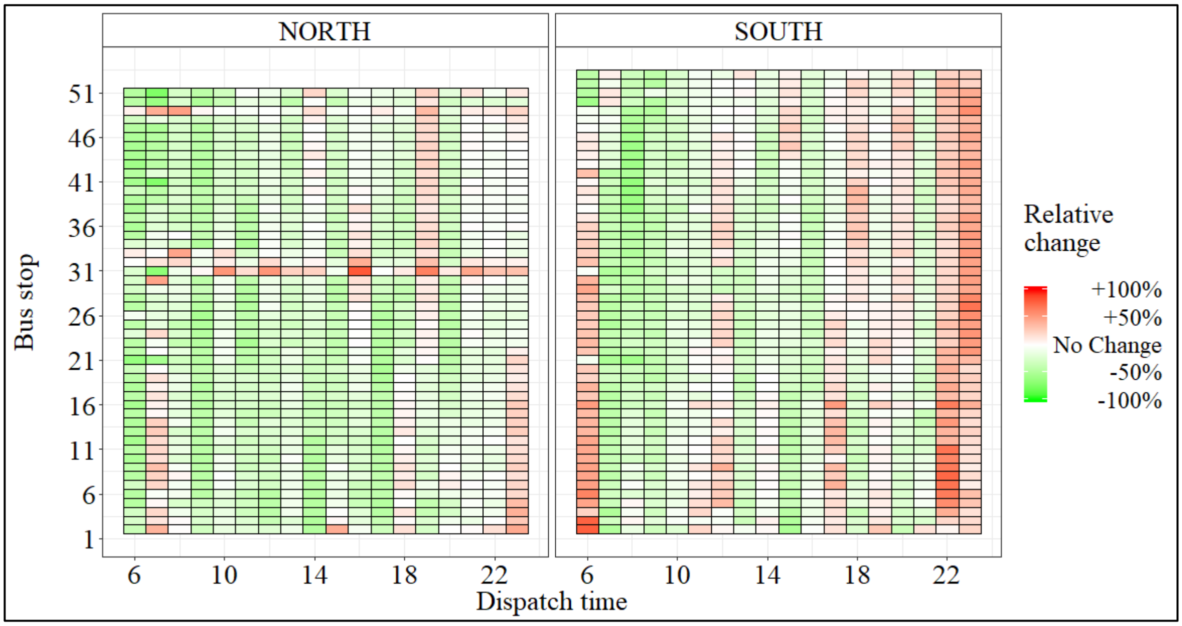

Figure 7.5 Relative change heatmap of the coefficient of variation of headways per bus stop and dispatch time

7.5 Benefits Evaluation

The following section presents the methodology, assumptions and results of the benefit evaluation of the headway control strategy field experiment. The methodology is based on Fadaei & Cats (2016), with some amendments tailored for this case study. The results are divided into three sections: passenger benefits, provider's costs, and overall evaluation.

7.5.1 Passenger Benefits

Passenger benefits are comprised of two components, as explained in the previous section: waiting times and travel times. For calculating waiting times, two variables are needed: actual headways and the corresponding number of passengers boarding each bus at each stop during the analysis period. With regards to the former, bus arrival times at each bus stop is sufficient to compute accurately the headway from the previous bus. The automatic passenger counter (APC) data collected in the case study is unfortunately deemed to be unreliable for individual trips, though it is able to produce reliable averages for boardings and alightings at each stop by time of day. Consequently, the following correction is made: based on the assumption of random passenger arrivals at bus stops, there exist a directly proportional relationship between the number of boarding passengers and headways. For instance, if a specific headway is twice as long as the planned headway, it is expected that the number of passengers boarding the bus is approximately double the historical average for the planned headway.

Mathematically, the number of boarding passengers, of a specific bus i and a specific bus stop s, $b_{i,s}$, that is within the time period t is:

$$b_{i,s} = \overline{b_{t,s}} \cdot \frac{h_i}{h_t^p} \tag{2}$$

Where h_t^p is the planned headway at the time period t, h_i is the headway of a specific bus and $\overline{b_{t,s}}$ is the historical average number of boarding passengers at a time period t and bus stop s.

Then, the perceived average waiting time, assuming waiting times are valued twice as much as in-vehicle time (Ortúzar & Willumsen, 2011), is:

$$PAWT = 2 \cdot \frac{\sum_{i,s} b_{i,s} \cdot \frac{h_i}{2}}{\sum_{i,s} b_{i,s}} \tag{3}$$

A similar approach is adopted for travel times. Again, the position information is accurate enough to estimate travel time between consecutive bus stops. However, it is not possible to rely on APC information for estimating the load on-board each vehicle. Thus, load information was estimated based on previously estimated boarding data, historical alighting patterns and the initial assumption of empty buses upon departure from the origin terminal. Then:

$$l_{\mathrm{i},s} = l_{\mathrm{i},s-1} + b_{\mathrm{i},s-1} - l_{\mathrm{i},s-1} \cdot p_{t,s-1}^{alight} \tag{4}$$

Where $l_{\mathrm{i},s}$ is the load of a specific bus i and a specific bus stop s, and $p_{t,s}^{alight}$ is the probability to alight at the time period t and bus stop s. An important side-effect of more evenly distributed headways is the reduction of average crowding on-board vehicles (Cats, 2014). Based on (Björklund & Swärdh, 2015), a perceived measure of in-vehicle travel time depending on the crowding level can be computed. This means that travel time is perceived differently depending on whether one is seated or standing and also depending on the total number of people per square metre inside the vehicle. Then, the perceived average in vehicle time is:

$$PAIVT = \frac{\sum_{i,s} \alpha_{i,s} \cdot t_{i,(s-1,s)}}{\sum_{i,s} b_{i,s}} \tag{5}$$

Where $t_{i,(s-1,s)}$ is the travel time between stops $s-1$ and s of a specific bus i, and the perception multiplier $\alpha_{i,s}$ is:

$$\alpha_{i,s} = \left(\min\left\{ l_{i,s}, \delta_i \right\} \cdot \beta_{i,s}^{\mathrm{sitting}} + \max\left\{ 0, (\mathrm{l}_{i,s} - \delta_i) \right\} \cdot \beta_{i,s}^{\mathrm{standing}} \right) \tag{6}$$

Considering δ_i as the number of seats of a specific bus i, and

$$\begin{aligned} \beta_{i,s}^{\mathrm{sitting}} &= 0.973 + 0.0652 \cdot \gamma_{i,s} \\ \beta_{i,s}^{\mathrm{standing}} &= 1.565 + 0.0685 \cdot \gamma_{i,s} \end{aligned} \tag{7}$$

And $\gamma_{i,s}$ corresponds to the standing passenger density factor (i.e. the total amount of standing passengers divided by the available area inside the vehicle i.

7.5.2 Service Provider's costs

The service provider's costs can also be divided into two parts: fleet size costs and vehicle-hour costs. Note that the distance travelled by buses remains unchanged in the field experiment.

Regarding fleet size costs, a fixed β^{fixed} cost is considered for each bus. For the variable costs, the fleet's requirements per time period z_t is calculated in the following way:

$$z_t = \frac{TT_{t,P90\%}^{Nd} + TT_{t,P90\%}^{Sd} + \varepsilon}{\left(\frac{h_t^{p,Nd} + h_t^{p,Sd}}{2}\right)} \tag{8}$$

where $TT_{t,P90\%}^{\text{direction}}$ is the 90th percentile for the end-to-end travel time in a specific direction and time period, $h_t^{p,\text{direction}}$ is the planned headway for a specific direction and time period, and ε considers recovery and terminal layover times. The use of the 90th percentile running time is a widespread practice among public transport agencies to ensure fleet availability.

Then, the total service provider's cost is defined by the following expression:

$$c^{operator} = \sum_{\forall t}\left(\beta^{fixed} \cdot z_t + \frac{3600}{\left(\frac{h_t^{p,Nd} + h_t^{p,Sd}}{2}\right)} \cdot \left(\beta^{hr} \cdot \left(\overline{TT}_t^{Nd} + \overline{TT}_t^{Sd} + \varepsilon\right)\right)\right) \tag{9}$$

where β^{hr} is the cost per vehicle-hour and $\overline{TT}_t^{\text{direction}}$ is the average end-to-end travel time in a specific direction and time period.

7.5.3 Overall evaluation

Service users' waiting times and travel times as well as service provider savings or costs are calculated based on the comparison of AVL data of April 2017 and April 2018 and the estimated time-dependent passenger demand profile per line. The daily average difference per time period and passenger is calculated for each cost component. Then, these values are multiplied by the total number of passengers per time period and added up to obtain the overall daily savings/costs. Finally, time measures are multiplied by the Value of Time for commuting, which is assumed to be $14.38 USD/hr for this case study area (based on (White, 2016) for 2016 all purposes value of travel time savings and adjusting the value by 1% each year). The results are presented as follows in Table 7.1.

Table 7.1 Total daily savings per route and direction

Total Savings	**70 North**	**70 South**	**79 North**	**79 South**
PAWT minutes	846 min	3,648 min	4,171 min	3,392 min
PAWT seconds per passenger	19 s	94 s	201 s	230 s
PAWT dollars	$203 USD	$874 USD	$1,999 USD	$1,626 USD
PAWT cents per passenger	7 ¢	38 ¢	80 ¢	92 ¢
Total *PAWT* yearly savings	**1,128,519 USD**			
PIVT minutes	-2,165 min	5,983 min	4,577 min	-662 min
PIVT dollars	-$519 USD	$1,434 USD	$1097 USD	-$159 USD
Total *PIVT yearly savings*	**444,789 USD**			
Total time saving per passenger (*PAWT* + *PIVT*)	**-30 s**	**246 s**	**422 s**	**185 s**
Fleet size	0.26 buses		-0.15 buses	
Hours of operation	6.11 hours		-0.75 hours	
Operator's savings	$683 USD		-$103 USD	
Total operator's yearly savings	**$139,279 USD**			
Total yearly savings	**$1,712,587 USD**			

The assessment indicates annual savings of approximately $1.7 million USD associated with the field trial. Unlike what might be expected, holding buses does not necessarily slow down overall route operations. In this analysis, overall benefits in terms of passenger's travel time, hours of operation and fleet size can be observed. Even though service regularity can lead to more even loads which can improve speeds, the headway control strategy is presumably not the only contributor explaining all these benefits. An analysis of the labour cost incurred by the experiment would enable an assessment of the effectiveness of the experiment execution. Some other facts that may explain these improvements may pertain to changes in traffic conditions related to roadworks and police enforcement. Notwithstanding, the most substantial change which is chiefly attributed to the control strategy pertains to waiting time savings, amounting to $1.1 million USD per year of savings of social benefits for the passengers.

7.6 Conclusions

The potential advantages of headway control strategies on high frequency routes have been examined and demonstrated in a large number of analytical and simulation studies. Nevertheless, the applicability of a headway-based holding strategy is still constrained by organizational and technical challenges, especially in circumstances where buses are not equipped with monitoring displays and operators are not accustomed to follow such service management practices. In this study, we add to the accumulated empirical experience in implementing headway management by sharing the lessons gained from a field experiment in Washington DC.

The evaluation of the field experiment suggests that waiting time savings amount to a total of $1.1 million USD per year. This outcome is achieved by reducing passenger waiting time by 1.1 minute on average. While substantial, further reductions can be potentially attained if key shortcomings in the experiment execution will be overcome in the future. As can be seen in Figure 7.6, the additional potential waiting time reductions are approximately three times larger than those that have been already attained. Considering all time periods, the average headway was 12.4 minutes, which means that if services were running perfectly regularly, the average waiting time would be 6.2 minutes. The experiment reported in this study reduced the average waiting time from 10.4 minutes to 9.3 minutes, meaning that there are 3.1 minutes of excess waiting time remaining.

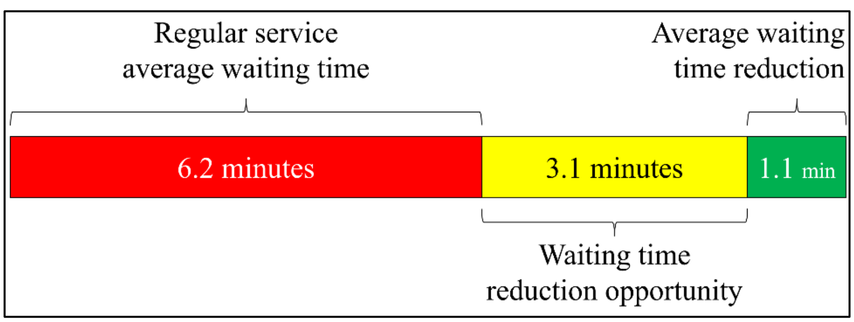

Figure 7.6 Case study waiting time decomposition

Service users expect service providers to leverage technological advancements. In the era of real-time journey planners and on-demand transport services, bus bunching is not only a costly phenomenon but also a visible indication of poor service performance. Real-time vehicle positioning data enables counteracting this otherwise inherent service deterioration. The design and deployment of data and communication systems has been traditionally driven by fleet circulation and fare collection considerations. Service management aspects should be taken into consideration when detailing the user cases, requirements and purchasing details of automated data collection and communication systems to avoid hindering the applicability of operational and control schemes such as speed adjustments and holding strategies.

Shifting from schedule-based operations to headway management involves a substantial organisational shift for operators, street supervisors, and communications centre staff. Many of the operational departments have been training staff on the importance of adhering to schedules for decades, meaning that significant training can be required to shift that mindset. To achieve this kind of change, it is important to communicate properly the positive impacts a measure like headway control might have for customers. Changing the performance metrics is hence an important aspect of the process. These new metrics should be passenger-oriented rather than operations-oriented and they should also be easily understandable for all the people involved in service provision and management.

Similar efforts to the one described here are staff-intensive, at least initially. The easiest way to deploy a trial in some specific routes to test the effectiveness of the headway-based approach is based on street supervisors and a proper communication channel. There are opportunities to mitigate the staff needs with in-vehicle technology, such as specialized tablet-like communications systems which indicate the exact amount of holding time or changes in speed between bus stops (Delgado, Muñoz, Giesen, & Cipriano, 2009). The deployment of a driver display unit, as in Stockholm and the Netherlands will involve initial investment cost but then practically eliminate the operational costs associated with communicating this strategy. Moreover, the quality and frequency of the information provided will be considerably superior to those attained with street supervisors, enabling greater service improvements than those achieved in the experiment. While rail services have been running autonomously using headway control strategies in many cities for years, autonomous headway control has not yet been applied in the more complex operating conditions of bus service. The real-world effect of headway management strategies such as that in use at WMATA will provide valuable experience as autonomous buses are deployed in the coming years. However, none of these will happen before everyone in the agency understands and supports headway management.

Acknowledgements

This research was supported by the FONDECYT project number 1150657 and the scholarship funded by CONICYT for Ph.D. studies (CONICYT-PCHA/Doctorado Nacional/2016).

8. CONCLUSIONS

Public transport should be one of the preferred transport modes to make cities more sustainable. Thus, transport planners should be very attentive to public transport traveller's experience. In addition to traditional attributes, such as in-vehicle travel time or fare, passengers consider a wide variety of aspects, such as safety, comfort, and reliability when making the travel choices. Reliability is directly related to many negative attributes perceived by public transport users. For instance, passengers reject long waits, lack of vehicles, over-crowded travels, buses skipping their stops, vehicle bunching, to mention a few. Thus, a better understanding of its causes and effects could orient and encourage agencies' focus to reliability. This is essential to make public transport an attractive travel alternative, and therefore a path to follow for urban sustainability.

One possible limitation of this dissertation is that most of the conclusions were supported by the same study of the public transportation system of the same city, Santiago de Chile. Therefore, the results obtained could be directly applied only to this city. However, the public transportation system's characteristics offered in this city resembles those which are proper of many different cities worldwide, especially in emerging countries. This type of public transportation systems operates usually in highly populated cities, with long travel distances and high frequency offered. This means that passengers do not know in advance when the next bus will arrive, and their travel is shared with many others in the same direction. Thus, the conclusions presented in this dissertation are highly valuable and valid for many different public transportation systems.

As shown in this dissertation, it is essential to know what people seek when they are travelling on public transport. Operationally speaking, we know passengers desire a fast trip, short waits, a comfortable ride, and a reliable experience. In the last decades, public transport agencies have focused mostly in the first three attributes. The irruption of BRTs as a clear example, in which increasing speed is at the core of this mode. By increasing speed capacity rises, since it takes less time to complete a cycle. The main purpose of this dissertation is to extend our knowledge regarding public transport reliability.

Based on the results and conclusions of the different articles comprised in this dissertation, it is clearer now public transport modes must become much more reliable to satisfy its users and attract new ones. When the focus is placed on traveller's experience, reliability should play a role equally important as speed has today. Faster vehicles bring travellers closer to their desire destination, but all those benefits vanish if unreliability causes people to experience long waits and crowded buses. Headway irregularity is one of the sources of this irregularity, damaging users' satisfaction and probably, makes shifting to a private car more attractive if they have one available, or taking new app-powered taxi services like Uber which are becoming more ubiquitous and convenient.

Different data sources were analysed through the different chapters of this document. In this big-data era, every day, more (and new) data sources become available. Thus, an unpredicted issue turns relevant, as it is harder to analyse large volumes of data, which also changes day-to-day. Most statistical analysis conducted in this dissertation consisted of intuitive visualisations of reliability differences between different modes, the impact of specific infrastructure in headway regularity, marginal rate of substitutions for different choice models, among others. Based on this type of analysis, it was easy to find significant differences between metro and buses' reliability level, where the former presented acceptable levels by users.

In terms of the analysis of the causes of the reliability difference between surface and underground public transport modes, we conclude it is due mostly by infrastructure and operational disparities. The headway variability propagation model showed that the most significant attributes were related to segregated corridors, and off-board payment stops. These two infrastructure characteristics resemble the way metro operates, where passengers tap in when they enter the platform area and trains move through rails and tunnels. This difference also raises the risk of a vicious circle because buses availability at the terminal depends on cycle time reliability. Then, dispatch regularity worsens.

When analysing the impact of service reliability three different perspectives are presented, which are related within each other. Firstly, we studied the effect reliability had at an aggregate level in the public transport alternative election. The coefficient of variation of headways turned out to be a significant attribute when explaining modal preferences beyond the sole impact of excess waiting time. In fact, this attribute replaced the bus alternative specific constant, which means it is a crucial attribute when explaining this kind of choices. Secondly, the effect on passengers' satisfaction was examined. We observed that reliability has indirect effects on this matter, based on the amount of denied boardings and the increase in passenger density. Thirdly, behavioural considerations were analysed when modelling passengers' alternative choice. Again, the coefficient of variation of headways had a significant impact when explaining users' choices.

Overall, we observed a substantial effect of headway variability when explaining the aggregate modal choice, users' satisfaction and individual behaviour. Besides, in both the satisfaction and individual choice models, significant socio-economical perception differences were found, both by latent classes and latent attitudinal variables. An interesting fact to emphasize is the relationship between the curvature of satisfaction in terms of passenger density and the significant impact of the number of seats available in the choice model. The convexity of the curve means that passengers might prefer, to some extent, variable passenger density services if the average is kept constant. One possible explanation is as the possibility of travelling seated is significant, and there might not be considerable differences between travelling standing at different density levels.

One direct consideration is the need to incorporate the coefficient of variation of headways, or any significant reliability attribute, in forthcoming public transport behavioural models. Otherwise, the omission of this attribute will bias the estimated related parameters. For example, average waiting time as well as average passenger density estimated parameters will be overestimated, as they will explain the impact of the omitted variable.

Regarding the cost-benefit analysis, a simple headway regularity intervention was analysed. This analysis considered all time savings related effects with this phenomenon, such as excess waiting time and time valuation by passenger density. By improving headway regularity, it was shown that there are measurable benefits both in terms of time savings and comfort improvement. This type of experiences should promote agencies to consider headway control to a bigger extent.

This dissertation provides a better global understanding about public transport system level of service reliability importance. In a frequency-based context, we need to understand reliability from the viewpoint of headway regularity. We have demonstrated that regular headways not only enhance wait time but also comfort, travel time and operational costs. This claim gets more considerable when analysing emerging cities and or developing countries situations, where high frequency services is the common mobility solution to transport millions of people.

In addition, headway unevenness, which leads to vehicle bunching, have significant distributional effects among passengers. Inspired by the antipoet Nicanor Parra, we can summarise these effects as follows: “There are two buses. Yours travels empty. Mine travels full. Average occupancy: 50%”. As shown in this dissertation, performance indicators should consider the number of passengers riding and boarding each vehicle, in opposition to consider total averages per service. Only this way the indicators will reflect real passenger experience. Otherwise, they will continue extending the gap between public transport agencies’ view and people’s perception.

“Frequency is freedom” maxim got popular by Jarret Walker and his work “Human Transit” (Walker, 2012). He explains how high frequency enables passengers to access different opportunities freely, without adjusting their schedules to their preferred public transport services’ availability. After all the results and conclusions of this dissertation, we would add “reliability is the path” to that motto. It is not hard to find good public transportation systems “on paper”, which offer high-frequency services across complex networks with poor passengers’ evaluation. We have reached the conclusion that all the possible benefits from the efforts put in frequency and speed might vanish in people’s perception when their day-to-day experience varies from one end to another.

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