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Estimation of crowding factors for public transport during the COVID-19 pandemic in Santiago, Chile

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ABSTRACT

A sharp decrease in public transport demand has been observed during the COVID-19 pandemic around the world. In this context, it is relevant to understand how mode preferences have changed since the surge of COVID-19.

In order to better understand how the pandemic changed mode choice, particularly regarding the impact of crowding and face mask use in public transport, we conducted a stated preference on-line and on-street survey in Santiago, Chile. Our sample is balanced in gender but has a higher proportion of individuals with college degrees and those under 45 years of age than the population of Santiago.

The data collected was then used to estimate two multinomial mode choice models, a latent class model and a mixed logit model with latent variables.

The models yielded a value of travel time in crowded conditions (4 pax/m²) and low face mask use (50%) of 3.0-5.1 times higher than the case with low crowding (0.5 pax/m²) and 100% face mask use. Moreover, women tend to be more sensitive than men to the use of face masks in public transport. Besides, young and low-income people are relatively less sensitive to crowding.

The crowding penalization obtained is higher than in pre-pandemic models calibrated for Santiago for similar passenger densities. Also, as we expected, it grows non-linearly with passenger density. Disinfection of vehicles, as well as the perception of health risk, cleanliness, safety and comfort, were also relevant in explaining mode choice. Further research shall discuss how the change of mode preferences together with new demand patterns influence the operational design of public transport services.

1. Introduction

1.1. Context and objectives

As a result of the COVID-19 pandemic, the demand for public transport has fallen sharply around the world, both in countries or cities with high and low infection rates (Transport Strategy Centre, 2020). Unlike other recent health crises, such as the 2008 swine flu, the decline resulting from the pandemic is more pronounced and lasting (Vickerman, 2021).

Even though the Americas had a lighter decrease in public transport ridership compared to other regions (Transport Strategy Centre, 2020), the impact in Santiago de Chile was significant. According to official statistics (Metro de Santiago, 2020), Metro trips fell by 68% between January and September 2020 compared with the same period of 2019. Considering exclusively the third quarter of 2020, the demand drop according to the same report is almost 80%. A recent official news report (Red Metropolitana de Movilidad, 2021) registered an average drop of 60% in Santiago bus transactions during the pandemic, with a maximum of 86% in June 2020. It is worthwhile noting that these figures refer to the number of transactions, which differ from the system demand given the very high and highly variable evasion rates observed in the bus system of Santiago (Munizaga et al., 2020).

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In this context, we aim to estimate how people evaluate public transport travel in different conditions, by applying a stated preference survey that considers pandemic-related policies such as the use of masks and the disinfection of vehicles in public transport. The resulting models allow estimating penalties for crowding in public transport vehicles that vary not only with passenger density, but also with the type of user and the use of a mask by other users. Finally, since data was gathered before the pandemic and once it kicked in Santiago, crowding penalties calibrated for data before and during the COVID-19 pandemic were compared.

1.2. Relevant literature

The impact of COVID-19 on public transport systems has been studied from different perspectives, which include the analysis and comparison of the measures adopted to mitigate contagions, ridership statistics in different countries and cities, and qualitative and quantitative studies to explain individual behavior changes under this particular context.

Policy-oriented studies include the review of measures adopted to mitigate COVID-19 spread in public transport (Tirachini and Cats, 2020), general guidelines to policymakers and planners regarding physical health and subjective well-being (de Vos, 2020), and health recommendations to minimize spread in public transport for operators (UITP, 2020) and planners (Parashar, 2020; Pardo et al., 2021). The existing literature emphasizes promoting social distancing among passengers, as well as the use of masks and the disinfection of surfaces, not only in vehicles but also in stations and workspaces (Parashar, 2020). The maximum occupancy recommendations also depend on the duration of the trips, the ventilation of the vehicles and the climate (Pardo et al., 2021).

A second type of studies focuses on the analysis of mobility data gathered by third parties such as Google® or Apple® comparisons of data for different cities can be found in articles focused on transport such as Tirachini and Cats (2020) or in epidemiological analyzes such as Badr et al. (2020). There are also more detailed analyzes based on regression models for countries such as Hungary (Bucsky, 2020), Italy (Cartenì et al., 2021), New Zealand (Wen et al., 2021) and Sweden (Jenelius and Cebecauer, 2020), that relate transit ridership with socioeconomic variables and mobility restrictions among other factors. Statistics show a significant reduction in the demand for public transport, even in countries which were relatively little affected by COVID-19, such as New Zealand (Wen et al., 2021), and despite the maintenance of pre-pandemic service levels as in Sweden (Jenelius and Cebecauer, 2020). In Santiago, bus frequencies fell around 23% – much lower than passenger trips – compared with pre-pandemic figures (DTP Metropolitano, 2021).1

A third type of studies, based on surveys, aim at understanding the causes of the drop in the use of public transport, both in absolute terms and compared with private modes.

Abdullah et al. (2020) analyzed the factors that affected mode choice during the pandemic, based on an online survey with most participants from Asia. Using 5-point Likert scales to compare the relevance of different factors before and during the pandemic, the study yielded that risk of infection, social distancing, face mask use, safety and security were significantly more important during COVID-19. Meanwhile, women and workers gave greater importance than men and students to pandemic-related factors when choosing their transport mode.

Beck and Hensher (2020) conducted an online survey in the early phases of the pandemic (March and April 2020) in Australia. Most of the participants were “extremely concerned” with hygiene in public transport, while bus and train were considered “least comfortable” compared to other modes. In addition to observing a significant decrease in the modal split of public transport compared to the pre-pandemic situation, the respondents planned to keep their travel choices in the near future.

Vallejo-Borda et al. (article under review as of March 2022) conducted a survey in five South American capitals and developed a Structural Equation – Multiple Indicator Multiple Cause Model to explain the demand drift from public transport to private motorized modes and active transport, based on socioeconomic characteristics and attitudes. These surveys show a drop of more than 50% in the number of trips made by public transport in every city. Low income people were more likely to switch to active transport, while women and people with formal jobs were more likely to switch to private transport. Switching to motorized modes was higher among those who were more satisfied with their personal situation.

Astroza et al. (2020) conducted a survey in Santiago de Chile in the early stages of the pandemic. Crowding in public transport was one of the main concerns of the respondents. Members of low-income households were particularly affected, since telecommuting is not an option for most of them and they were more afraid of the consequences of getting infected.

These recent surveys show that overcrowding in public transport worries users due to its relationship with COVID-19 infections. This effect adds to the preference users already had for travelling with lower levels of occupancy, penalizing time travel in crowded environments not only in vehicles, but also in station platforms and entrances (Li and Hensher, 2011).

According to literature reviews carried out before the pandemic (Wardman and Whelan, 2011; Li and Hensher, 2011), in-vehicle crowding was generally analyzed through stated preference surveys. In recent years, crowding was also studied through smart-card revealed preference data (Tirachini et al., 2016; Yap et al., 2020).

Crowding penalties are reported to increase with occupancy levels both for seated and standing passengers. Moreover, pre-pandemic penalizations were usually higher for standing travel (Wardman and Whelan, 2011; Tirachini et al., 2017).

Even though most previous studies estimate linear penalization functions for crowding, both exponential and potential functions have been proposed (MVA Consultancy, 2008; Tirachini et al., 2016). Although most studies report no differences in crowding perception by gender, Shin et al. (2020) found that women are more sensitive both to travel time and transfer congestion than men in Seoul Metro.

1 Comparison of 2020 vs 2018, 2nd semester. During the last months of 2019, widespread protests affected the provision of transport services in Santiago.
1.3. Article structure

Following this introduction section, we explain the surveys performed and the types of models estimated in Section 2. In Section 3, the main results from the models are presented, followed by a discussion on their policy implications in Section 4. Finally, Section 5 presents the conclusions.

2. Methodology

2.1. Description of surveys

We conducted a stated preference survey in Santiago de Chile, which was programmed with the Qualtrics® online platform. After a pilot in July 2020, the survey was carried out in two stages: a first phase via web during August and September 2020 and a second phase in person, using the same form via tablet (October 2020), in the surroundings of four important Metro stations. The surveys contained questions about the availability and use of different modes, the perception of the public transport level of service, measurement of attitudes to identify latent variables, and socioeconomic information that included health related questions. Average response time was around 12 min.

Five modes were considered, including 3 public transport options (Metro, Red bus, Transantiago bus) as well as car and bicycle. We distinguish two type of bus services, since Santiago has recently modernized part of its fleet (some of it electric) with enhanced comfort standards. This new fleet called “Red” operate together with the standard diesel “Transantiago” buses that have up to 12 years of operation (Hurtubia and Leonhardt, 2021).

The participants were divided into 11 groups according to the availability to different modes on their commuting trip and the frequency of their use. Each participant faced four hypothetical choice situations in which they selected their preferred mode among two or three options (depending on their group) for their commuting trip. In each scenario the respondent could also opt for “none of them”. A total of 455 valid surveys were obtained, corresponding to 1820 choice scenarios. This resulted in 1791 positive choices as in 29 of them the respondent opted for “none”.

Among the participants, 104 (22.9%) were traveling by car or bicycle before the pandemic, and they chose this same mode in all survey scenarios. As discussed below, these people are likely “non-traders”, who always choose their usual mode regardless of travel conditions. For this reason, models were estimated both for the complete sample (with 455 individuals and 1791 total responses) and for the sample without likely “non-traders” (with 351 individuals and 1376 total responses).

Fig. 1 below presents an example of a choice scenario. As can be seen, the scenarios contained both typical characteristics of the modal choice experiments, such as travel time (divided in “access time” and “in-vehicle time” for public transport modes) and trip cost, and variables associated to the risk of catching the virus during the pandemic: percentage of passengers without a mask and frequency of disinfection of public transport vehicles, apart from crowding level and standing or sitting travel, in which passenger location is represented by a star in the vehicle diagram. We assumed a fixed fare for public transport modes, while for car and bicycle only two

Fig. 1. Choice example from stated preference survey.
variable attributes were considered: cost and travel time.

Three or four levels were set for each variable attribute. In the case of the total travel time, the levels were set as proportions of each individual’s actual travel time to the main activity, which was previously asked in the survey. In turn, car cost levels depend on both a fixed component (e.g. parking costs) and a variable cost which we assumed proportional to travel time (e.g. fuel consumption, tolls). A detail of choice situation attributes and levels used in the survey is shown in Table 1 below.

Depending on the levels of the attributes, 16 orthogonal combinations were obtained for each alternative (Kocur et al., 1981). From these combinations, 4 randomized choice situations were generated for each participant, eliminating repeated and trivial combinations (see for example Sanko, 2001).

By crossing crowding levels and face mask use %, we obtained 13 different levels for the densities of passengers wearing face masks, ranging between 0.5 and 4 pax/m². We also obtained 13 levels for passengers not wearing a mask in the vehicle, ranging between 0 and 2 pax/m².

2.2. Models used

Mode choice was estimated through 2 multinomial Logit models. Additionally, nested logit models were also estimated, proposing two correlation structures, one with a specific nest for the two bus options and the other with a specific nest for the 3 public transport options (Metro, Red bus and Transantiago bus) and separate nests for both car and bicycle, but they did not yield significant results.

Model 1 is a Latent Class model. In a Latent Class model consisting of M classes, the probability associated with the choice of an alternative “i” for an individual “q” is:

\[ P_{iq} = \sum_{m=1}^{M} s_{mq} \left( \frac{\exp^{b_{mq} x_{iq}}}{\sum_{m=1}^{M} \exp^{b_{mq} x_{iq}}} \right) \]

(1)

where \( s_{mq} \) is the probability that the individual “q” corresponds to the class “m”, depending on her socio-economic characteristics, and the expression in brackets corresponds to the Logit probability conditional on each class, where \( b_{mq} \) is a vector of class-specific coefficients and \( x_{iq} \) is a vector of alternative and individual-specific variables (see for example Kamakura and Russell, 1989; Train, 2009).

Model 2 is a mixed logit model, which considers random parameter for public transport travel time. The probability of choosing an alternative “i” by an individual “q” can be expressed as:

\[ P_{iq} = \int L_{iq}(\theta) f(\theta) d\theta \]

(2)

where \( L_{iq}(\theta) \) corresponds to the Multinomial Logit probability evaluated at a set of parameters \( \theta \). The mixed logit probability is a weighted average of Logit functions in which \( f(\theta) \) is the mixing distribution, that usually corresponds to a normal distribution (see for example Ben-Akiva and Bolduc, 1996; Ortúzar and Willumsen, 2011; Train, 2009).

In this case, we proposed a log-normal distribution for the transit travel time parameter \( \beta_{tt} \), which can be expressed as:

\[ \beta_{tt} = -\exp(b_{tt} + s_{tt} \mu_{tt}) \]

(3)

where \( b_{tt} \) and \( s_{tt} \) correspond to the mean and standard deviation of \( \log_{10}(\beta_{tt}) \) to be estimated, and \( \mu_{tt} \) is a standard normal deviate. Contrary to the usual normal distribution of coefficients, the log-normal distribution ensures that disutilities are higher when transit travel time increases (see for example Revelt and Train, 1998).

In model 2 considers, in addition to this mixed parameter, three Latent Variables.

Table 1
Choice situation attributes and levels.

| attribute                        | levels |
|----------------------------------|--------|
| Metro in-vehicle travel time     | 1: 60% of reported travel time, 2: 75%, 3: 90% |
| Bus in-vehicle travel time       | 1: 70% of reported travel time, 2: 85%, 3: 100% |
| Car travel time                  | 1: 80% of reported travel time, 2: 100%, 3: 120% |
| Bicycle travel time              | 1: 100% of reported travel time, 2: 130%, 3: 160% |
| Metro access time                | 1: 6 min, 2: 12 min, 3: 18 min |
| Bus access time                  | 1: 5 min, 2: 10 min, 3: 15 min |
| Public transport travel cost     | $ 800 [fixed] |
| Car travel cost                  | 1: $2000 + 10 \* reported travel time (minutes), 2: $2500 + 20 \* reported travel time (minutes), 3: $3000 + 20 \* reported travel time (minutes) |
| Bicycle travel cost              | 1: $ 0, 2: $500, 3: $1000 |
| Public transport cost            | 1: 0.5 pax/m² (“free seats”), sitting |
|                                 | 2: 1 pax/m² (“few standing”), sitting / standing |
|                                 | 3: 2 pax/m² (“intermediate”), sitting / standing |
|                                 | 4: 4 pax/m² (“full”), standing |
| Face mask use (% of passengers)  | 1: 100%, 2: 90%, 3: 70%, 4: 50% |
| Disinfection frequency           | 1: once per hour, 2: once each 3 h, 3: twice a day, 4: once per day |
In such models, also called hybrid or MIMIC models, the utility functions of an alternative “i” for an individual “q” have the following form (see for example Morikawa and Sasaki 1998; Ortúzar and Willumsen, 2011):

$$V_{iq} = \sum_k \theta_k x_{ik} + \sum_l \beta_l \eta_{ilq} \tag{4}$$

where the first sum represents the utility given by the traditional variables \( x \), and the second sum corresponds to the utility given by the latent variables \( \eta \).

In turn, values of latent variables \( \eta \) are estimated simultaneously through two sets of equations (see for example Bollen, 1989; Ortúzar and Willumsen, 2011):

$$\eta_{ilq} = \sum_r \alpha_{lr} S_{iq} + \omega_{ilq} \tag{5}$$

$$y_{ipq} = \sum_l \delta_l + \gamma_{ilp} \eta_{ilq} + \epsilon_{ipq} \tag{6}$$

where the index \( i \) refers to an alternative, \( q \) to an individual, \( l \) to a latent variable, \( r \) to an explanatory variable and \( p \) to an indicator.

Structural equations relate latent variables to user characteristics \( S_{iq} \) with parameters \( \alpha_{lr} \) to be estimated, while \( \omega_{ilq} \) are error terms, which we assume to distribute Normal with an expected value of 0 and a variance of 1.

Meanwhile, measurement equations explain perception indicators \( y_{ipq} \) through latent variables and parameters \( \gamma_{ilp} \) to be estimated. Here, \( \delta_l \) are constants for each latent variable and \( \epsilon_{ipq} \) represent the random component of each attitudinal response, which we estimated through an ordered model (Daly et al., 2012).

The results for both models, which were estimated through Apollo (Hess and Palma, 2019) are presented in the following section, along with the main descriptive statistics.

3. Results

3.1. Sample characteristics and descriptive stats

Table 2 below shows some characteristics of the sample (gender, age and educational level) compared with the general population of Santiago de Chile.

It is observed that the sample is representative of the population of Santiago in gender, but overrepresents high income, younger and more educated individuals, particularly when likely non-traders are included. This may be due to the survey methodology, which considered both responses sent via the web and face-to-face surveys. It is known that web surveys tend to have coverage bias, with a tendency to overrepresent high-income young people (Sue and Ritter, 2012). In this sense, the application of face-to-face surveys partially corrected the bias which resulted from the original web sample. On-street surveys were performed near Metro stations located in neighborhoods of high average income (Providencia, Las Condes), middle average income (La Florida, Maipú) and low average income (La Cisterna).

The surveys allowed us to identify perceptions about the quality of service provided by the three public transport options in the survey through a 5-point Likert scales, which were included as latent variables in Model 2. As can be seen in Fig. 2 below, Metro has a significantly better average score than the traditional buses of the Transantiago system in the four attributes studied: comfort, safety

| Table 2 basic demographics of sample. | Survey (2020) | Santiago de Chile | (Source) |
|--------------------------------------|-------------|-----------------|--------|
|                                      | Full sample (N = 455) | Traders only (N = 351) | (Source) |
| Average household income (CLP/month) | 2,344,710  | 1,986,101       | 1,204,524 \( \text{(1)} \) \[2020\] |
| Gender                              |             |                 |        |
| Women                                | 53.5%       | 52.8%           | 51.3% \( \text{(1)} \) \[2017\] |
| Age (adults only)                    |             |                 |        |
| 18–29                                | 35.5%       | 40.7%           | 26.7% \( \text{(2)} \) \[2017\] |
| 30–44                                | 38.4%       | 35.9%           | 28.6% |
| 45–59                                | 21.1%       | 18.2%           | 24.7% |
| 60 +                                 | 5.0%        | 5.2%            | 20.1% |
| Educational level                    |             |                 |        |
| Basic – High School                  | 26.1%       | 30.2%           | 61.5% \( \text{(3)} \) \[2017\] |
| Tertiary - Technical                 | 16.6%       | 16.5%           | 11.2% |
| College grade                        | 38.6%       | 39.6%           | 24.2% |
| Postgraduate                         | 18.8%       | 13.7%           | 3.1% |

Information Source:
(1) (Encuesta CASEN 2020, 2021).
(2) (Censo de Población y Vivienda, 2017).
(3) (Instituto Nacional de Estadística, 2017).
and cleanliness of stations and vehicles. However, it is interesting to note that the new buses of the Red system, some of which are electric, receive a similar assessment to the Metro in terms of the perceived quality of service once the person boards them.

Fig. 3 below shows the detail of the perceptions of comfort, safety/security, vehicle and station cleanliness associated with each public transport option. It can be observed that most of the respondents assigned high marks (4/5 or 5/5) to the quality of the service in Metro and the new Red buses. On the other hand, more than 40% of the sample assigned low marks (1/5 or 2/5) to all aspects of the service on regular Transantiago buses.

Apart from questions regarding transit level of service perceptions, surveys included 10 questions with 5-point Likert scales (“strongly agree”, “agree”, “neither agree nor disagree”, “disagree”, “strongly disagree”) aimed at measuring behaviors that could be related to a more or less cautious attitude when traveling. The statements, as well as their average score among the respondents, are shown in Table 3 below.

Using an oblique factor analysis, which includes correlations between possible latent variables (Taherdoost et al., 2014), two potential latent variables were identified (using a minimum correlation of 0.4) with these indicators. One corresponds to attitude questions 1, 2 and 3, which are related to physical activity and health protection, and the other is associated with travel comfort and waiting time (indicators 4, 5, 8 and 10). Unfortunately, both candidate variables were discarded in final models as they were non-significant.

3.2. Model results

Table 4 shows the general characteristics of Latent Class (1) and Mixed Logit With latent variables (2) models, both for the full sample (N = 455) and the traders-only sample (N = 351).

Variables included in the utility functions for the Latent Class model (1) are shown in Fig. 4 below. This model considers two latent classes. Individuals belonging to Class 1 penalize crowding in public transport only when sharing trips with people not wearing face mask use, while persons belonging to Class 2 penalize crowding independently of the use of masks. Individuals with college degree tend to belong to Class 2, while young people (age below 30) are more likely to belong to Class 1. We also estimated 3-class models but did not obtain satisfactory specifications.

Table 5 includes coefficient values, t-tests and standard errors for each parameter of this model.

Variables included in the utility functions for the Mixed Logit with Latent Variables Model (2) are shown in Fig. 5 below. This model considers 3 latent variables, one for each public transport mode. Every latent variable is related to five 5-point perception indicators: comfort, safety/security, vehicle cleanliness, station cleanliness, and health risk. In turn, latent variables for public transport service perception vary with age, gender and for heath staff depending on mode. Table 6 and Table 7 show coefficient values, t-tests and standard errors for each parameter of this model.

Women show a more cautious attitude than men, as well as people working in the health sector. On the contrary, youngsters are less cautious. In turn, people with college degree tend to better evaluate transit level of service. This will be discussed in the following

Fig. 2. Perception of Metro and Bus service quality in surveys. (*) “Seguridad” in the original survey, which means both safety and security in Spanish.
In order to compare disutilities in public transport for different crowding conditions, all parameters that depend on travel time in public transport apart from travel time itself, such as crowding, disinfection frequency and perceptions of transit level of service shall be considered. Crowding penalties \( C_r \) depending on passenger density \( \delta \) and percentage of users not wearing face masks \( \rho \) can be expressed, for each alternative \( i \), as a quotient related to ideal travel conditions – minimum passenger density and 100% face mask use – through equation [7]:

\[
C_r(\delta, \rho) = \frac{\beta(\delta, \rho)}{\beta(\delta_0, 0)} = \frac{\beta_2 n^{n1} + \beta_2 n^{n2} + \beta_1 LV(i)}{\beta_2 \delta_0^{\delta1} + \beta_1 LV(i)}
\]  

(7)

**Table 3**  
Behavior indicator statements average scores.

| Statement / Indicator | Average score |
|-----------------------|---------------|
| “Whenever I leave my home I put my health at risk” | 3.64 |
| “Even if I am cold indoors, I prefer to keep a window open” | 3.75 |
| “If I have to go up to the second floor of a building that has an elevator, I always use the stairs” | 3.93 |
| “I prefer to leave my home earlier and always arrive on time” | 4.23 |
| “I would travel in hours with less traffic if I could do it” | 4.60 |
| “Even if the bus or train is very full, I always try to get into the vehicle” | 2.53 |
| “I would be willing to wait for the next bus or train, if I knew that it was emptier than the previous one” | 4.44 |
| “Even if there are free seats, I prefer to travel standing and keep my distance from others” | 3.94 |
| “I avoid holding onto the handrail when traveling standing, even if I am carrying a load” | 3.64 |
| “I prefer to travel sitting in public transport, even if there are people standing next to me” | 2.80 |

**Table 4**  
General characteristics of models.

| Model | Latent Class (1) | Mixed Logit with latent variables (2) |
|-------|-----------------|--------------------------------------|
| Sample | Full (N = 455) | Traders-only (N = 351) | Full (N = 455) | Traders-only (N = 351) |
| Correlation structure | Multinomial | | | |
| Crowding penalization | Non-linear in crowding, functions depending on gender and face-mask use | | | |
| Non-fixed parameters | 21 | 21 | 40 (including LV parameters) | 40 (including LV parameters) |
| Significant (greater than 95%) parameters | 17 | 17 | 38 | 39 |
| Log-likelihood estimation | Direct | | Simulated, 300 mlhs draws. Simultaneous estimation of LV | |
| Initial Log-Likelihood (Choice) | –1803.81 | –1394.92 | –1803.81 | –1394.92 |
| Model Log-Likelihood (Choice) | –1296.73 | –1139.95 | –1267.34 | –1129.84 |

section.

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\[
C_r(\delta, \rho) = \frac{\beta(\delta, \rho)}{\beta(\delta_0, 0)} = \frac{\beta_2 n^{n1} + \beta_2 n^{n2} + \beta_1 LV(i)}{\beta_2 \delta_0^{\delta1} + \beta_1 LV(i)}
\]  

(7)
Here, $\beta_{tt}$ is the travel time parameter for public transport, $\beta_{c1}$ and $\beta_{c2}$ are the crowding coefficients for sharing travel with people using and not using masks, $n_1$ and $n_2$ are densities of passengers with and without face masks, $N_1$ and $N_2$ the crowding multiplier power factors shown in Table 4, $\beta_{LV}$ is the coefficient associated to the latent variable representing level of service perception for each public transport mode, and $LV(i)$ is value of each latent variable as reported in Table 6.

Fig. 6 a) and b) show the crowding penalties as a function of passenger density, gender, and percentage of passengers wearing face masks yielded by Model 1, using the traders-only sample. In turn, Fig. 6 c) to h) show the penalties as a function of density, gender, mode and percentage of passengers wearing face masks obtained from Model 2, using the same sample.

In order to consider the variability of the transit travel time parameter, individual-level parameters were estimated by conditioning the simulated maximum likelihood estimate across choices for each person (see for example Hensher and Greene, 2003). By applying this procedure, we can guarantee that $\beta(\delta_0, 0)$ will take a negative value for every individual in our sample. Otherwise, the typical simulation of the population distribution - using mean and standard deviation parameters of $\beta_{tt}$ - could result in inconsistent estimates of $Cr_i(\delta, \rho)$ due to the existence of some negative values. For a discussion on both methods, see for example Sillano and Ortúzar (2005).

We can see that in both models, women penalize crowding more than men. The difference is more pronounced as the total density and the percentage of passengers without masks grows, particularly in the latent class model.

The implications of the results obtained are discussed next.

4. Discussion

4.1. Traders and non-traders

A high proportion of users in our sample never chose public transport: nearly half of the respondents who had the option “car” or “bicycle” chose this option in their 4 choice situations. This behavior, called non-trading, can be associated in this case with an extreme preference for avoiding public transport. It is worthwhile noting that respondents who always chose private modes are likely, but not definitely, non-traders: no direct questions upon their willingness to use public transport in favorable conditions were made, and the number of scenarios per survey is relatively low.

Although the inclusion of an inertia parameter improves the fit of the mixed logit model for the complete sample, a bias in the coefficients associated with travel time cannot be ruled out (Hess et al., 2010). In this case, inertia factors represent around 30 min of car travel time and 50 min of bicycle travel time. Given that the choice of assumed non-traders is independent of public transport crowding in the choice situations, this behavior should be represented by high inertia factors and a low sensitiveness to crowding in public transport disutilities. Crowding should be in fact under-estimated if some of the assumed non-traders would actually choose public transport under certain trip conditions which were not represented in their choice situations.

In the Latent Class model, the existence of two classes with different modal constants for public transport options allows us to identify which users are more likely to be non-traders. Those who are more likely to belong to Class 2 (people over 30 years old, with high per capita income) have mode constants that are equivalent to a penalty of up to 181 min of travel by car for the Transantiago bus, 142 min for Red bus and 85 min for Metro in relation to traveling by car when the complete sample is considered. This indicates that users with these characteristics tend to avoid using public transport, regardless of the travel conditions.
When using the sample without inertial individuals (i.e. removing those participants who traveled by car or bicycle before the pandemic and also did not choose public transport in any of the choice situations), the coefficients associated with the variables of both models maintain their sign. However, the significance of transit travel time in the Latent Class Model improves significantly, different between mode constants are lower and the crowding penalties of both models (see Fig. 6) are more similar. This could indicate that such individuals are actually non-traders, hence we suggest using the models with non-traders only sample for prediction purposes.

### 4.2. Crowding penalties and risk perceptions

There are two recent studies that analyzed the crowding penalties when traveling by public transport in Santiago before the pandemic: Batarce et al. (2016) and Tirachini et al. (2017). Both studies are based on stated preference surveys, with bus and Metro options in Batarce et al. (2016) and only with metro in Tirachini et al. (2017).

A comparison of the results obtained in our study with these articles allows us to identify differences in the crowding penalties in Santiago de Chile before and during the pandemic.

Table 8 below compares the coefficients associated with travel time for a density of 4 passengers / m², the maximum assumed in A priori for time, cost & crowding coefficients, 1-tail T-tests shall be applied. Hence, coefficients are significant to 95% confidence if T-test greater than 1.64.

### 4.2.1. Comparing crowding penalties between studies

| Parameter | Description | Full sample (N = 455) | Traders-only (N = 351) |
|-----------|-------------|----------------------|-----------------------|
| **Mode Constants** | | | |
| Metro ASC | | [1] −1.19 [1] | [1] 0.73 [2] |
| | | [2] −2.79 [2] | [2] 0.56 [2] |
| Red bus ASC | | [1] −1.47 [1] | [1] 0.72 [2] |
| | | [2] −4.97 [2] | [2] 0.71 [2] |
| Transantiago bus ASC | | [1] −1.94 [1] | [1] 0.73 [2] |
| | | [2] −6.02 [2] | [2] 0.73 [2] |
| Car ASC | | 0 [fixed] [1] | 0 [fixed] [1] |
| Bicycle ASC | | [1] −0.92 [1] | [1] 0.66 [2] |
| | | [2] 0.72 [2] | [2] 0.71 [2] |
| **Time and cost (**)** | Transit access time (min) | −4.72.10 −3.66 1.29.10 −2 | −4.89.10 −3.68 1.33.10 −2 |
| | Transit travel time | −7.43.10 −0.83 9.00.10 −3 | −1.41.10 −1.55 9.11.10 −3 |
| | Car/bicycle travel time | −3.02.10 −4.11 7.34.10 −3 | −2.23.10 −3.10 7.21.10 −3 |
| **Crowding and disinfection (*)** | Car/bicycle cost (CLP/100) | −5.61.10 −2.45 2.23.10 −2 | −9.60.10 −2.72 3.53.10 −2 |
| Crowding 1 - women (total pax/sqm) * travel time | | | |
| | Class [2] only | −5.18.10 −4.24 1.22.10 −3 | −4.43.10 −2.45 1.81.10 −3 |
| Crowding 1 - men | | −2.59.10 −1.95 1.33.10 −3 | −2.98.10 −2.34 1.27.10 −3 |
| Crowding 2 - women (pax without face masks/sqm) * travel time | | | |
| | Class [1] only | −3.60.10 −5.44 6.61.10 −3 | −4.09.10 −4.17 9.80.10 −3 |
| Crowding 2 - men | | −2.23.10 −4.08 5.46.10 −3 | −2.50.10 −4.13 6.05.10 −3 |
| Time between disinfections | | | |
| Class Membership Model | Ln of time (h) * travel time | −2.99.10 −2.22 1.34.10 −3 | −3.30.10 −2.18 1.51.10 −3 |
| Class [1] intercept | | 2.38 3.03 0.78 | 1.87 1.98 0.94 |
| Age < 30 | (dummy) | 0.73 2.82 0.26 | 0.92 3.01 0.30 |
| Frequent trip | (dummy), 1 if trip frequency maintained during pandemic | −0.69 −2.02 0.34 | |
| Income | Ln of per capita hour income in household | −0.37 −3.16 0.11 | −0.33 −2.07 0.16 |

[1] [2] correspond to Class-1 and Class-2 specific parameters.

(*) As a negative sign is expected a priori for time, cost & crowding coefficients, 1-tail T-tests shall be applied. Hence, coefficients are significant to 95% confidence if T-test greater than 1.64.
our survey, against the coefficient associated with the minimum occupancy level.

If all passengers wear a mask correctly, the penalty for crowding in both models is higher to that found by studies before the pandemic, yet the minimum difference is of only 10%. This result may seem surprising, considering the high health risk that users perceive to travel in crowded vehicles independently of the use of face masks: 95% of the respondents of the survey do not feel safe in terms of health when traveling with an occupancy of 4 pax/m2.

Moreover, when considering that average crowding has fallen because of the sharper decrease in demand compared with the decrease of transit frequency, average crowding coefficients are surprisingly comparable with those found before the pandemic. This is shown in Table 9 below, which compares the average crowding factors in relation to a density of 0.5 pax / m2, assuming a 50% decrease in demand during the pandemic, a 20% reduction in the frequency offered and a 90% face mask use, which is consistent with the data reported in the introduction.

It shall be noted that likely non-traders are excluded from this comparison. In this sense, one possible explanation is that part of the health risk perception is captured by variables independent of travel time such as modal constants. Further work should study the effect of COVID-19 on public transport disutilities in base conditions in order to allow for a more comprehensive comparison.

As the proportion of passengers without face masks increases, penalties for crowding become higher than those found before the pandemic in all models, particularly for women. If half of the passengers do not wear a mask correctly, 1 min of travel facing a density of 4 pax/m2 would be considered equivalent by a user to between 3.4 and 5.1 min with minimum occupancy depending on the model and gender. Like the estimates when everyone wears a mask, coefficients for the latent class model are higher than for mixed logit models, which is consistent with findings from Tirachini et al. (2017).

The best fit functions for both models are non-linear with respect to passenger density, so the importance of limiting boarding grows as these variables increase. In this sense, both Batarce et al. (2016) and Tirachini et al. (2017) proposed crowding factors that grow linearly with passenger density, although another study in Santiago that used stated preference and revealed preference data, Batarce et al. (2015), also observed non-linear penalties.

Regarding the socioeconomic attributes that influence the penalties for crowding, men and young people are less sensitive, which matches findings by Tirachini et al. (2017) before the pandemic. Several studies suggest that women have a higher perception of health risk during the COVID-19 pandemic (e.g. Abdullah et al. (2020), Barber and Kim (2021), Gerhold (2020)). In contrast, age-specific risk perception findings are mixed: according to Barber and Kim (2021) and Gerhold (2020), the elderly tend to worry less about the pandemic. Bruine de Bruin (2021) found that older adults have a higher perception of the risk of death if they contract COVID-19 but a lower perception of the risk of contagion in relation to other age groups. Vallejo-Borda et al. (2021) found a lower perception of risk among young people in Lima, without significant differences by age in other South American capitals. Finally, Beck and Hensher (2020) found no differences regarding hygiene risk perception in public transport according to age groups.

According to the latent class model results, individuals with higher income and frequent travelers during the pandemic tend to belong to Class 2, which is more sensitive to crowding. This is consistent with pre-pandemic studies such as Haywood et al. (2017) which found that people with higher income are more unwilling to travel in crowded vehicles. However, the survey carried out by Astroza et al. (2020) in the early stages of the pandemic shows that high-income people in Chile were less afraid of being infected with COVID-19 and less worried about crowding in public transport. Likely explanations given by Astroza et al. (2020) is that those with higher incomes usually do not use public transport, so they are less exposed to crowded environments, and can also afford better health services. Frequent travelers’ attitude could also be explained by their daily exposure level to the virus.

Daily exposure to the virus is also relevant in explaining socio-demographic patterns regarding transit level of service perception.
Table 6
Mixed Logit with Latent Variables Model (2) results.

| Parameter                          | Description                                                                 | Full sample (N = 455) | Traders-only (N = 351) |
|------------------------------------|-----------------------------------------------------------------------------|-----------------------|------------------------|
|                                    |                                                                             | value  | t-test | standard error | value  | t-test | standard error |
| **Mode Constants**                 |                                                                             |        |       |               |        |       |               |
| Metro ASC                          | 0 [fixed]                                                                   |         |       |               | 0 [fixed] |       |               |
| Red bus ASC                        | −0.40 −2.01 0.20                                                          |         |       |               | −0.53 −2.89 0.18 |       |               |
| Transantiago bus ASC               | −1.16 −5.70 0.20                                                          |         |       |               | −1.04 −6.05 0.17 |       |               |
| Car ASC                            | 1.93 2.91 0.66                                                            |         |       |               | 1.73 2.58 0.67 |       |               |
| Bicycle ASC                        | 0.85 1.66 0.51                                                            |         |       |               | 0.46 0.97 0.48 |       |               |
| **Time and cost (\(*\))**         |                                                                             |         |       |               |         |       |               |
| Transit access time (min)          | −5.36 10 2 −3.65 14.70 10 2                                               |         |       |               | 5.07 10 2 −3.53 14.3 10 2 |       |               |
| Transit travel time (average)      | −3.10 −13.20 0.24                                                         |         |       |               | −2.12 −11.95 17.8 10 2 |       |               |
| Transit travel time (error term)   | 0.72 5.14 0.14                                                           |         |       |               | 2.56 3.96 0.65 |       |               |
| Car travel time                    | −5.81 10 2 −5.90 9.50 10 3                                               |         |       |               | −5.38 10 2 −5.33 10 1 1 |       |               |
| Bicycle travel time                | −3.72 10 2 −4.00 9.30 10 3                                               |         |       |               | −3.35 10 2 −3.85 8.7 |       |               |
| Car/bicycle cost                   | −4.05 10 2 −1.95 2 1.26 10 2                                              |         |       |               | −3.81 10 2 −1.77 2 15 |       |               |
| **Crowding and disinfection (\(*\))** |                                                                             |         |       |               |         |       |               |
| Crowding 1 - women                 | (pax with face masks/sqm) * travel time                                    | −6.80 10 4 −5.37 12.7 10 4 |       |               | −6.75 10 4 −5.55 12.2 10 4 |       |               |
| Crowding 1 - men                   | −3.41 10 4 −2.25 15.2 10 4                                               |         |       |               | −3.13 10 4 −2.23 14 |       |               |
| Crowding 2 - women                 | (pax without face masks/sqm) * travel time                                  | −4.31 10 2 −6.32 6.82 10 3 |       |               | −4.30 10 2 −6.39 6.7 10 3 |       |               |
| Crowding 2 - men                   | −3.72 10 2 −5.99 6.21 10 3                                               |         |       |               | −3.45 10 2 −5.61 6.15 10 3 |       |               |
| Time between disinfections          | Ln of time (h) * travel time                                               | −2.65 10 3 −1.5 13.7 10 3 |       |               | −3.12 10 3 −2.38 13.1 |       |               |
| Inertia & pseudo-panel effect      |                                                                             |         |       |               |         |       |               |
| Car-bicycle inertia                | Error term, all modes, dummy, 1 if stated choice = current mode trip in all 4 scenarios | 1.10 12.09 9.10 10 2 |       |               | 0.75 7.81 9.6 10 2 |       |               |
| Latent variables                   |                                                                             |         |       |               |         |       |               |
| Metro service perception           | LV explained by 5 indicators (see Table 7) *                               | 1.23 10 2 5.74 2 15.10 10 3 |       |               | 7.09 10 3 3.41 2.08 10 3 |       |               |
| Red bus service perception         | travel time                                                                | 1.80 10 2 5.98 3 0.10 10 3 |       |               | 1.13 10 2 4.04 2.80 |       |               |
| Transantiago bus service perception |                                                                             | 1.30 10 2 4.73 2 7.4 10 3 |       |               | 6.60 10 3 2.41 2.73 |       |               |

(*) As a negative sign is expected a priori for time, cost & crowding coefficients, 1-tail T-tests were applied. Hence, the corresponding coefficients were considered as significant to 95% confidence if T-test greater than 1.64.

While the worse perception assigned by women and health workers to the quality of service in metro and bus service reflected by the latent variables’ structural equations is straightforward, the fact that people with college degree have a better perception of Metro and Transantiago bus services requires a more elaborate reasoning. As individuals with higher education tend to have more income and more car and bicycle availability, their exposure to crowded public transport travel (as reported by Astroza et al. (2020)) should be lower. Moreover, average commuting travel time in Santiago is higher among low income households (Iglesias et al., 2019; Gainza and Livert, 2013), thus people without college education are more likely to make longer trips in more crowded public transport vehicles.

As the risk of suffering serious consequences after a COVID-19 infection increases with factors such as hypertension (Li et al., 2020), obesity (Dietz and Santos-Burgoa, 2020) and diabetes (Fang et al., 2020), it should be expected that those with a previous health condition adopt a more cautious attitude when traveling. That said, people with health problems did not report a more cautious travel behavior, even though this might seem unintuitive.

Previous studies have identified people living with families including children (He et al., 2020) and students knowing susceptible population (Ding et al., 2020) as groups having more perception of risk towards COVID-19. For these individuals and for other potentially sensitive group as people living with elderly or travelers who had previously suffered a health urgency while using public transport, we neither found significant differences with respect to the general sample.

Note that, unlike Tirachini et al. (2017), we did not find significant differences between crowding perceptions when travelling sitting versus standing. Indeed, from one of the attitude questions (“I prefer to travel sitting in public transport, even if there are people standing next to me”) it can be observed that almost half of respondents prefer traveling standing. Model tests with latent classes and taste variation did not identify significant differences between the perception of traveling sitting or standing in our sample.
residence or the date of the survey. Chile has implemented a 4-step warning system during the pandemic, which regulates allowed activities depending on the incidence of COVID-19 in each city or neighborhood (Martínez et al., 2020). Even though our surveys covered zones in steps 1 (full lockdown), 2 (weekend lockdown) and 3 (most activities allowed), sensitivity to the occupation of public transport and the non-use of masks was independent of the associated variables. This makes us think that the impact of the coronavirus on travel preferences could last longer than the active phase of the pandemic.

### 4.3. Other relevant factors

Perception of transit quality service attributes, such as comfort, safety and cleanliness, is still relevant to explain mode choice. This is a significant advantage of the model with Latent Variables, that identifies the impact of these perceptions on utilities. The differences between crowding penalties for different modes due to the effect of these perceptions, considering the same conditions of density and face mask use, represent up to 30% of the disutility associated with travel time.

Finally, the frequency of disinfection of public transport vehicles is also significant: in both models, a daily cleaning of the vehicles implies a penalty equivalent to more than 20% on the travel time for the minimum level of occupancy compared with hourly disinfection. In practice, the disinfection frequency should balance its impact in the protection of passengers' health and in vehicle availability which directly influences the required frequency of the service and therefore transport capacity and crowdedness inside the vehicles, which we discuss later.

Value of time.

Value of time for a given mode i, expressed as:

\[
\text{VoT}_i = \frac{\partial V_i}{\partial t_i}
\]

(8)

Where \( V_i \) is the representative utility function of the mode, \( C_i \) the monetary cost and \( t_i \) the travel time (see for example Jara-Díaz, 2007), can only be obtained for car and bicycle in our models as no cost coefficients were estimated for metro and bus utilities. Considering the Mixed Logit with Latent Variables Model, with traders-only sample, value of time estimates are of 8.478 Chilean peso/h for car travel and 5.283 Chilean peso/h for bicycle travel. These figures, which represented around 11 and 7 US dollars/h respectively during surveys, are markedly higher than the average travel time savings used in the ESTRAUS strategic model (Fernandez and De Cea Ingenieros Consultores, 2005) although recent studies have reported even higher values for value of time among car users (Ortúzar et al., 2021) than our models. As reported in Table 2, our survey sample overestimate high income individuals. Lower values of time should be expected for a more representative sample in terms of wealth.

### 4.4. Limitations of the study

Beyond the contributions of the study, it is necessary to point out some limitations of the analysis. Given that the choice experiment was relatively complex, with up to 3 alternatives and 6 variable parameters per mode in each choice situation, a fixed fare was considered for the public transport options, with a value similar to the current price of the adult ticket in Santiago. Consequently, no cost parameters were estimated for the Metro, Red Bus and Transantiago Bus modes, so no direct

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**Table 7**

Mixed Logit with Latent Variables Model (2) Parameters and t-test of latent variables.

| Mode / Parameter | Metro Full sample | Metro Traders-only | Red bus Full sample | Red bus Traders-only | Transantiago bus Full sample | Transantiago bus Traders-only |
|------------------|-------------------|-------------------|---------------------|---------------------|-----------------------------|-----------------------------|
| Structural model |                   |                   |                     |                     |                             |                             |
| Intercept        | 2.14 (23.24)      | 1.70 (23.23)      | 1.35 (23.76)        | 1.24 (23.58)        | 1.33 (18.09)                | 0.91 (13.79)                |
| Woman (dummy)    | -0.42 (-5.37)     | -0.20 (-2.72)     | -0.38 (-5.63)       | -0.32 (-4.60)       | -0.38 (5.80)                | 0.48 (6.61)                |
| College education (dummy) | 0.25 (3.22) | 0.31 (4.31) | 0.38 (5.80) | 0.48 (6.61) |                             |                             |
| Health staff (dummy) | -0.43 (-4.11) | -0.34 (-3.08) | -0.33 (-4.18) | -0.27 (-3.45) |                             |                             |
| Measurement model |                   |                   |                     |                     |                             |                             |
| \( \eta \) - Service perception (latent variable) | 1.23.10^{-2} (5.74) | 7.09.10^{-3} (3.41) | 1.80.10^{-2} (5.98) | 1.13.10^{-2} (4.04) | 1.30.10^{-2} (4.73) | 6.60.10^{-2} (2.41) |
| \( \gamma \) - indicator coefficients |                     |                   |                     |                     |                             |                             |
| 1: comfort,      | I1: 1.69 (2.31)   | I1: 2.12 (2.31)   | I1: 2.27 (2.31)     | I1: 2.84 (2.31)     | I1: 2.17 (2.31)            | I1: 2.83 (2.31)            |
|                  | I2: 1.79 (2.31)   | I2: 2.30 (2.31)   | I2: 1.98 (2.31)     | I2: 2.48 (2.31)     | I2: 2.10 (2.31)            | I2: 2.72 (2.31)            |
| 2: safety / security (*), |                     |                   |                     |                     |                             |                             |
|                  | I3: 1.00 (fixed)  | I3: 1.00 (fixed)  | I3: 1.00 (fixed)    | I3: 1.00 (fixed)    | I3: 1.00 (fixed)           | I3: 1.00 (fixed)           |
| 3: vehicle cleanliness, |                     |                   |                     |                     |                             |                             |
|                  | I4: 1.76 (3.32)   | I4: 2.16 (3.32)   | I4: 1.47 (3.32)     | I4: 1.48 (3.32)     | I4: 1.40 (3.32)            | I4: 1.46 (3.32)            |
| 4: station cleanliness, |                     |                   |                     |                     |                             |                             |
|                  | I5: 0.76 (3.32)   | I5: 0.69 (3.32)   | I5: 0.87 (3.32)     | I5: 0.56 (3.32)     | I5: 0.78 (3.32)            | I5: 0.54 (3.32)            |
| 5: health risk (**)) |                     |                   |                     |                     |                             |                             |

(*) “Seguridad” in the original survey, which means both safety and security in Spanish.

(**) Scale was reversed (5–1) as a higher value in the original response implies a worse level of service perception.

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Table 8
Crowding penalties in public transport, pre-pandemic versus pandemic conditions (traders-only sample).

| Source                          | Crowding factor (4 pax/m² vs 0.5 pax/m²)                  |
|--------------------------------|-----------------------------------------------------------|
| Latent Class Model (1)          | Women: 2.82 (100% face masks) / 5.12 (50% face masks)    |
| Mixed Logit with LV (2) – individual coefficient values (*) | Women: 2.30 (100% face masks) / 3.65 (50% face masks)    |
| Batarce et al. (2016)           | Men: 2.26 (100% face masks) / 3.67 (50% face masks)      |
| Tirachini et al. (2017)         | Men: 1.63 (100% face masks) / 3.06 (50% face masks)      |
| Latent Class: 1.60 (sitting) / 2.00 (standing)                              |

(*) average of Metro, Red bus and Transantiago bus factors.

Fig. 6. Crowding penalties per mode, gender and pandemic (traders-only sample).
estimates of value of time for public transport were obtained.

Sample size (N = 351, with 1376 choice responses when excluding inertial individuals) is particularly limited for groups such as elderly people or individuals without college education as shown in Table 2. Therefore, model results should be taken with care when considering these groups.

Vehicle design, and more specifically seat provision, shall be relevant to study in future articles. Given that no significant preferences were found for travel seated, and that buses or trains with fewer seats could lead to a more uniform distribution of passengers within vehicles, a reduced perception of disutility could arise from the non-linear penalty for crowding found in our models. In this sense, upcoming studies should specifically analyze the effect of crowding differentiated by the location of passengers within public transport vehicles.

Finally, a limitation inherent to any study should be pointed out, but which is especially relevant in these times of instability: it is not possible to be sure if these findings are replicable in other cities or if they will be representative of Santiago de Chile in the months and years to come. In particular, recent published studies (Lewis, 2021; Goldman, 2020) assert that COVID-19 transmission through surfaces is rare, despite previous recommendations that stressed the importance of cleaning to mitigate the spread of virus in health care facilities (World Health Organization, 2020) and public places including transport (Pan American Health Organization, 2020). This could affect the relevance of disinfection frequency in mode choice.

The following paragraphs discuss the implications of the study results for public policy, particularly related to the design of transportation lines.

4.5. Implications for public policy

The results of the models are relevant for the design of public transport corridors. Various authors (Tirachini et al., 2014; Batarce et al., 2016; Moccia et al., 2020) have studied the trade-off between increased capacity (and operating costs) and lower waiting times and crowding that reduce the cost perceived by users in transit lines. In this sense, the non-linear nature of crowding penalties makes especially relevant to minimize the number of trips with high passenger density. Measures such as the reinforcement of frequencies or the use of higher capacity vehicles in areas and times of greater demand could be useful to achieve this objective.

From the findings of this study, two additional trade-offs emerge. First, a greater use of face masks implies a lower travel time penalty, which would allow capturing more trips in a public transport corridor. In addition, a greater use of masks effectively reduces the risks of contagion (Eikenberry et al., 2020; Ngonghala et al., 2020; Cheng et al., 2020), which results in health and economic benefits. Although the use of face masks in public transport is mandatory in Chile since April 2020 (Ministry of Health, 2020), some people do not wear a mask or do it incorrectly. Increasing the correct use of face masks has an associated cost, both in public campaigns and in controls to penalize non-compliance.

In turn, face mask use by passengers is a positive externality, since it not only reduces the risk of contagion for those who use them, but also both actual and perceived risk or nearby passengers, the latest of which is reflected in a lower penalty associated with travel time. In this sense, model results can be useful to set fines so that those unwilling to wear masks are forced to internalize this effect.

Second, a higher frequency of disinfection is associated with less travel disutility, which results in savings in terms of generalized travel cost. In this sense, there are recommendations to disinfect vehicles after each trip (GIZ, 2020). However, it should be noted that this implies a longer cycle time, which reduces the offered capacity, increases user waiting times and leads to more crowding. However, almost every public transport service reduces the frequency during off-peak periods providing a perfect opportunity to disinfect vehicles then.

Third, the results of the model with latent variables show that the perceived quality of the service is still relevant in explaining travel time penalties. In particular, the favorable evaluation of the Red buses compared to Transantiago’s older units shows that it is possible to significantly reduce disutilities by incorporating newer, more comfortable and cleaner vehicles.

Finally, in a public transport in crisis due to the drop in demand, it is essential to analyze how the optimal frequencies vary, not only because of the capacity restrictions that result from social distancing, which was considered in Gkiotsalitis and Cats (2021), but also because of these new trade-offs described.

5. Conclusions

Through a stated preference survey carried out in Santiago de Chile, we estimated mode share models that allow us to point out the
importance of crowding in travel decisions during the COVID-19 pandemic. Compared to the pre-pandemic situation, people penalize occupation to a greater extent when the fraction of people in their vehicles who do not use face masks grows. In addition, women, adults over 30, and high-income individuals show a more cautious attitude towards crowding, and perceptions of public transport level of service as well as the frequency of disinfection of vehicles are also significant in explaining mode choices.

These results are relevant for the planning of public transport lines and networks during the pandemic, where the determination of optimal frequencies not only depends on a new restricted capacity and a lower demand, but also on the trade-offs that occur between crowding, level of service, disinfection, and face mask use enforcement.

In terms of the time dimension of public transport operations, operators should take advantage of the frequency drop happening in almost every urban service during the night and during the middle of the day to disinfect their vehicles. During these periods many vehicles are parked providing the perfect moment to take these actions. They should be communicated effectively to users so that they reduce their risk perception inside the vehicles.

Finally, thinking in the spatial dimension of public transport operations, COVID19 has drastically changed urban mobility patterns affecting the share of trips captured by every mode. In most cities these changes are not uniform across the city, because activities of cities and residential types are not evenly distributed throughout the territory. Thus, the relocation of vehicles between services that cover different areas of a city seems like a sensible opportunity. The results of this paper should be relevant to orient such strategy.

CRediT authorship contribution statement

Paul Basnak: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft, Visualization.
Ricardo Giesen: Conceptualization, Writing – review & editing, Supervision, Funding acquisition. Juan Carlos Muñoz: Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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