Characterization of travel time variability in multimodal transport networks: new results from Santiago

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Abstract

Service level attributes like travel time variability (TTV) and passenger crowding are attracting attention among policy makers, practitioners and transport modellers, due to the increasing awareness that users pose a high value on these level-of-service variables. In this paper, we analyse the travel time variability and modal reliability of cars and public transport trips. We characterize travel time variability in each stage of a trip by public transport (access, waiting, in-vehicle bus, in-vehicle metro and transfer), and estimate the effect of each stage on the variability of travel time for complete door-to-door trips. We use data from travel time surveys collected in Santiago, in which surveyors are asked to perform predetermined trips and record access, waiting, in-vehicle and transfer times, several different days between 2007 and 2011. Using the standard deviation (SD) on minutes per kilometre to characterize TTV on motorised modes, we find a stronger relationship between SD and mean travel time for cars and bus than for metro, and by fitting linear relationships between SD and mean travel time, we obtain that bus presents the most variable travel time, followed by car and metro. A multivariate regression for the variability of total (door-to-door) public transport travel time shows that bus waiting and in-vehicle time are highly significant in explaining total TTV, whereas walking and metro travel time do not have a significant effect. Implications for policy making are discussed.

Keywords: travel time variability, modal reliability, waiting, walking, bus, metro, congestion.

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1. Introduction: the relevance of characterizing travel time variability

Travel time variability reflects the degree of variation in travel time of a trip repeated in similar conditions over several days. Travel time variability is a key factor that travellers and shippers take into account when making basic travel decisions such as mode, route and departure time. Studies that attempt to quantify how much people value reductions of travel time variability abound (Jackson and Jucker, 1982; Senna, 1994; Noland and Small, 1995; Bates *et al.*, 2001; Lam and Small, 2001; Li *et al.*, 2010, among many others). Basically, a reduction in travel time variability allows for a more predictable travel time, and therefore better activity scheduling decisions for all users of a transport network, including car drivers, public transport riders, cyclists and cargo operators.

In order to monetise the value of reductions in travel time variability, two modelling approaches are usually put forward: the scheduling model and the mean-variance model. Whereas the scheduling model assumes that being early or late at a destination is a source of disutility for travellers, the mean-variance approach suggests that travel time variability is a cost by itself, no matter if travellers arrive early or late (see Carrion and Levinson, 2012 for a review). Fosgerau and Karlström (2010) show that the scheduling and mean-variance models are equivalent under certain conditions, however, empirical evidence suggests that the value of travel time variability reductions from a scheduling model may be smaller than that of a mean-variance model (Börjesson *et al.*, 2012), possibly because uncertainty is considered a source of disutility as such, regardless if the final outcome is arriving early, on-time or late at a destination.

Even though we have plenty of evidence on how much travel time variability matters to travellers, there is no agreement on which is the best way to measure it. Several constructs have been used to analyse the level of variability in travel times for different modes and travel conditions, and a number of studies are devoted to compare different measures of network reliability or travel time variability, either for particular roads or modes (e.g., Lomax *et al.*, 2003; van Lint *et al.*, 2008; Cambridge Systematics *et al.*, 2013). The measures of TTV proposed and analysed in the literature can be roughly classified in two groups (Pu, 2011): (i) performance reliability measures, introduced to quantify the performance of transport systems, and (ii) measures to estimate travellers responses to unreliability, usually to improve travel behaviour models (such as the standard deviation of travel time and the probability of arriving early or late at a destination, for introduction in mean-variance or scheduling models, respectively). A summary of travel time reliability measures proposed in the literature is presented in Table 1. The advantages of the standard deviation of travel time are its simplicity and the fact that it can be readily introduced in a mean-variance model to analyse users' responses to travel time variability, which makes the standard deviation an attractive measure to characterize the reliability of travel times and travel modes.

Table 1: Selected measures of travel time variability on different studies

TTV measure	Source
Standard deviation of travel time	May *et al.*(1989) Eliasson (2007) Mahmassani *et al.* (2012) Peer *et al.* (2012) Tirachini *et al.* (2014)
Difference between 90th and 10th percentile of travel time	Eliasson (2007) Tu *et al.* (2007) van Lint and van Zuylen (2005)
Coefficient of variation	May *et al.*(1989) Eliasson (2006)
Standard deviation of delay (delay: difference between actual travel time and free flow travel time)	Mott MacDonald (2008b; 2008a)
Variance of delay	Mott MacDonald (2008b; 2008a)
Travel time index (TTI) (Ratio of actual travel time to free-flow travel time)	Cambridge Systematics *et al.* (2013)
80% percentile TTI	Cambridge Systematics *et al.* (2013)
Buffer time index (Difference between 95th percentile travel time per km and average travel time per km, divided by travel time per km)	Lomax *et al.* (2003) van Lint *et al.* (2008)
Misery index (Average of the highest 5% or 20% of travel times, divided by free-flow travel time)	van Lint *et al.* (2008) Kim *et al.* (2013)
Planning time index (The 95th percentile travel time divided by free-flow travel time)	Lomax *et al.* (2003) Kim *et al.* (2013)

Given the relevance of travel time reliability for travellers satisfaction and network performance assessment, it is useful to have a relationship between a TTV measure and a measure of mean travel times, because the latter is easier to estimate either with empirical, analytic or simulation methods. Several authors have estimated functions to link average travel time with a measure of travel time variability, usually the standard deviation, as done for cars by May *et al.*(1989), Mahmassani *et al.* (2012), Peer *et al.* (2012), Cambridge Systematics *et al.* (2013) and Tirachini *et al.* (2014), and for buses by Mazloumi *et al.* (2010) and Moghaddam *et al.* (2011).

The analysis of travel time variability by public transport is more complicated than that of car traffic, because of, at least, three factors (Tirachini *et al.*, 2014): (i) buses and trains stop for the boarding and alighting of passengers, a process that involves other sources of variability (speed and number of passengers boarding and alighting, choice of fare payment method, number of buses stopping), (ii) unreliable travel times have a negative effect on waiting times at bus stops and train stations, and (iii) the uncertainty of travel times in public transport also induces a cost on service providers, who may introduce larger recovery times in the schedule if travel times are less reliable. Ad-hoc measures proposed to analyse the reliability of a public transport service go beyond the standard deviation of travel time to include constructs such as the probability of on-time performance, the travel time ratio (observed travel time/scheduled travel time) and several measures of the variability of headways, which increases waiting times (Abkowitz and Engelstein, 1983; Strathman and Hopper, 1993; Strathman *et al.*, 1999; El-Geneidy *et al.*, 2008).

In this article we aim at characterising the reliability of both cars and public transport trips using data from Santiago de Chile. We count with two databases of repeated observations of trips in different areas of the city, one database for cars and another one for multimodal public transport trips (includes both buses and metro). The contributions of this article to the literature on travel time variability are two-fold. First, we compare the travel time variability of three modes using a single distance-free measure, which allows us to compare results on in-vehicle time by car, bus and metro. Second, in the case of public transport trips, our database encompasses door-to-door trips repeated over several days, therefore we can go beyond previous public transport studies that focus on travel time or headway reliability, to analyse each stage of a trip separately (walking, waiting, in-vehicle bus, in-vehicle metro and transfer time), and how each of these stages influences the total (door-to-door) travel time variability. In particular, we are able to estimate which stages, and to what extent, are statistically significant in explaining total travel time variability, and which stages are not statistically significant. To the best of our knowledge, this is the first study that includes walking and waiting to understand total travel time variability in public transport. Policy implications are discussed.

The rest of the article is organised as follows: Section 2 describes the data used in this article. In Section 3 we analyse the probability distributions of travel times in car and multimodal public transport trips. In Section 4, the variability of travel time is analysed per mode and trip stage (in the case of public transport). Section 5 presents the study of door-to-door travel time variability in public transport. Section 6 concludes.

2. Data description

Two datasets are used in order to investigate the characteristics of travel time variability in Santiago. The first is a database of travel times by car provided by UOCT (*Unidad Operativa de Control de Tránsito*), the public agency that controls traffic signals for the Santiago Metropolitan Area. These data record travel time by car for 25 different road stretches, on different time periods. Trips recorded in the morning (8:00-9:00) and afternoon (18:00-20:00) peak periods were obtained. Between 3 and 6 repetitions of the same trip are recorded in the morning peak, and between 6 and 10 are recorded in the afternoon. Data is recorded one working day every three months, and the total database contains 2,616 travel time measurements between 2010 and 2014. A floating car is used to measure travel time.

The second database comes from a large project on the observation of travel times in multimodal public transport trips in Santiago, that spans from 2007 and 2012. The surveys are requested by the Metropolitan Public Transport Agency (DPTM, *Directorio de Transporte Público Metropolitano*) and carried out by a private consultant, who hires surveyors to do specific trips day after day, and record the time taken in each stage of a trip. The main difference with other databases used to analyse public transport reliability, is that ours record trips door-to door, i.e., including access, waiting, in-vehicle time (by bus and/or metro), transfer and egress time, for 66 different origin-destination pairs in the metropolitan area. Trips were made in 1, 2, 3 and 4 vehicles in peak and off-peak periods. We have a total of 35,340 observations for different stages of trips. Table 1 summarises relevant information about the two databases. Peak periods differ between the databases as periods were defined by the authorities in charge of each survey.

Variable	**Car database**	**Public transport database**
Observation period	March 2010 - June 2014	May 2007 - December 2012
Time periods	Morning peak: 08:00 - 09:00 Afternoon peak: 18:00 - 20:00	Morning peak: 6:30 - 9:30 Off-peak: 9:30 - 12:30 Afternoon: 14:30 - 16:30 Afternoon peak: 17:30 - 20:30 Night: 20:30 - 01:00
Total number of observations	2,616	O-D pairs: 66 Trips stages: 35,340
Average speed (km/h)	Car morning peak: 24.1 Car afternoon peak: 20.7	Bus morning peak: 19.5 Bus off-peak: 21.6 Metro morning peak: 29.7 Metro off-peak: 32.3
Average trip length (km)	2.4	Bus: 5.6 Metro: 9.7

Table 1: Description travel time databases

3. Probability distribution of travel times

Travel time variability (TTV) is the result of random variations in travel time caused by a number of variables whose impact cannot be anticipated by travellers (Tu, 2008). Amongst the most common causes of TTV we can mention temporal demand differences (peak/off-peak, weekday/weekend), driving attitude, weather, roadwork, accidents, special events, network effects (effect of traffic in one road over travel times on adjacent roads) and differences in traffic signal programming and other traffic control devices (Tu, 2008; Cambridge Systematics *et al.*, 2013; Kim *et al.*, 2013). These factors make that travel time vary both within one day and day-to-day. By recording repeated observations of a trip on the same route at the same time (or time period) every working day, it is possible to analyse day-to-day travel time variability, which is what users take into account when making commuting decisions.

In this section, we estimate probability distributions for travel time by car, bus and metro. In general, knowing if any parametric distribution is reasonable accurate to model travel time observations in a particular route is an useful tool to perform analytical comparisons between different reliability measures (standard deviation, buffer index, planning time index and others), as done by Pu (2011) assuming a lognormal distribution.

Some articles have estimated continuous probability distributions for car traffic, in cities like San Antonio (Rakha *et al.*, 2010), Adelaide (Taylor and Susilawati, 2012; Susilawati *et al.*, 2013), Paris (Aaron *et al.*, 2014), and Stockholm (Eliasson, 2007), among others; whereas for public transport we can mention the studies of selected bus routes in Melbourne (Mazloumi *et al.*, 2010) and Brisbane (Kieu *et al.*, 2014). Distributions like the Lognormal, Gamma, Burr and Weibull are the most commonly proposed to fit travel time distributions. An usual finding is that travel time is skewed, with long right tails (van Lint and van Zuylen, 2005; Cambridge Systematics *et al.*, 2013; Susilawati *et al.*, 2013), therefore asymmetrical distributions in theory are more suitable than symmetrical distributions to model travel time variability, however symmetrical distributions due exist as well (Eliasson, 2007). Even bimodality of the travel time distribution has been found in specific cases (Susilawati *et al.*, 2013).

We identified probability distributions that fit in-vehicle travel times of the three motorized modes in our study: car, bus and metro, based on the tests for goodness-of-fit Chi-square and Kolmogorov-Smirnov. See Appendix A for a brief description of both tests. The software *Statgraphics* was used for this task.

For travelling by car, results show that a lognormal distribution fit observed travel times for 80% of routes. The lognormal distribution has been previously proposed in the literature (e.g., Rakha *et al.*, 2010; Susilawati *et al.*, 2010; Pu, 2011). On the other hand for bus and metro, the loglogistic distribution fits well several observed travel times, which does not seem to have been found in the extant literature (for buses, Kieu *et al.*, 2014 also propose a lognormal distribution). Loglogistic and lognormal distributions are quite similar in shape, and are among the set of distributions used for reliability analysis for the lifetime of components and systems[1]. In the following figures we show examples of probability distributions for travel times by car, metro and bus. These findings confirm that the travel time distribution is usually but not always rightly skewed, as a symmetrical (normal) distribution is found as a good fit in 2 and 8 routes for bus and car, respectively.

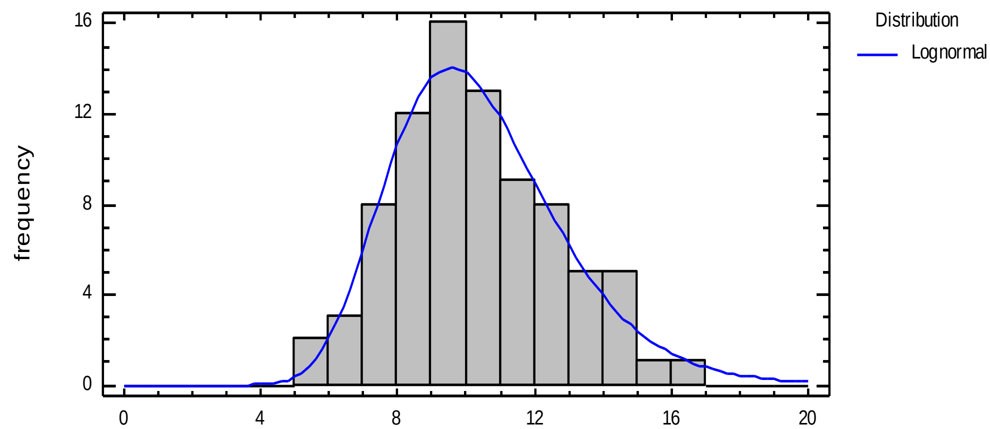


Figure 1: Histogram and lognormal distribution for car travel time (minutes), Eliodoro Yáñez Avenue, between Américo Vespucio and Los Leones

Lognormal
mean = 10,4211
standard deviation = 2,53113
Log scale: mean = 2,31517
Log scale: std. dev. = 0,239414
Chi-Squared test: P-Value = 0,78354
Kolmogorov-Smirnov Test: P-Value = 0,976698

Table 2: Lognormal parameters for car travel time (minutes), Eliodoro Yáñez Avenue, between Américo Vespucio and Los Leones

[1] Wolfram Documentation Center, http://reference.wolfram.com/language/guide/DistributionsUsedInReliabilityAnalysis.html, accessed 22 Dec 2014

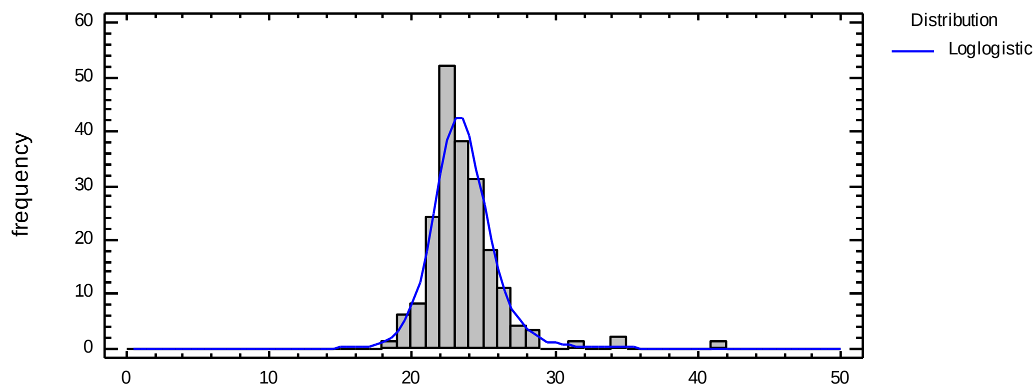


Figure 2: Histogram and loglogistic distribution for metro in-vehicle time (minutes) Trip between stations Plaza de Armas and Vicente Valdés

Loglogistic
median = 23,3787
shape = 0,0498192
Chi-Squared test: P-Value = 0,568847
Kolmogorov-Smirnov Test: P-Value = 0,818637

Table 3: Loglogistic parameters for metro in-vehicle time (minutes) Trip between stations Plaza de Armas and Vicente Valdés

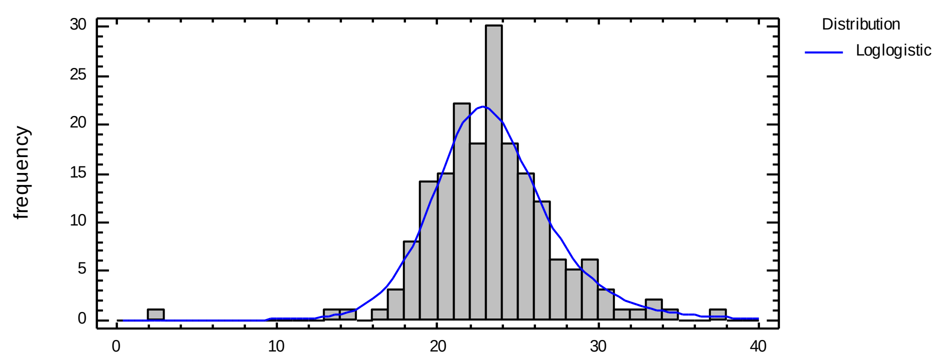


Figure 3: Histogram and loglogistic distribution for bus in-vehicle time (minutes), Trip made in bus service 105, from bus stop Cardenal Raúl Silva H. and Pegaso, to bus stop N°1 Metro San Alberto Hurtado

Loglogistic
median = 23,1796
shape = 0,091907
Chi-Squared test: P-Value = 0,966644
Kolmogorov-Smirnov Test: P-Value = 0,913392

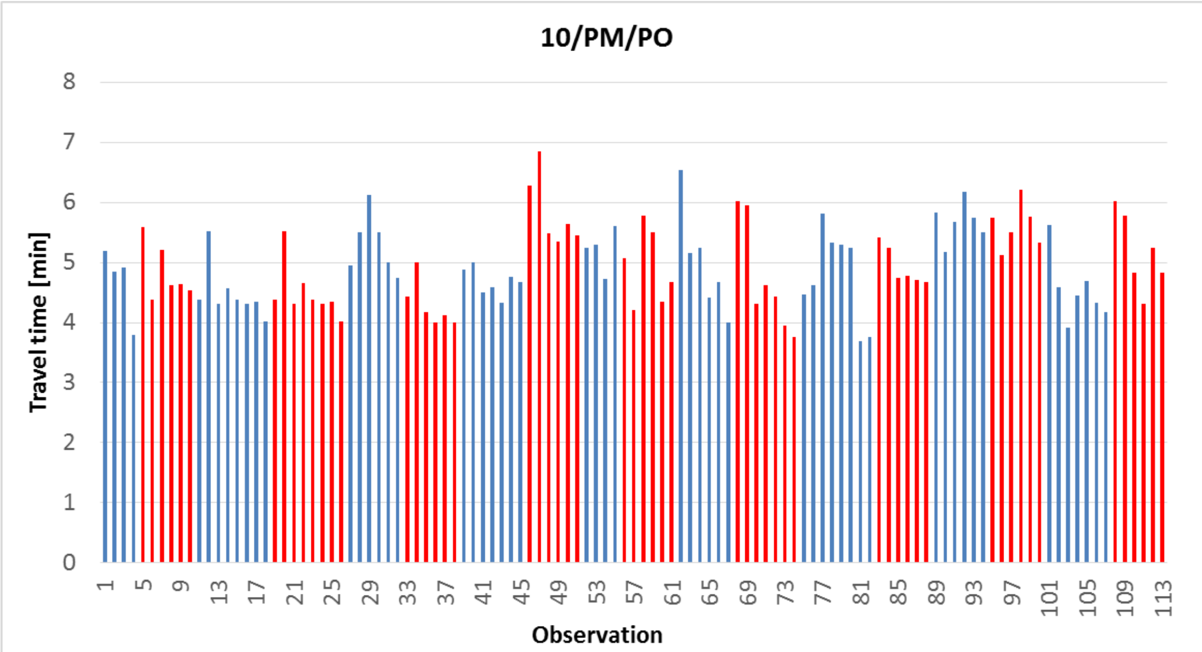
***Table 1: Loglogistic parameters for* bus in-vehicle time (minutes), Trip made in bus service 105, from bus stop Cardenal Raúl Silva H. and Pegaso, to bus stop N°1 Metro San Alberto Hurtado**

4. Travel time variability: modal differences

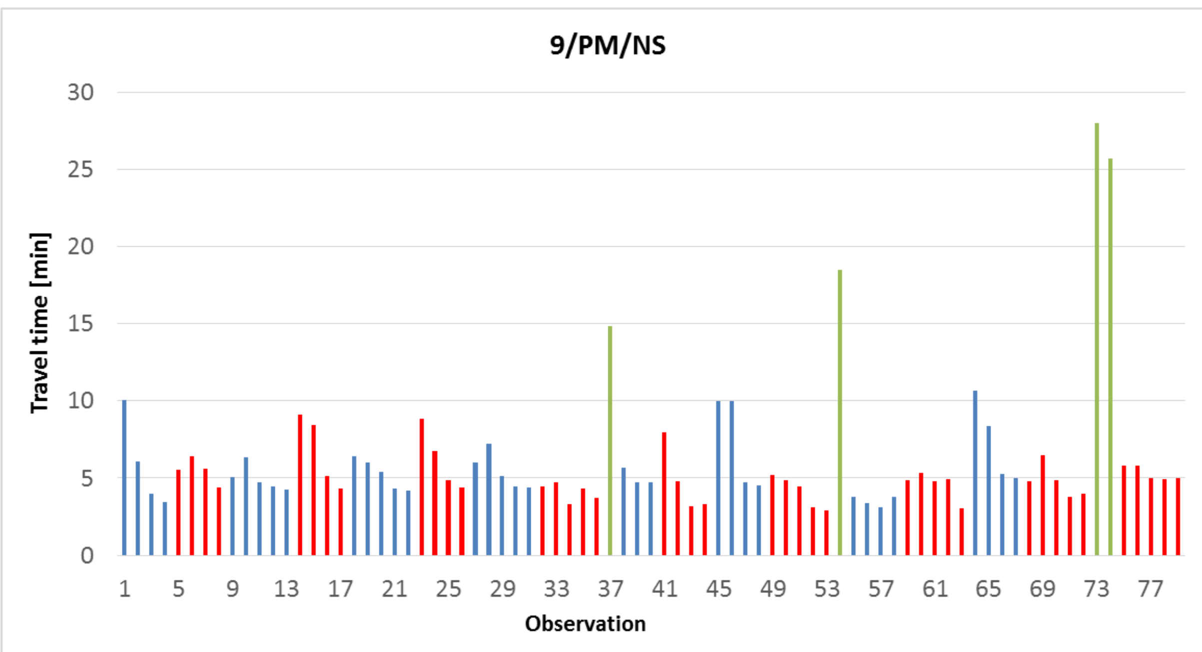
4.1 The identification of incidents

Traffic congestion as a source of travel time variability should be analysed by distinguishing recurrent congestion (e.g., the day-to-day increase in traffic in the morning peak in working days) and non-recurrent congestion, caused by incidents like accidents, extreme weather and others that may cause very long travel times, which are of rare occurrence (Tu, 2008). The infrequent existence of very long travel times make the travel time distribution to be usually skewed (van Lint *et al.*, 2008).

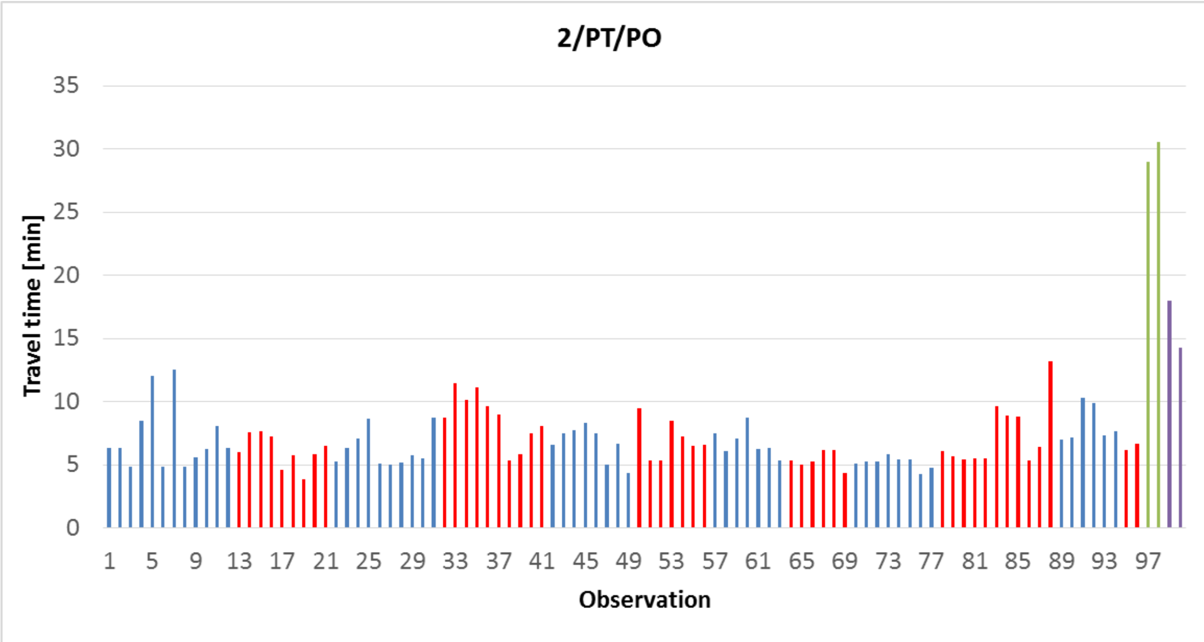
The influence of incidents is discernible in our data. Figure 4 shows the travel time observations of three different car trips. Figure 4.a depicts travel time in route 10 for 113 observations of morning peak trips (8:00-9:00), where sets of bars (either red or blue) represent observations on the same day. In Figure 4.a, there are no clear outsiders and all randomness seems to stem from recurrent congestion. On the other hand, Figure 4.b shows the travel time observations for route 9 in the morning peak period; four observations (green bars) stand out well above the others. These are trips likely taking place during an incident that enlarged travel time in a way that can hardly be explained by recurrent congestion. Three incidents seem to have occurred but four trips are affected. The identification of incidents is made using a test for outliers (a value around three standard deviations from the mean is candidate to be an outlier).



(a) Travel time Route 10, morning peak



(b) Travel time Route 9, morning peak



(c) Travel time Route 2, afternoon peak

Figure 4: Travel time variability, cases with and without incidents

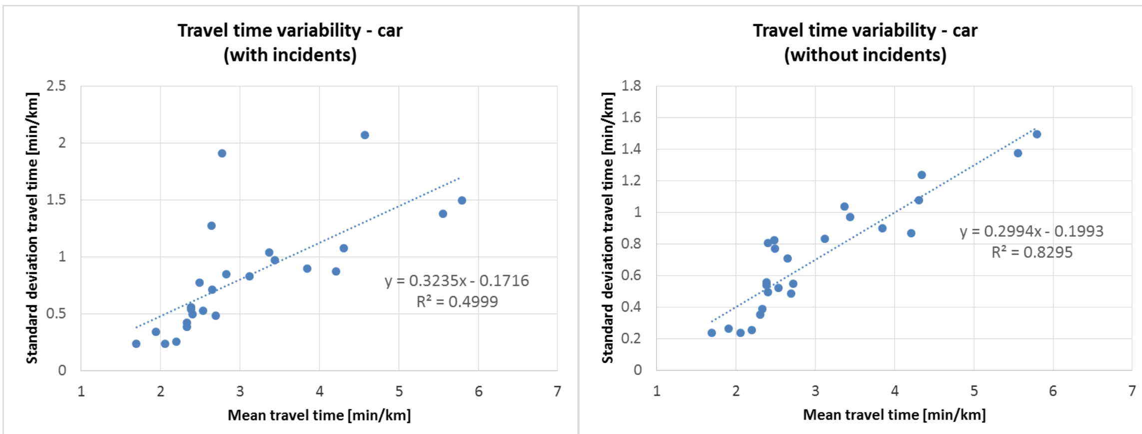
Finally, Figure 4.c shows another interesting case, in which two observations are identified as outliers (green bars), however, by looking at the two trips that follow (purple bars), it seems that the travel time of both trips is also larger than usual, owing to an incident that happened before (green bars) that had negative effects in the following minutes. Then, even though the purple bars might not be statistical outliers, they are considered as incidents as well. All in all, from a total of 2,616 car travel time observations from 25 routes, only 13 trips were detected as outliers, an another 4 were assumed as incidents as well, two of which are seen in Figure 4.c. Then, the total number of trips affected by incidents, detected with this procedure, is 17, that is 0.6% of the total. The effect of including or removing incidents on the characterisation of travel time variability is analysed in the next section.

4.2 Travel time variability of different modes and stages of a public transport trip

4.2.1 Car travel time

First, we analyse car trips. Figure 5 depicts the relationship between the mean and standard deviation of travel time in minutes per kilometre. The effect of incidents is illustrated when comparing both plots: incidents increase the variability of a few observations as shown in Figure 5.a. Removing incidents (0.6% of observations) produces the plot of Figure 5.b. Both scatterplots can be regressed with linear relationships. Interestingly, removing incidents has a great impact on the goodness-of-fit of the relationships found, but not on the slope of the linear relationship which reduces from

0.32 to 0.30 when removing incidents. Therefore, our data suggest that an increase of 1 minute per kilometre in mean travel time, in average is associated with an increase between 18 and 19 seconds, which is the same result found in Sydney by Tirachini *et al.* (2014), with a regression using data from 423 roads (slope equal to 0.32). A linear relationship between SD and mean travel times is a very simple way to apply a mean-variance model using only estimations of mean travel time, provided that the reliability ratio (ratio between the parameter of the mean travel time and the parameter of the SD of travel time) is also known. The evidence of Sydney and Santiago points to a slope of 0.3 for the relationship SD-mean when the unit is min/km; data from other cities would be necessary to assess the generalizability of this result.



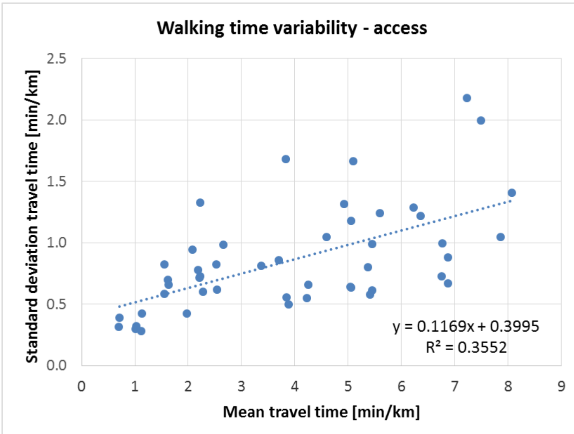
(a) All data **(b) Removing incidents**

Figure 5: Relationship between SD and mean travel time, cars

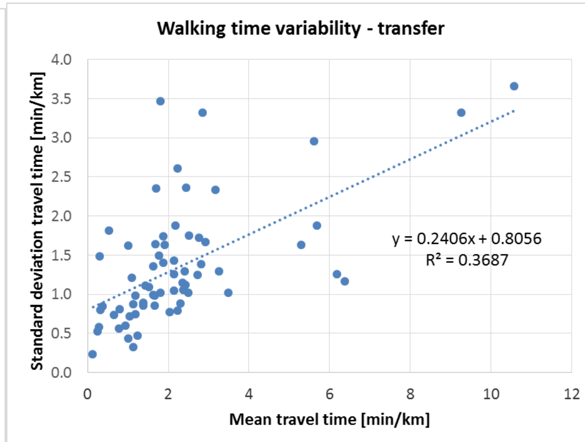
Moving to public transport, we characterise time variability for each stage in the next sections.

4.2.2 Walking time (access and transfers)

The characterisation of walking time variability is missing in previous studies on public transport reliability, even though walking is the predominant way to access bus stops and train stations in cities, and to transfer between vehicles in trips with more than one motorized stage. In our dataset, surveyors were required to walk from a given corner to a specific bus stop or metro station, and record their walking time over several days. The relationship between the mean and variability of time is depicted in Figure 6.a, where a positive but heteroscedastic relationship is distinguished, exposing evidence that for walking, in average, travel time variability seems to increase with travel distance. The tendency is less clear when analysing walking time variability when transferring between vehicles, as there are high variability points for both short and long average walking times (Figure 6.b). Going beyond average travel time to analyse system variables that influence walking time variability (e.g., number of signalised and priority intersections) is a direction of further research.



(a) Walking to access

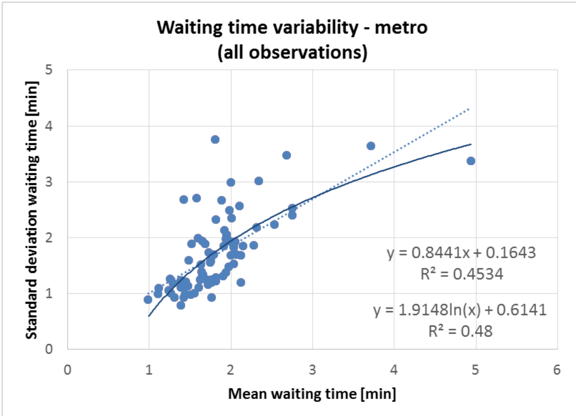


(b) Walking at transfer

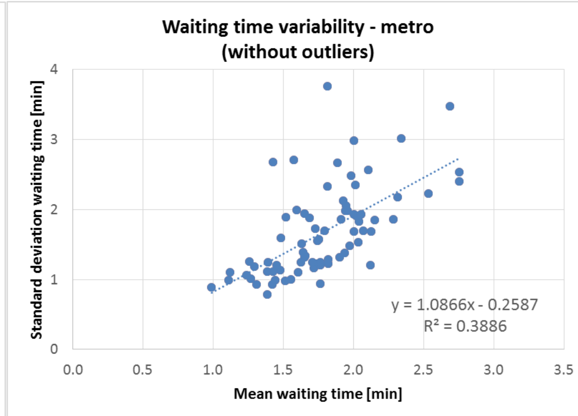
Figure 6: Relationship between SD and mean walking time

4.2.3 Waiting time

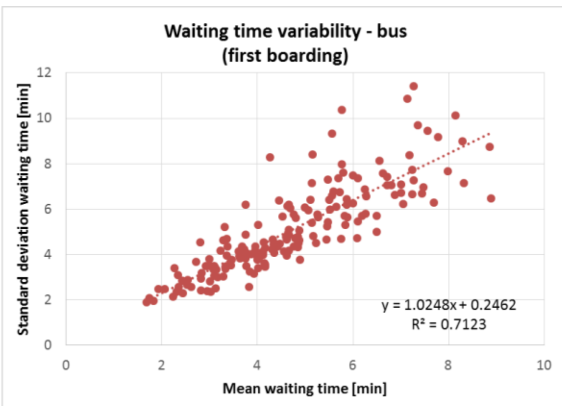
Several authors analyse the stability of bus headways (e.g., Strathman *et al.*, 1999; Chen *et al.*, 2009; Byon *et al.*, 2011) since it has been shown that headway variability increases mean waiting times (Osuna and Newell, 1972), and therefore, strategies like bus holding are studied and implemented in both frequency- and schedule- based services, in order to maintain intervals as even as possible. Even though the link between headway variability and mean travel time has long been established, the extension to understanding waiting time variability has not received attention in the literature, chiefly because while bus headways are easy to record with automatic vehicle location devices (e.g., GPS devises), obtaining repeated observations of actual waiting times for several routes over several days, is a more cumbersome task that usually requires field observation and/or video recording and processing. We are able to characterise day-to-day variation in waiting times thanks to the repeated surveys made to estimate travel times of different trips by public transport in Santiago.



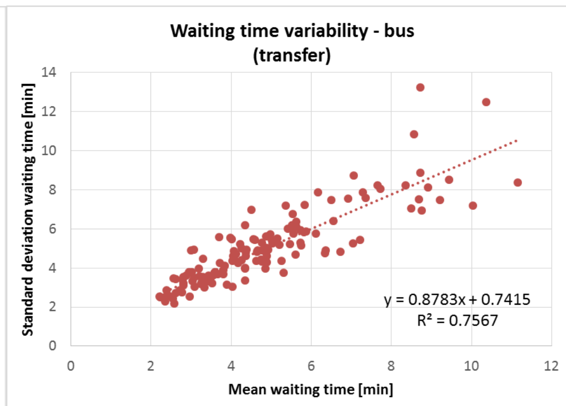
(a) Metro, all observations



(b) Metro, mean below 3 minutes



(c) Buses



(d) waiting at transfer

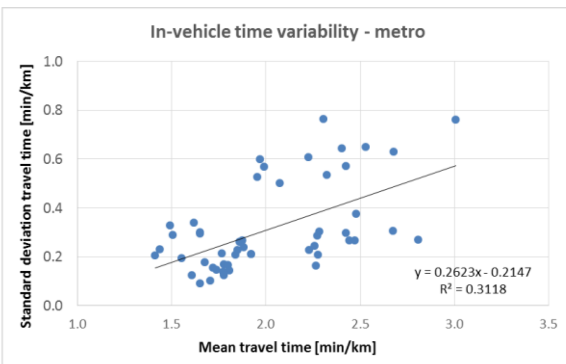
Figure 7: Relationship between SD and mean waiting time, bus and metro

For the Metro trips surveyed, most mean waiting times are below 3 minutes (75 out of 77 metro trip stages). When analysing all observations, Figure 7.a shows that the standard deviation of waiting time is increasing for trips whose mean waiting time is below 3 minutes, while for the two observations of mean waiting time over 3 minutes, SD is stable at around 3.5 minutes. This may point towards a concave relationship between mean and SD of waiting times (like the logarithmic regression in Figure 7.a), but the fact that there are too few observations with mean waiting times over 3 minutes, prevents us to conclude such result with certainty. On the other hand, by focusing on the 75 cases with mean waiting time bellow 3 minutes, Figure 7.b is obtained, in which a slope of 1.09 is obtained for the linear relationship between the mean and the SD of waiting times, value that is similar to the slope 1.02 obtained for buses (Figure 7.c). Finally, Figure 7.d presents the analysis of waiting time variability when transferring between buses, or between bus and metro. A fairly linear relationship is also found, with a slope slightly lower than the case of waiting time at first boarding (0.88 vs 1.02-1.08). Give that transfers between vehicles in Santiago are not coordinated, it is not expected to observe significant different between both regressions (Figures 7.c and 7.d).

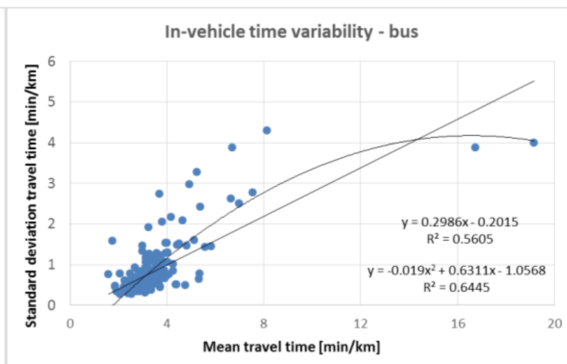
4.2.4 In-vehicle time, bus and metro

Finally, we study the travel time variability for in-vehicle time in public transport trips. As for the case of cars, we normalise travel times by distance (min/km), in order to grasp the relationship between travel time and congestion.

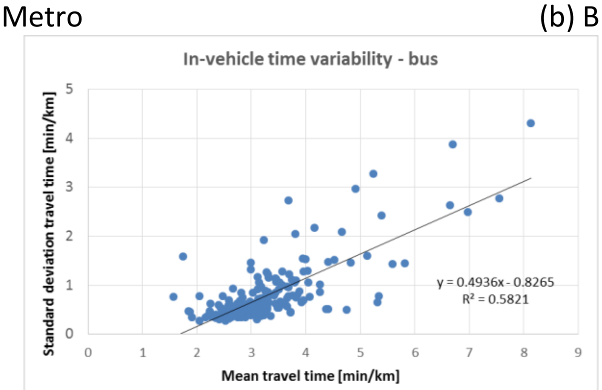
Figure 8.a depicts the standard deviation of travel time by metro. The data supports a positive relationship between mean and SD of travel time, although data shows high dispersion, meaning that travel time variability is weakly related to mean travel time, in apparent opposition to the relationships found in the other two modes according to Figures 5 and 8.c. However, it must be noted that mean in-vehicle time by metro is between 1.4 and 3.0 min/km in Figure 8.a, much lower than the range found for cars (between 1.6 and 6.0 min/km in Figure 5) and buses (between 1.5 and 8.2 in Figure 8.c). Therefore, in order to make a proper comparison, it would be useful to reduce the analysis of cars and buses to the range of speed at which metro operates, which is over 20 km/h (less than 3 min/km in Figure 8), as done later in this section.



(a) Metro



(b) Bus



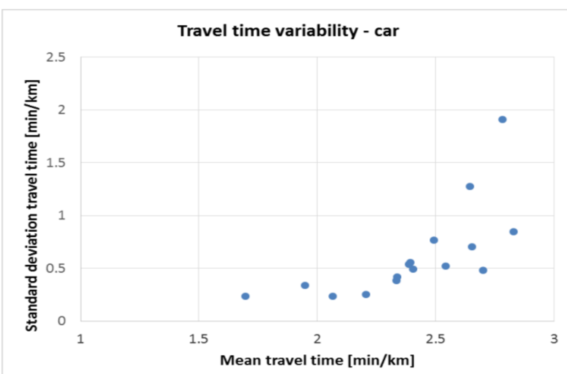
(c) Bus, mean bellow 9 min/km

Figure 8: Relationship between SD and mean in-vehicle time, bus and metro

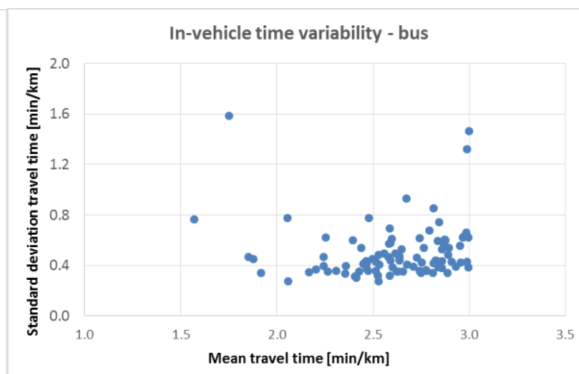
The bus travel time plot (Figure 8.b) shows some interesting issues. First, 207 out of 209 trip stages have a mean travel time lower than 8.2 min/km (commercial speed larger than

7.4 km/h), and only 28 trip stages (13%) have a mean travel time larger than 4 km/min (speed lower than 15 km/h). There is a positive relationship between SD and mean travel time in Figure 5.b, than tends to stabilise if the cases with extreme congestion in Figure 5.b are included (speed lower than 4 km/h). Removing the two cases of extreme congestion, we obtain Figure 8.c, in which a linear relationship has a stronger support.

Finally, we analyse fast trips in cars and buses, in order to observe the nature of TTV at speeds comparable to that of metro (Figure 8.a). Figure 9 shows the relationship between SD and mean travel time, for trips whose mean travel time is lower than 3 min/km by car and bus. In the case of cars (Figure 9.a), the few observations remaining still support a positive relationship between mean and SD of travel time, whereas for buses no relationship is clearly identifiable. All in all, we can conclude that in a large middle range of bus commercial speed -roughly between 8 and 20 km/h- an increase on average (commercial) speed will very likely induce a reduction of travel time variability, however it is not clear the implications on TTV of changes in average speed for speeds over (low demand and low congestion) or bellow (extreme congestion) that range.



(a) car



(b) bus

Figure 9: Relationship between SD and mean in-vehicle time, car and bus, mean travel time below 3 min/km.

5. Travel time variability: door-to-door trips by public transport

The previous analysis was performed for each trip stage independently, with the aim of observing differences on travel time variability for walking, waiting and in-vehicle times. Because we have repeated observations of door-to-door trips, we can go beyond that, to identify which trip stages, and to what extent, are statistically significant in explaining total travel time variability, which includes different stages and modes of transport. In this section, we estimate a regression model for the standard deviation and the variance of total travel time, as a function of the mean access, waiting, transfer and in-vehicle times per mode, as shown in equations 1 and 2 next:

$$\sigma = b_0 + b_1 t_{walk-access} + b_2 t_{wait-bus} + b_3 t_{wait-metro} + b_4 t_{veh-bus} + b_5 t_{veh-metro} + b_6 t_{walk-trans} \tag{1}$$

$$\sigma^2 = c_0 + c_1 t_{walk-access} + c_2 t_{wait-bus} + c_3 t_{wait-metro} + c_4 t_{veh-bus} + c_5 t_{veh-metro} + c_6 t_{walk-trans} \tag{2}$$

Table 5 shows the model estimation results for the standard deviation and variance models, obtained with the statistical package SPSS. Not all trips stages turn out to be statistically significant to explain total travel time variability. Only bus waiting time and bus in-vehicle time are significant (99% confidence level), whereas average walking and metro waiting and in-vehicle times are not significant. In Model 1, one extra minute of bus waiting time and in-vehicle time is roughly related to 30 seconds and 6 seconds increase on the standard deviation of total travel time, respectively. Therefore, we conclude that bus waiting time is the single strongest source of travel time variability, followed by bus in-vehicle time. The variability of walking and metro travel times is low enough not to produce a statistically significant effect on total travel time variability. This result points out at the fact that efforts to decrease travel time variability by public transport should be targeted at reducing mean waiting and running times by bus. Therefore, increasing bus frequency (not to the point to induce bunching) and introducing segregated busways and bus lanes are among policies that are expected to reduce total travel time variability.

Variable	Model 1: Standard deviation			Model 2: Variance		
	Parameter	t-ratio	p-value	Parameter	t-ratio	p-value
Constant	2.706	3.556	.001	-27.412	-1.765	.083
Average walking time (access)	.027	.330	.743	.300	.178	.859
Average bus waiting time	.524	**7.235**	**.000**	9.147	**6.188**	**.000**
Average metro waiting time	.855	1.472	.147	10.856	.916	.364
Average bus in-vehicle time	.090	**6.635**	**.000**	1.707	**6.186**	**.000**
Average metro in-vehicle time	.009	.188	.852	.231	.226	.822
Average walking time (transfer)	-.149	-1.286	.204	.220	.093	.926
Number of observations	62			62		
Adjusted R-square	0.666			0.659		

Table 5: Multivariate regression models

The fact that metro trip stages were not significant does not mean that metro waiting and in-vehicle time are not subject to variability, as shown in Figures 7 and 8. At least two factors can explain this conclusion; first, even though metro waiting and travel time are variable, the relationship between variability and mean waiting and in-vehicle times is not as strong as for buses (compare Figures 7.b and 7.c for waiting time, and Figures 8.a and 8.c for in-vehicle times), specially so for buses with commercial speed between 8 and 20 km/h. Second, the standard deviation of metro travel time is always lower than 0.8 min/km, whereas for buses is up to 4 min/km. Waiting times in metro are also lower and much less variable than that of buses.

6. Concluding remarks

In this article, we have studied the travel time variability of cars and public transport trips in the city of Santiago, Chile. Two databases are used for this purpose, one for cars trips obtained with the floating car method in different routes, and another one that account for door-to-door trips by bus and/or metro, performed over several days by surveyors.

The main results obtained are summarised next. It is found a clear and strong relationship between the standard deviation and mean times for car travel time, bus waiting and bus in-vehicle time, whilst walking time and waiting and travel time by metro are also subject to variability, but to a lesser extent than the other modes. Moreover, in the case of walking and metro in-vehicle time, the relationship between mean and standard deviation of travel time is not so clear. When analysing car travel time variability, a linear relationship between mean and SD of travel time has a slope between 0.30 and 0.32, equal to the result found in Sydney (Tirachini *et al*., 2014), i.e., an increase of 1 minute per kilometre in mean travel time, in average is associated with an increase between 18 and 19 seconds in standard deviation. Similar analyses from other cities should be performed to assess the generalizability of this finding.

Second, in door-to-door public transport trips, we obtained that total travel time variability is significantly explained by bus waiting and in-vehicle time, whilst walking and metro were not statistically significant. This has relevant policy implications on the interventions that should be preferred in order to reduce total travel time variability; such that increasing bus frequency and introducing bus priority measures (at least for bus commercial speeds in the range 8-20 km/h). The relationship between mean and variance of bus waiting time can be used to assess the value of reducing bus bunching, not only on reducing average waiting times, but also on decreasing its variability.

The fact that metro stages are not significant is mainly explained by the weak relationship between mean and variability of waiting and in-vehicle times by metro, and the fact that metro is generally more reliable than bus. It remains as a direction of further research to characterise metro travel time variability in a more precise way, beyond using mean values as explanatory variables. A detailed analysis of bus travel time variability for low and extreme congestion should also be introduced.

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APPENDIX A: Chi-square and Kolmogorov-Smirnov tests

The test of goodness of fit are statistical tests used to determine if observed data do or do not fit with any theoretical probability distribution, that is, whether there are statistically significant differences between the observed distribution (F_o) and the expected distribution (F_e). The statistical hypotheses that arise are:

H_0: Data analyzed follow a distribution M (null hypothesis)

$$F_o = F_e$$

H_1: Data analyzed do not follow a distribution M

$F_o \neq F_e$

In the case of the Kolmogorov-Smirnov test, the statistic D considers the deviation between the probability distribution function of the sample F_o, and the theoretical probability function F_e chosen, for a sample of size n.

$$D = \max_{1 \le i \le n} \left| \widehat{F_o}(x_i) - F_e(x_i) \right|$$

If the observed values $\widehat{F_o}(x)$ are similar to those expected $F_e(x)$, the value of D is going to be small. The greater the discrepancy between the two distributions, the greater the value of D. The decision may also be made by using the p-value associated with statistic D. The p-value is defined as:

$$p - value = P(D > D_{obs} \ / \ H_0 \ is \ true)$$

If the p-value is large, it means that if the null hypothesis is true, the observed value of the statistic D was expected. Therefore, there is no reason to reject this hypothesis. However, a small p-value implies that if the null hypothesis is true, it is very difficult for the value of D that has been observed to occur. In other words, the null hypothesis should be rejected. Thus, for a significance level α, the rule decision is:

If p-value $\geq \alpha \Rightarrow$ Do not reject H_0

If p-value $< \ \alpha \Rightarrow$ Reject H_0

In the case of Chi Square test, given a random sample of size n from a population with a specified distribution $f_o(x)$, and assuming that the sample observations are grouped into k classes, being o_i the number of observations in each class $i = 1,2,\ldots,k$, with the specified model $f_0(x)$ we can calculate the probability p_i that any data belongs to a class i, and the expected frequency e_i for class i, ie the amount of data that should be included in the class i by the specified model:

$$e_i = p_i\, n \qquad i = 1, 2, \ldots, k$$

Then, we have two frequency values for each class i: o_i is the observed frequency and e_i is the expected frequency. Given this, the χ^2 statistic is appropriate to test goodness of fit and thus evaluate the discrepancy between the two frequencies:

$$\chi^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i}$$

with $v = k - r - 1$ degrees of freedom, where r is the number of parameters of the distribution to be estimated from the sample. It is noteworthy that a necessary condition to apply this test is $e_i \geq 5\ \forall i$.

Given a significance level α, is defined a critical value χ^2_α for rejection of the proposed hypothesis $Ho\colon f(x) = f_0(x)$. The criteria for making the decision between the two hypotheses is:

If $\chi^2 \leq \chi^2_\alpha \Rightarrow$ Do not reject H_0

If $\chi^2 > \chi^2_\alpha \Rightarrow$ Reject H_0

Equivalently, if the p-value is less than α, H_0 should also be rejected.