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Impacts of an Urban Toll on Pollution and Road Accidents: evidence from São Paulo

Impactos do pedágio urbano sobre poluição e acidentes de trânsito: evidências de São Paulo

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Dissertação apresentada ao Programa de Pós-Graduação em Economia do Departamento de Economia da Faculdade de Economia, Administração e Contabilidade da Universidade de São Paulo, como requisito parcial para a obtenção do título de Mestre em Ciências.

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Abstract

In this paper, we investigate the effects of an urban toll on road accidents and pollution in São Paulo. Using the Origin and Destination (OD) database for 2017, we employ a Nested Logit model to estimate transportation demand in São Paulo. Our goal is to analyze the changes in demand resulting from the imposition an urban toll of R$ 0.47 per traveled kilometer in São Paulo Expanded Center. Additionally, we explore the impact of the toll on Consumer Surplus, as well as on pollution and accident externalities. Our findings reveal that the urban toll per traveled kilometer can significantly reduce the number of individuals opting for car mode, decreasing its share from 33.1% to 23.9%. This reduction in car usage enables us to estimate the total pollution that can be avoided by considering the vehicle emission factors. Finally, utilizing the social cost of pollution and accidents, we calculate that the implementation of the urban toll could lead to a social gain of R$ 153 million annually.

Key words: Car Externalities; Travel Mode demand

JEL Classification: D12, D62, L90, Q48, Q58.

Resumo

Nesse trabalho investigamos os efeitos de um pedágio urbano sobre poluição e acidentes de trânsito em São Paulo. Utilizando dados da Pesquisa Origem e Destino 2017, empregamos um modelo de escolha discreta, em particular um logit aninhado, para estimar a demanda por meio de transporte em São Paulo. Nosso objetivo é analisar a mudança na demanda decorrente da imposição de um pedágio urbano no valor de R$ 0,47 por quilômetro rodado dentro do Centro Expandido. No mais, analisamos o impacto do pedágio sobre o Excedente do Consumidor, bem como seus efeitos na redução de poluição e acidentes. Nossos resultados revelam que a adoção do pedágio urbano por quilômetro rodado é capaz de reduzir substancialmente o número de indivíduos escolhendo carro como meio de transporte, de 33,1% para 23,9% no nosso modelo. Essa redução no uso do carro possibilita o cálculo da emissão de poluentes evitada pela política, fazendo uso dos fatores de emissão veicular proporcionados pela CETESB. Por fim, utilizamos o custo social da poluição e de acidentes de trânsito e concluímos que a implementação do pedágio urbano pode gerar um ganho de bem estar social de R$ 153 milhões por ano.

Palavras-chave: Externalidades dos automóveis, Modelo de Escolha de Transporte

Códigos JEL: D12, D62, L90, Q48, Q58.

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1 Introduction

Car externalities are a well-known phenomenon present in the day to day life. Despite road congestion – an almost everyday experience for São Paulo residents – car usage is mainly responsible for road accidents and pollutant emissions. In spite of this, it is still the second most used mean of transportation in São Paulo Metropolitan Region (SPMR). In 2021, 43,087 accidents took place in São Paulo, with 720 being fatal[1]. Regarding congestion externalities, studies show that 89% of São Paulo work trips are delayed by traffic frictions. Also, car usage is the main responsible of local pollutant emissions in Sâo Paulo (Andrade et al. (2012)) and one of the main responsible for greenhouse gases emissions[2]. Most of these externalities can be reduced by curbing vehicle miles traveled (Parry et al. (2007), Parry (2002)).

São Paulo's government and population have a history of prioritizing car usage in the last decades. From 1967 to 1997, the SPMR population multiplied by 2.5, whereas the motorized vehicle fleet was multiplied by six (Vasconcellos (2005)). More recently, from 2007 to 2017, SPMR's population grew by 6%, while motorized travel increased by 12.4%. The straightforward consequence of increasing the number of cars was the growth in congestion. In order to reduce road congestion during peak hours, São Paulo's government enacted Municipal Law 12,490 in 1997, which limits car circulation by imposing a license plate-based vehicle restriction scheme, in which some vehicles are forbidden to circulate on certain weekday hours. Soon after imposing this system, congestion decayed by 18% in the Expanded Center, CO levels were reduced by 12%, and weekly CO_2 emissions decreased by 17 tons (Hook & Ferreira (2004), Câmara & Macedo (2004)). However, in the following years, congestion began to rise again, mainly to due car fleet growth.[3]

[1]Available in: https://g1.globo.com/sp/sao-paulo/noticia/2022/01/21/numero-de-acidentes-de-transito-aumenta-12percent-em-sp-em-2021-aponta-levantamento-do-infosiga.ghtml

[2]Available in www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-dataSector

[3]While the city experienced an 18% population growth in the last 20 years, fleet size grew 78% in the last 15 years. According to IBGE, São Paulo had a population of 10.4 million in 2000 and 12.4 million in 2022. Its vehicle fleet, on the other hand, grew from 5 million in 2006 to 8.9 million in 2021.

It is documented that the license-plate restriction system encourages wealthy individuals to buy second cars with different license plate numbers in order to escape the restrictions (Lucinda et al. (2017)). International evidence also points to the direction that despite having short-term effects on pollution and congestion, driving restrictions are not effective in the long run due to second car purchasing (Davis (2008), Gallego et al. (2013)).[4]

In this matter, an efficient way to discourage car usage to reduce congestion and externalities caused by pollution and accidents is still an open question to policymakers. Despite the attempt to achieve these results with the imposition of a license-plate restriction system, the economic theory generally prescribes the imposition of a Pigouvian tax, which is often capable to internalize the social costs imposed by car usage and price these negative externalities properly.

In this paper, we follow the approach developed in classical works such as McFadden (1974) and Ben-Akiva et al. (1985) to study the effects of the application of an urban toll in São Paulo on road accidents and pollution. We carry out a nested logit model in order to estimate the transportation demand in São Paulo, making use of the Origin and Destination (OD) database for the year 2017. Once the discrete choice model is estimated, we investigate the changes in demand of applying an urban toll of R$ 0.47 per traveled kilometer in Expanded Center, analyzing its impact on Consumer Surplus, as well as pollution and accident externalities.

Our results indicate that the imposition of the urban toll per traveled kilometer is capable to reduce the share of individuals choosing car mode from 33.1% to 23.9% in our model. With this reduction in car usage, we can estimate the total pollution averted based on the vehicle emission factors calculated in CETESB (2017). Finally, based on estimations of the social cost of pollution and accidents presented in Parry et al. (2013) we calculate that the imposition of the urban toll results in a social gain of R$ 153 million annually.

[4] Some studies find that driving restrictions policies may be effective at reducing externalities in Chinese cities (Sun et al. (2022)) and in Quito (Carrillo et al. (2016)).

When studying pollution emissions, one can separate them into two parts: global and local pollution. Global pollution regards mainly greenhouse gases (GHG) emissions. The most famous pollutant in this designation is carbon dioxide (CO_2), although many others are also considered such as methane (CH_4), ozone (O_3), and nitrous oxide (N_20). These pollutants cause damage on earth regardless of the point of emission, hence the assignment to global pollutants. Once these pollutants are emitted, about 40% remain in the atmosphere for centuries and the rest are stored on the surface, with 30% being absorbed by the ocean, causing ocean acidification (IPCC (2014)).

Local pollution usually relates to pollutant emissions that rest in local areas, not reaching the atmosphere. For that matter, they tend to disappear within weeks. These local pollutants do not include CO_2 and other GHG described above. The main pollutants responsible for local pollution are nitrogen oxides (NO_x), hydrocarbons (HC), carbon monoxide (CO) and particular matter ($PM_{2.5}$). $PM_{2.5}$ are solid particles or liquid particles emitted directly mainly by transportation exhausts and coal power plants or formed in the atmosphere by the reaction of SO_2 and NO_x. The latter is usually produced from the reaction of nitrogen and oxygen during the combustion of fuels, responsible for forming smog and acid rain. Local pollutants are also associated with a rise in health risks, HC and NO_x react in the presence of sunlight to produce ozone, responsible for pulmonary diseases (Parry et al. (2007)) and $PM_{2.5}$ exposure may increase blood pressure, lung cancer, and heart diseases (Humbert et al. (2011), Burnett et al. (2014)).

Road accidents impose substantial costs on society related to fatal or non-fatal injuries, property damage, travel delays, and loss of productivity. Estimations from accident costs indicate that cost related to fatalities accounts for one-third of total costs and costs related to non-fatalities, property damage and other externalities account for two-thirds (Parry et al. (2007)). In order to curb road accidents, Parry (2004) shows that the differentiated mileage tax policies are better at improving social welfare, when compared to uniform mileage tax policy or a gasoline tax policy.

Urban tolls are not only a theoretical policy designed to reduce externalities, but they were implemented in many cities around the world showing effective potential to suppress car externalities. Singapore was the first city to implement an urban toll scheme in 1975 and is unique in its long experience with road pricing policies. Studies show that Singapore's tax was able to drop congestion by 31% in 1988 (Keong (2002)). In London, the congestion charge scheme was first introduced in 2003, covering part of the central business district with a flat weekday fee of £ 5.[5] Soon after the tax imposition, the number of vehicles entering the charging zone decayed by 18%. Local pollutants emissions such as NO_x and PM_{10} fell by 13.4% and 7%, respectively, and CO_2 levels fell 15% (Bhatt et al. (2008)). Long-time effects on pollution reduction can be confounded by the arrival of new non-pollutant car technologies, although many studies show the link between the imposition of the congestion charge and pollution decrease (Green et al. (2020), Ding et al. (2022), Keivabu & Rüttenauer (2022))[6]. There is also work that investigates the relationship between the London congestion charge and traffic accidents, pointing to the direction that the policy influences a substantial reduction in both the number of accidents and the accident rate (Li et al. (2012), Green et al. (2016)).

Our work relates to ex-ante analysis of a policy applying a discrete choice model methodology as in Lucinda et al. (2017), Durrmeyer & Martinez (2022) and Lucinda et al. (2019). We propose the application of an urban toll per kilometer as an optimal tax to curb externalities and improve welfare (Pigou (1920), Vickrey (1963), Walters (1961), Parry (2002)). Moreover, we contribute to the literature on the distributional effects of the urban toll, assessing the welfare impacts per decile, as in Lucinda et al. (2019). Lastly, we attempt to calculate the reduction in externalities derived from the policy, in particular in the form of local pollution, global pollution and accidents, as in Parry et al. (2013), Currie & Walker (2011), Atkinson et al. (2009).

[5] The pricing area has grown over the last years, as well as the driving fee, which reached £ 15 in June 2020.

[6] Although, not all studies point to a uniform reduction in overall pollution since some of them found a link between congestion tax and a slight increase in some pollutants, due to substitution effect to diesel-powered transportation.

This paper is organized as follows: Chapter 2 describes the econometric model applied; Chapter 3 presents our dataset, some descriptive statistics and the data preparation for the econometric estimation; Chapter 4 estimates the transportation discrete choice model; Chapter 5 investigates the impacts of the imposition of the urban toll on travel demand, pollution and accidents externalities; and Chapter 6 provides some concluding remarks.

2 Methodology

The empirical analysis relies on the random utility framework seminally developed in McFadden et al. (1973). Random Utility Models (RUM) were designed to assess behavior responses, which were first applied in psychology (Thurstone (1927)). One of the main approaches to this framework concerns travel demand models, as in McFadden (1974) and Ben-Akiva et al. (1985).

The use of these models is based on the idea that the individuals' probability of choosing a given option is a function of their socioeconomic characteristics and the relative attractiveness of this option (Palma et al. (2011)). In the context of travel demand an individual i chooses a mean of transport j $\in$ J if the utility obtained by this choice is greater than the others available. The utility can be defined as

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

The first part, V_{ij}, is a function of observable characteristics that depend on unknown parameters to the researcher and can be estimated. In this analysis, $V_{ij} = \beta x_{ij}$, in which x_{ij} relates to individual characteristics, such as income, education, gender and age; and alternative characteristics, such as travel time and travel cost. The second part, ϵ_{ij}, represents the random component, reflecting the individuals' idiosyncratic tastes, unobservable from the researcher's perspective. It is defined depending on the context, with the purpose of better representing the choice structure.

From a probabilistic representation, the individual chooses j in a way that:

$$P(y = j) = P(U_j > U_k,\ \forall\ k\ \in\ J) \tag{2}$$

$$P(V_j + \epsilon_j > V_k + \epsilon_k,\ \forall\ k\ \in\ J) \tag{3}$$

$$P(\epsilon_k - \epsilon_j < V_j - V_k,\ \forall\ k\ \in\ J) \tag{4}$$

$$P(y = j) = \int_{\epsilon} I(\epsilon_j - \epsilon_k < V_j - V_k, \forall\ k\ \in\ J)\ f(\epsilon)\ d\epsilon \tag{5}$$

The class of discrete choice models depends on the specification of the probability density function $f(\epsilon)$, in a way that the integral defined above may have a closed form depending on the assumption of $f(.)$. The most common cumulative distribution function chosen is called the Gumbel or Extreme Type I distribution. This choice results in the Multinomial Logit Model.[7] In this work, the Nested Logit Model is applied, in such a way that $f(\epsilon)$ is considered as having the GEV - Generalized Extreme Value - cumulative distribution, defined as:

$$\exp(-\sum_{k}\sum_{j \in B_k} \exp(-\epsilon_{nj}/\lambda_k)^{\lambda_k}) \tag{6}$$

In which B_k represents the nests and λ_k is a measure of the degree of independence in unobserved utility between the alternatives in nest k. If $\lambda_k = 1$, the alternatives in nest B_k are independent and the model structure is simply a multinomial logit. Negative values of λ_k are not compatible with utility-maximizing behavior and imply that making a mode more attractive (e.g lowering the trip cost) has a negative effect on the probability that the mode is chosen. According to Train (2009) λ_k values above 1 implicates that the model is consistent utility-maximizing behavior for some range of the explanatory variables. Examples can be found in Lee (1999) and Train et al. (1987). If $\lambda \in (0, 1)$, the model is consistent with the utility-maximizing behavior.

[7]The Gumbel distribution has a cumulative distribution function defined as $f(\epsilon) = exp(exp(-\epsilon))$. The Multinomial Logit Model implies some hypotheses such as the Independence of Irrelevant Alternatives which postulates that the probability ratio between two alternatives depends only on the ratio of the observable characteristics of those two modes. In that way, other mode variables are irrelevant to define substitution patterns between two alternatives and a change in a variable from another option would alter probabilities proportionally.

The nested logit relaxes the independence from irrelevant alternatives (IIA) property exhibited in standard logit models, in a way the errors for individual $\epsilon_i = [\epsilon_1, ..., \epsilon_J]$ are correlated within nests. The goal of using the nested logit model in this context is to capture the correlation between alternatives, e.g. it is more likely for an individual to switch his travel choice from bus to subway than from bus to taxi.

Thus, the probability that an individual i chooses an alternative j in nest B_k has a closed form defined by:

$$P_{nj} = \frac{\exp(\beta x_{ij}/\lambda_k)(\sum_{i \in B_k} \exp(\beta x_{ij}/\lambda_k))^{\lambda_k - 1}}{\sum_{l=1}^{K}(\sum_{i \in B_l} \exp(\beta x_{ij}/\lambda_l))^{\lambda_l}} \tag{7}$$

Another way of interpreting the nested logit framework is to think of it as a sequential choice. An individual first chooses a nest B_k, given the characteristics W_k, and then an option j within this nest, given the characteristics Y_j. Given that, the nested logit can be written as a conditional probability in which the probability of the individual i choosing j is

$$P_{ij} = P_{ij|B_k} * P_{iB_k}, \tag{8}$$

where $P_{ij|B_k}$ is the probability of choosing option j given that the nest B_k was chosen and P_{iB_k} is the probability of choosing $Bk \in BK$.

Separating the nested probability into two parts is interesting because the marginal probabilities can be written as:

$$P_{iB_k} = \frac{\exp(W_{ik} + \lambda_k I_{ik})}{\sum_{l=1}^{K} \exp\left(W_{il} + \lambda_l I_{il)}\right.} \tag{9}$$

$$P_{ij|B_k} = \frac{\exp(Y_{ij}/\lambda_k)}{\sum_{n \in B_k} \exp\left(Y_{in}/\lambda_k\right)} \tag{10}$$

$$I_{in} = \ln(\sum_{n \in B_k} \exp(Y_{in}/\lambda_k)), \tag{11}$$

in such a way that the probability of choosing a nest B_k is given the characteristics, W_k and the utility obtained from that nest is given by $\lambda_k I_{ik}$. The term I_{ik} is called the inclusive value or inclusive utility and it is useful for the calculation of social welfare.

With the estimated coefficients such as travel time and travel cost, the Value of Time analysis becomes possible. The Value of Time reflects the extra money a person would be willing to incur to save one unit of time. In other words, it represents the Marginal Rate of Substitution between money and time:

$$VOT_i = \frac{dU_i/dT_i}{dU_i/dY_i} \tag{12}$$

Since the model estimation regards individual demand, welfare effects are defined in terms of consumer surplus. Under nested logit assumptions, the consumer surplus has a closed form, easy to assess. The consumer surplus, for every individual i is given by the greatest utility he can achieve given his alternatives divide by the marginal utility of income. In that sense, Consumer Surplus is $EC_i = \frac{1}{\alpha_i} max_j(U_{i,j} \ \ \forall j \in J)$. Since utility is not observable by the researcher, the expected consumer surplus can be defined as in Train (2009):

$$E(CS_i) = \frac{1}{\alpha_i} ln \sum_{j \in J} exp(V_{ij}) + C \tag{13}$$

The first term, $1/\alpha$, represents the inverse of the marginal utility of income. The second term is called log-sum measure. The integration constant C reflects the idea that the model cannot establish the absolute value of utility, therefore, the analysis proceeds to measure the welfare change. The derivation of the consumers' surplus formula yields from the assumptions of the stochastic utility components ϵ_j of logit models and the equivalence of Marshallian and Hicksian demands. The variation of consumer surplus, as defined in Small & Rosen (1981) can be written as:

$$\Delta(CS_i) = \frac{1}{\alpha_i}\left[ln\sum_{j\in J} exp(V_{ij})\right]_{V_{ij}^0}^{V_{ij}^1} \tag{14}$$

3 Data

Descriptive Statistics

The data used in this work comes from the Origin and Destination (OD) survey, performed by the São Paulo Subway Company. The OD 2017 survey has 183,092 observations, in which each observation accounts for a trip carried out on a specific day. The study area includes 39 municipalities in São Paulo Metropolitan Region, including São Paulo city itself. The researchers separate the study area into zones, adding up to 517 zones in the geographical scope. São Paulo city includes 342 of these zones and São Paulo's Expanded Center comprises 108 of them.

The researchers drew 116,000 households, of which 32,000 were valid to proceed with the survey. In these households, all residents were interviewed. The information required in the survey included individual attributes such as income, age, degree of education, gender, car ownership and trip characteristics such as geographic coordinates from the origin and the destiny, the mode of transportation, time demanded from the trip and the purpose of the trip.

In the survey, individuals had the option to choose between 16 modes of transport. Each individual is allowed to choose up to four different modes of each travel. The OD survey hierarchies these modes in order to form the variable "Main Mode". The way to arrange these modes consists in the following order of choice: (i) Subway, (ii) Rail, (iii) Bus, (iv) Hired Bus, (v) School Bus, (vi) Taxi, (vii) Car, (viii) Car Lift, (ix) Motorcycle, (x) Bicycle, (xi) Others and (xii) Walk. This means that if an individual report that he or she walked to a bus station, took the bus and then took the subway to get to work, the Main Mode registered would be Subway.

In Figure 1, we see the Main Mode frequency reported in the OD. It is clear that despite the mode Walk having the lowest preference in the order of choice, it is still the most frequent mode chosen. Following the Walk mode, we see that car travels still represent 25% of all travel made. Differences in the sums are due to rounding.

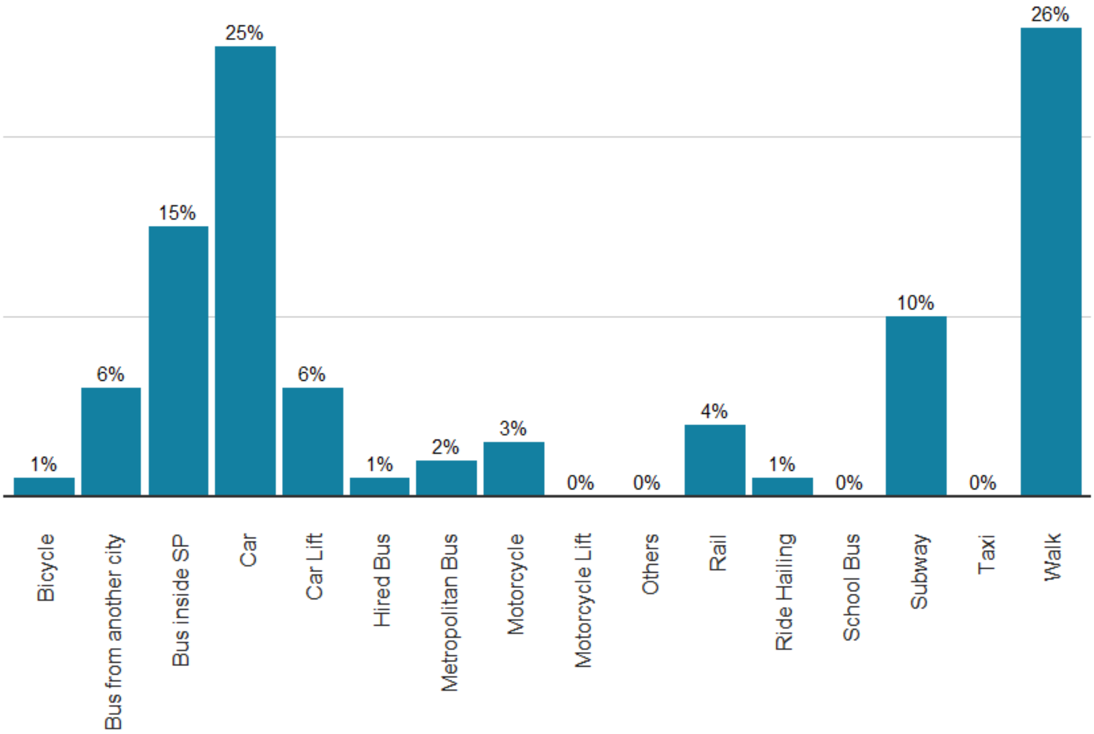

Figure 1 – Mode Frequency

For the purpose of simplification to estimate our discrete choice model, these modes were aggregated into six options, as follows:

- Subway: accounting for trips made by rail, monorail, and subway.
- Bus: accounting for trips made by all types of buses in the São Paulo Metropolitan Area.
- Car: accounting only for trips made by car.
- Motorcycle: accounting only for trips made by motorcycle.
- Taxi: accounting for trips made by conventional taxis or ride-hailing cars.

- Walk: accounting for trips made by walking, bicycle, car lifts, motorcycle lifts, and others.

The figure 2 below summarises the distribution of trips made between these modes:

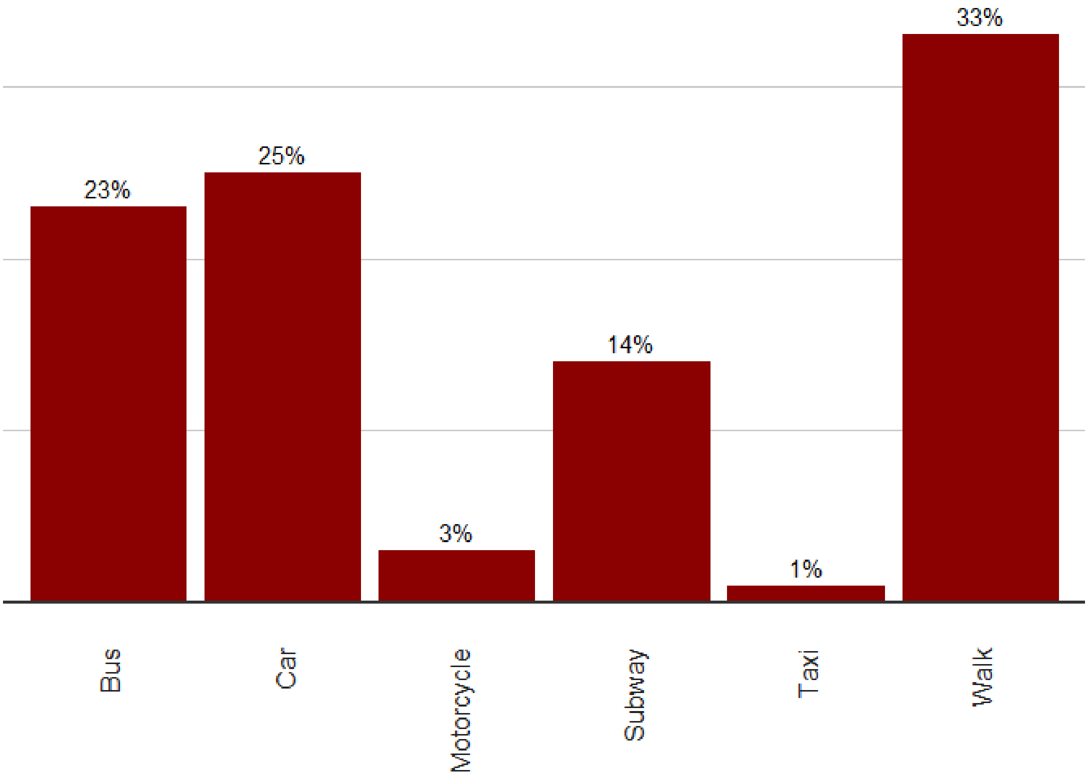

Figure 2 – Aggregated mode frequency

Car trips are the second most frequent mode of transportation, behind the Walk aggregated mode. Aside from being one of the main means of transportation, car usage is very present in the Expanded Center. Figure 3 shows the number of car destinations by district. It can be seen that most of the trips made by car are destined to São Paulo's Expanded Center [8].

[8] Appendix A displays São Paulo's Expanded Center districts.

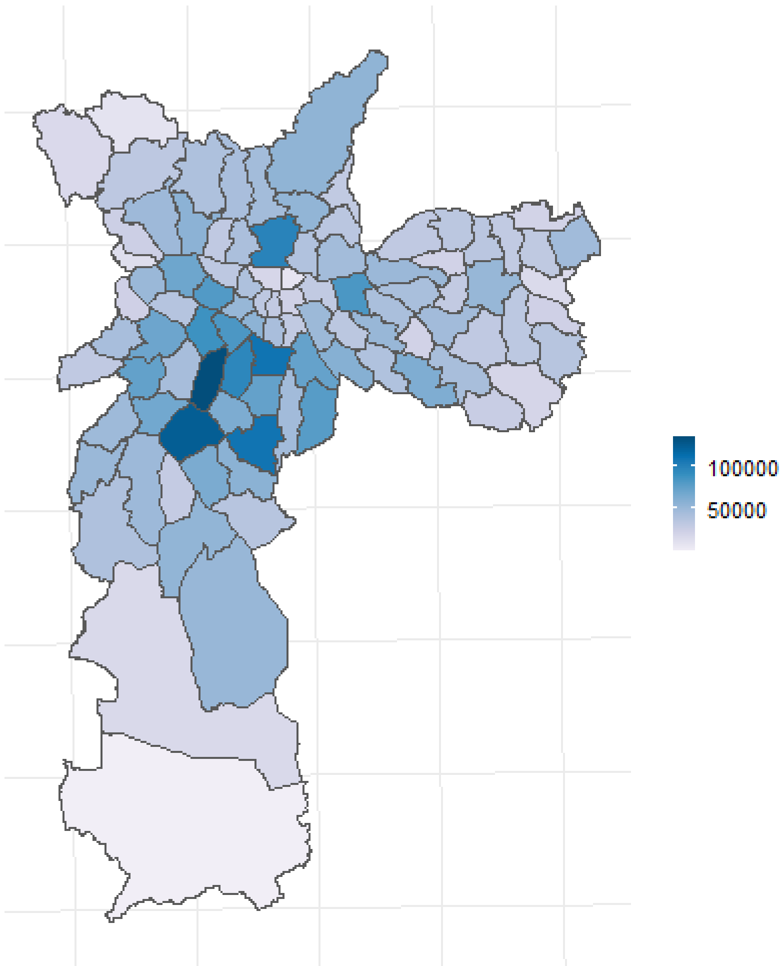

Figure 3 – Car trips by district

Table 1 shows the individual and trip characteristics associated with each mode choice. As it is shown, individuals who use the car to commute have a significantly higher income in comparison to other means of transportation, except for the mode Taxi. Not only do the individuals have a higher income at mean, but they also have higher levels of education. As expected for a car-centric city like São Paulo, the time spent commuting via car is lower than the time spent commuting via public transportation, for example Bus and Subway.

Table 1 – Trip Characteristics

Mode	Time (hours)	Distance (km)	Income	Education	Age	Trips (%)
Bus	0.91	6.93	R$ 3,995	3.66	42.23	23 %
Car	0.46	5.85	R$ 8,116	4.36	46.81	25 %
Motorcycle	0.40	7.86	R$ 5,121	3.92	36.67	3 %
Subway	1.24	13.65	R$ 5,206	4.08	40.03	14 %
Taxi	0.42	4.66	R$ 8,246	4.38	49.79	1 %
Walk	0.25	1.67	R$ 5,308	3.80	43.26	33 %

The wealthiest families live in the Expanded Center, commute mostly by car and have a lower trip time. Table 2 describes the trip and individual characteristics by income decile. The mean monthly income varies from R$1.303 – the first decile – to R$19.430 – the last decile. The percentage of people residing in the Expanded Center grows with the deciles, reaching 54% in the highest decile. We also see that in the first five deciles the most frequent mode is Walk, whereas in the last five deciles the most frequent mode is Car. Thus, the wealthiest families not only occupy the Expanded Center of São Paulo but also commute mostly by car.

Table 2 – Characteristics by Income Decile

Decile	Mean Income	% in EC	Trip time	Frequent Mode
1	R$ 1,303	9%	0.64	Walk
2	R$ 2,083	11%	0.66	Walk
3	R$ 2,644	15%	0.65	Walk
4	R$ 3,186	20%	0.63	Walk
5	R$ 3,800	20%	0.60	Walk
6	R$ 4,557	31%	0.57	Car
7	R$ 5,546	39%	0.53	Car
8	R$ 7,112	45%	0.50	Car
9	R$ 9,734	50%	0.49	Car
10	R$ 19,430	54%	0.45	Car

In that sense, São Paulo's Expanded Center, where there is higher accessibility to workplaces (Vieira & Haddad (2015), Pereira et al. (2022)), is populated by the richest individuals with a large amount of them commuting by car. Table 3 describes the individual and trip characteristics of those who reside in the

Expanded Center. According to the OD survey, 11% of the trips made in the São Paulo Metropolitan Area are carried out by those who live in the Expanded Center. Living in that area gives those individuals more access to public transportation since most of the subway lines are concentrated in the EC. Table 3 shows that almost 28% of individuals still choose to drive their car to commute daily. On the other hand, people still walk as their prevalent means of transportation, and these trips are characterized as having low distances, an average of 1.16 kilometers.

Table 3 – Trips Characteristics for those who live in Expanded Center

Mode	Time	Distance	Income	% of Trips
Bus	0.88	6.67	R$ 5,487	19.24 %
Car	0.46	5.26	R$ 10,480	21.05 %
Subway	1.03	10.95	R$ 5,948	26.56 %
Motorcycle	0.41	7.38	R$ 7,434	2.31 %
Taxi	0.41	4.08	R$ 9,084	2.87 %
Walk	0.22	1.37	R$ 7,554	27.97 %

Regarding pollution, the Expanded Center also concentrates higher levels of pollutant emissions in comparison to other areas of the city. In Figure 4 we can see the daily emission (in kilograms) of Particular Matter (PMs) by district area (in km^2) for the year 2015[9]. PM emissions are originated from combustion and the wear of tires, brakes, and tracks. As expected, in the Expanded Center – an area with a higher volume of car flow – we observe higher levels of PM emissions.

[9]Source: Inventário de Emissões Atmosféricas do Transporte Rodoviário de Passageiros no Município de São Paulo

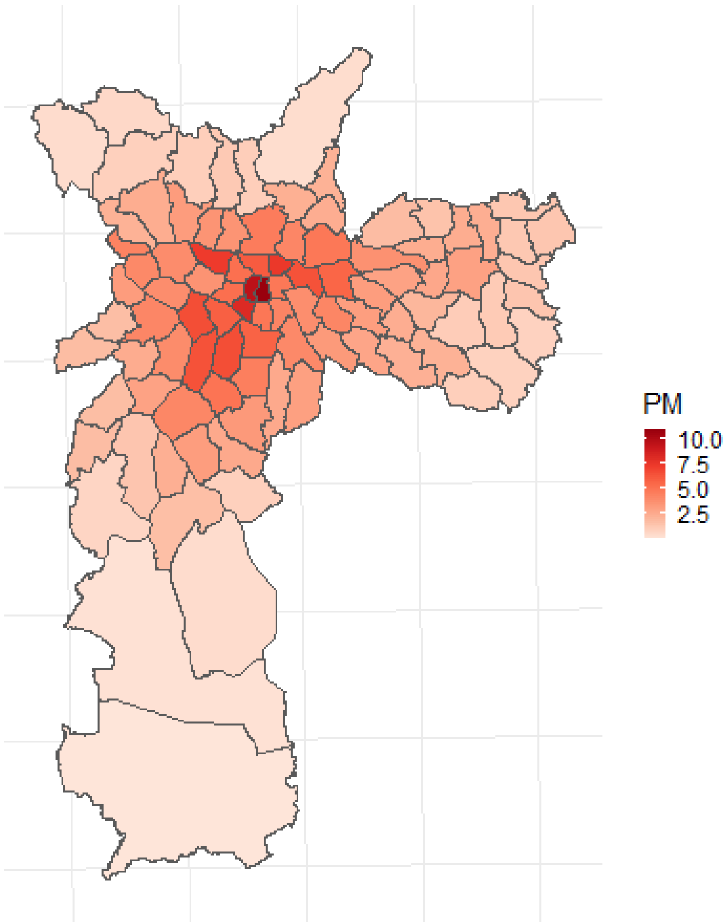

Figure 4 – Daily PM emissions (in kg/km^2) by district

As also presumed, higher car usage impacts road safety, not only for car users but also pedestrians and cyclists. Figure 5 summarises the number of road accidents divided by district area (in hectares) in 2022. It shows that accidents also tend to be concentrated in the Expanded Center – the region with the highest car flows – although not in such prominent levels as pollutant emissions.

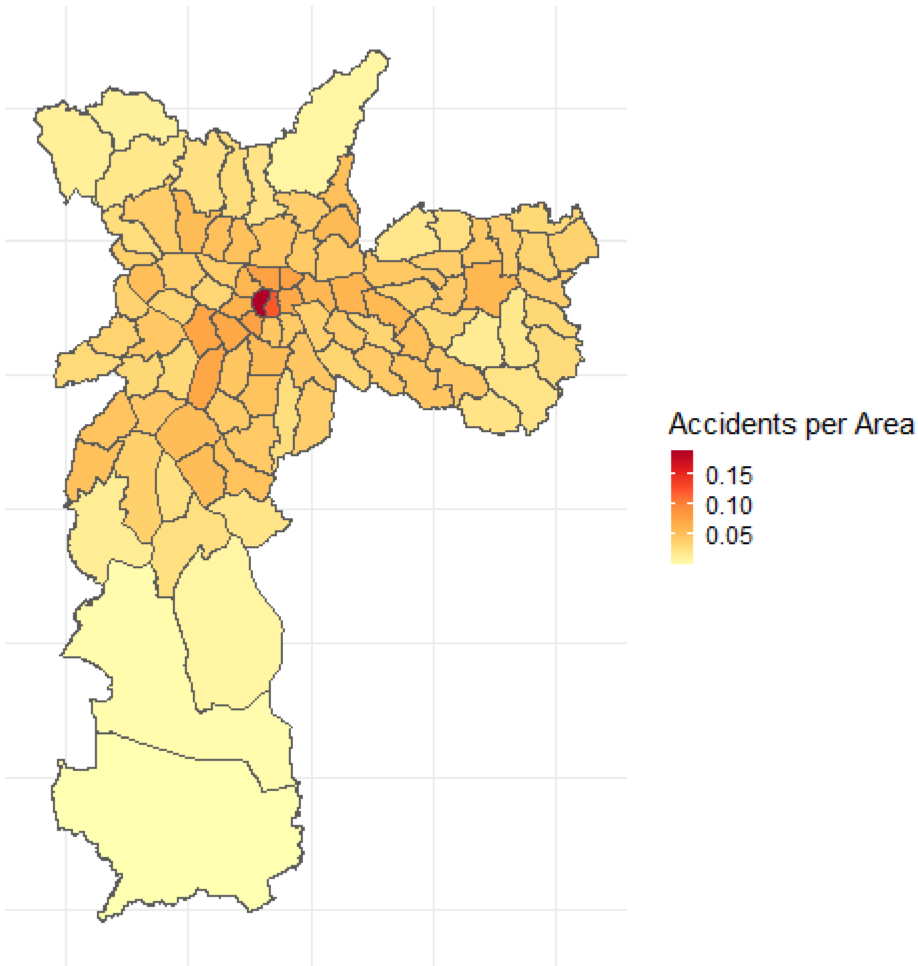

Figure 5 – Numbers of accidents divided by district area

Econometric preparation

To estimate the discrete choice model for travel demand, we have to adequate our database. The alternative-specific variables in our utility function are: (i) Cost; (ii) Time; (iii) Cost/Income; (iv) Time/Income[10]. The OD survey already has an income variable and a trip time variable (the researchers asked how many minutes did the trip take), however, they did not register how much the trip cost. To estimate our cost variable, we used strategies presented in the literature as in Lucinda et al. (2017) and Lucinda et al. (2019).

[10]For both the third and fourth variables, the Income variable was divided by a thousand.

Bus cost is set on the price charged by the São Paulo Transport Company (SP Trans) – R$4. When the trip involved an inter-city commute, a price was estimated for the ticket fare charged by the EMTU (São Paulo's Metropolitan Company for Urban Travel) – R$ 5.2, at the mean. When integration with the subway was needed, an additional R$3.20 – 70% of the original fare – was computed into its cost. We set the cost at zero when the individual alleged that his or her employer paid for the trip.

Subway cost is set on the price charged by the São Paulo Subway Company – R$4. When integration with the bus was needed, we also computed an additional R$3.20 – 70% of the original fare – into his cost. We set the cost at zero when the individual alleged that his or her employer paid for the trip.

Car cost is estimated as a function of the euclidean distance traveled (d), the mean fuel price (p), and the mean car autonomy (m_c). In that sense, car cost for an individual i is

$$C_i = \frac{d_i}{m_c} * p \tag{15}$$

Motorcycle cost is also estimated as a function of the euclidean distance traveled (d), the mean fuel price (p), and the mean motorcycle autonomy (m_m). In that sense, motorcycle cost for an individual i is

$$C_i = \frac{d_i}{m_m} * p \tag{16}$$

Taxi cost is a function of an initial travel fee fixed at R$4.50 in 2017 and an additional charge for kilometer drove. Walk costs, bicycle costs, and others are fixed at zero.

Not only a cost variable estimation is required to proceed with the discrete choice model analysis, but we also need to observe the cost and time variable for the means of transportation that the individual did not choose. The OD survey only reports the information regarding the mode chosen by the decision maker, not the characteristics of the trips available but not chosen by him.

To estimate these variables, several approaches are available. We proceed with the most common strategy, developing a linear regression to predict time travel and cost travel based on observable variables such as arrival time, departure time, the distance of the trip, and a dummy that equals one if the individual works and lives in the same OD zone. We run a separate regression for each mode and the results of the simulated choices and the observable choices are presented in Table 4[11].

Table 4 – Alternative variables for simulated and observable choices

	Observed choices		Simulated choices	
	Mean	SD	Mean	SD
Cost (in R$)				
Bus	2.43	2.19	4.00	0.00
Car	2.93	3.27	2.75	3.62
Subway	3.06	3.07	4.00	0.00
Moto	0.79	0.76	0.55	0.72
Taxi	16.15	11.65	18.71	17.96
Walk	0.00	0.00	0.00	0.00
Time (in hours)				
Bus	0.91	0.53	0.74	0.46
Car	0.46	0.37	0.48	0.37
Subway	1.24	0.64	0.67	0.51
Moto	0.40	0.29	0.36	0.26
Taxi	0.42	0.29	0.49	0.35
Walk	0.25	0.25	2.46	2.18

For simplicity, bus, and subway simulated costs are fixed in R$4 – the ticket fare in 2017. The observed costs for these variables have lower means since there are individuals who do not pay for the travel. For car, motorcycle, and taxi travel,

[11]For the Walk Mode, the linear regression was not providing reliable estimations for travel time. For that reason, we applied a simpler method, in which we just divided the trip distance by an average walking speed.

simulated costs are very similar to the observed ones. Walk mode is also fixed in zero. The estimation of the time variables is also in line with the observed ones for all modes.

4 Transportation Choice Model

Model specification

The econometric model estimated is based on the methodology described in Chapter 2. As detailed, the first step is defining the dependent variable. In our case, the choice set is given by six mode options: the aggregated five modes (bus, subway, car, motorcycle, taxi) and the outside option (walk, bicycle, and others). For the Nested Logit, it is required to determine which alternatives compose each nest. In this work, we determined two nests: (i) Public and (ii) Private. The Public nest includes alternatives available in public transportation (bus and subway) or active mobility (walk, bicycle, and others). The Private nest includes the others alternative (car, taxi, and motorcycle). In Appendix B we run several regressions using different nests specifications to check the robustness of the results.

Each individual decides a single mode in such a way that $y_i = 1$ for his choice and $y_i = 0$ for the others. In that sense, we have six observations for each individual, with variables that vary within alternatives and individuals – alternative-specific – and variables that vary only within individuals – case-specific. The variables used to explain the transportation choice are as follows:

- Alternative specific
  - Cost
  - Time
  - Cost/ Income (in R$1000)
  - Time/ Income (in R$1000)

- Case specific
  - Income (in R$1000)
  - Age

- Distance
- Dummy for Male gender
- Dummy for Expanded Center trip

Utility individual i obtains choosing mode j is defined below. Z_{ij} is a vector of the case-specific variables and ϵ_{ij} is the random error, with cumulative distribution described in equation 6.

$$U_{ij} = \beta_1\, Time + \beta_2\, \frac{Time}{Income} + \beta_3\, Cost + \beta_4\, \frac{Cost}{Income} + Z_{ij}\, \gamma + \epsilon_{ij} \tag{17}$$

Estimation results

Aside from the main specification – the nested logit model – we also run a multinomial logit, where we disregard the correlations between alternatives. Also, as recommended in Adler & Ben-Akiva (1979) we run a third and fourth regression (columns (2) and (4)) in which our sample is restricted to account only for trips motivated by work. This analysis is important since work trips are usually unavoidable, therefore present different characteristics in comparison to other motivated trips. In that context, Table 5 presents the results for the four estimations, displaying the results for the alternative-specific variables.

Table 5 – Discrete choice models estimations

	(1) Multinomial	(2) Multinomial (work only)	(3) Nested	(4) Nested (work only)
Time	-3.640^{***}	-3.639^{***}	-3.208^{***}	-4.010^{***}
	(0.026)	(0.046)	(0.030)	(0.046)
Time/Income	0.191^{***}	0.857^{***}	0.235^{***}	0.938^{***}
	(0.036)	(0.125)	(0.016)	(0.069)
Cost	-0.640^{***}	-1.051^{***}	-0.506^{***}	-1.203^{***}
	(0.006)	(0.009)	(0.006)	(0.014)
Cost/Income	-0.072^{***}	-0.126^{***}	-0.049^{***}	-0.120^{***}
	(0.006)	(0.012)	(0.005)	(0.012)
IV Public			0.770^{***}	1.171^{***}
			(0.009)	(0.017)
IV Private			1.098^{***}	1.240^{***}
			(0.014)	(0.020)
Observations	124,667	76,217	124,667	76,217

Note: For individuals who did not have a car or a motorcycle, we excluded the possibility of them choosing those options. Furthermore, subway option was excluded for those who reside in zones in which there were no records of an individual choosing subway.

Analyzing the main model (third column), we can see that the coefficients of the alternative-specific characteristics all have the expected sign, for example, the negative coefficient in the Time variable reflects the idea that individuals' probability of choosing any mode with respect to the outside option decays as the trip time grows. The same interpretation suits the cost variable: expensive trips are associated with a lower probability of choice in comparison to the outside option. The negative sign in the Cost/Income variable should be interpreted as follows: as income grows individuals value less the cost of transportation modes. On the other hand, the positive sign in the Time/Income reflects the opposite: as income grows, the individuals' valuation of time spent on transportation also grows.

In Appendix C we show the estimated coefficients for case-specific variables. A larger monthly income is associated with a greater probability of commuting by car and taxi, in comparison with the outside option. On the other hand, lower incomes are associated with a higher probability of using the bus, subway, and motorcycle mode in spite of the outside option.

Being of the gender male is associated with a greater probability of choosing a motorcycle and car in comparison with the walk mode. As expected, a greater trip distance is associated with a larger probability of choosing any mode with respect to walking. As age grows, decays the probability of choosing the subway or motorcycle as the mode to commute. Finally, if the trip takes place in the Expanded Center, greater is the probability of commuting by taxi and subway.

The value of λ_k is important for inferring if the model is consistent with utility-maximizing behavior. If $\lambda_k \in (0, 1) \; \forall \; k$, it is known that the model is consistent with utility maximization for all possible values of the explanatory variables. In our case, we have the λ of the public nest within the expected range, but the λ of the private nest lies above 1. In Train (2009), however, it is stated that not in all cases the model should be rejected if the value of λ lies outside 0 and 1. It is presented that values below zero are inconsistent with utility maximization, but values above 1 are consistent with utility maximizing behavior for some range of the explanatory variables.

Value of Time

The Value of Time is, by definition, the extra money a person is willing to give in order to spare a unit of time, in other words, it is the opportunity cost of time. As described in section 2, it reflects the marginal rate of substitution between income and time.

However, in our work, income is not an alternative-specific variable, i.e its estimated coefficients vary within alternatives, therefore we cannot use it to calculate the Value of Time. As seen in Train (2009), a possible alternative is to use the partial derivative with respect to cost. By construction of the model, a variation in cost should be equivalent to a variation in income. In other words, a reduction in one unit of cost should be equal to an increase in one unit of income.

In that regard, the Value of Time can be written as:

$$VOT_i = \frac{dY}{dT} = -\frac{dC}{dT} = \frac{dU_i/dT_i}{dU_i/dC_i} = \frac{\beta_3 + \beta_4/Income}{\beta_1 + \beta_2/Income} \tag{18}$$

Table 6 displays the Value of Time estimates based on the Multinomial and Nested Logit. Analyzing the Nested Logit estimations it is shown that individuals value their time, on average, in R\$6.03/h. Supposing an individual works 8 hours a day, 22 days a month, this gives a total of R\$ 1,061 per month. The average individual income in our database is R\$ 2,586, which means that individuals value their time by 41% of their monthly income.

Table 6 – Value of Time (R\$/h)

Model	Average VOT	Median VOT
Multinomial	5.42	5.47
Nested	6.03	6.09

This result is consistent with previous literature. Parry & Small (2009) estimates the Value of Time at roughly 50% of individuals' hourly wage in London and Washington. Dalbem et al. (2010) suggests that individuals may value time in a range of 10% to 50% of their hourly wage. Haddad et al. (2015) conclude that individuals in the SPMR value their time in the short run by 48% of their hourly wage. A meta-analysis done in Waters & William (1996), in which 54 Value of Time estimates from 14 countries are reviewed, also suggests that the average VOT/ Wage lies around 48% (Small & Verhoef (2007)).

Since β_4 (Time/Income) has a positive sign and β_2 (Cost/ Income) has a negative sign, the value of time increases as income grows, i.e the numerator becomes larger and the denominator decreases. This effect is expected and also present in Lucinda et al. (2019) and Small & Verhoef (2007).

Elasticities

Table 7 summarises the cost elasticities for each mode based on the Nested Logit estimation. Car mode has a -0.18 cost elasticity, which means that a 1% cost increase reduces car demand by 0.18%. We see in our analyses that car is the second most elastic mode and, in the next section, when we proceed with applying the kilometer-based urban toll, we will see that demand migration is notable for this mode. Walk was excluded from the table rows because it is not possible to simulate a 1% cost shock in that mode since we set the mode trip cost at zero.

Table 7 – Elasticities for the nested logit estimation

	Bus	Car	Subway	Moto	Taxi	Walk
Bus	-0.22	0.06	0.05	0.00	0.01	0.09
Car	0.06	-0.18	0.07	0.01	0.01	0.02
Subway	0.06	0.05	-0.14	0.00	0.01	0.02
Moto	0.00	0.00	0.00	-0.00	0.00	0.00
Taxi	0.04	0.05	0.04	0.00	-0.17	0.03

Table 8 presents the cost elasticities based on our multinomial logit estimations. We see that estimates are similar between models with cost elasticities for car trips being slightly higher.

Table 8 – Elasticities for the multinomial logit estimation

	Bus	Car	Subway	Moto	Taxi	Walk
Bus	-0.23	0.08	0.05	0.01	0.01	0.09
Car	0.08	-0.22	0.08	0.01	0.01	0.03
Subway	0.05	0.06	-0.14	0.00	0.01	0.02
Moto	0.00	0.00	0.00	-0.01	0.00	0.00
Taxi	0.06	0.07	0.04	0.00	-0.21	0.04

As suggested by Cameron & Trivedi (2009), elasticities were estimated by manually applying a 1% cost increase in one mode. We used the predicted probability derived by the estimation of the Nested and Multinomial Logit and calculated the difference after applying a 1% cost increase in determined modes.

Lastly, in Table 9 we present the cost elasticities based on our Nested Logit model, but sub-setting it to account only for work-motivated trips. Trip cost elasticities for car use are in line with other estimations for São Paulo's context, such as Lucinda et al. (2019) and Lucinda et al. (2017)[12], with the latter estimating a value of -0.36. Other cost elasticities, such as the one for bus mode, are also roughly in line with international estimations such as Nesheim & Molnar (2010).

Table 9 – Elasticities for the nested logit work-motivated estimation

	Bus	Car	Subway	Moto	Taxi	Walk
Bus	-0.23	0.10	0.04	0.01	0.01	0.08
Car	0.12	-0.37	0.15	0.03	0.02	0.05
Subway	0.04	0.09	-0.17	0.01	0.01	0.03
Moto	0.00	0.01	0.00	-0.01	0.00	0.00
Taxi	0.05	0.09	0.05	0.01	-0.24	0.04

[12]Lucinda et al. (2017) also estimated mode elasticities subsetting it to account only for work-motivated trips.

5 Application of the urban toll

Impacts on mode choice

Once our discrete choice model is estimated, the goal is to investigate the impacts of the application of an urban toll on transportation demand. The proposed urban toll imposes an R$0.47 cost for a traveled kilometer in the Expanded Center, aligned with the one suggested on the PITU 2025.

The urban toll is charged for each traveled kilometer in the Expanded Center, however, we do not observe the actual route taken by each individual. What we observe, on the other hand, is the euclidean distance between the origin coordinate and the destiny coordinate, which is always the smaller distance between two points. In that way, by using the euclidean distance as a proxy for traveled kilometers, we are underestimating the urban toll fare for each car trip.[13]. The migration in the transportation demand after the imposition of the urban toll is shown in Table 10. Each row shows the percentage of individuals that remained in their original mode and where they switched their demand.

Table 10 – Demand Migration

	Walk	Bus	Car	Subway	Motorcycle	Taxi	**Total**
Walk	40.95%	0.00%	0.00%	0.00%	0.00%	0.00%	40.95%
Bus	0.00%	13.28%	0.00%	0.00%	0.00%	0.00%	13.28%
Car	1.54%	2.37%	23.89%	4.75%	0.51%	0.06%	33.13%
Subway	0.00%	0.00%	0.00%	10.52%	0.00%	0.00%	10.52%
Motorcycle	0.00%	0.00%	0.00%	0.01%	2.09%	0.00%	2.09%
Taxi	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.03%
Total	42.49%	15.64%	23.89%	15.28%	2.59%	0.09%	100.00%

As seen in Table 10, car trips represented 33.13% of total trips in the sample. That percentage decayed to 23.89% of total trips in the sample after the

[13]In order to attenuate this bias, we try to offset the effect by charging all trips that have their origin or destiny in the Expanded Center.

toll. From this 9.24 p.p reduction in car trips, most of the change was directed to Subway mode – 4.75 p.p. Behind Subway mode, we observed a 2.37 p.p migration to the Bus mode. Smaller migrations were accounted for Walk, Motorcycle, and Taxi modes.

Table 11 – Demand migration for work trips

	Walk	Bus	Car	Subway	Motorcycle	Taxi	**Total**
Walk	38.17%	0.00%	0.14%	0.00%	0.00%	0.01%	38.32%
Bus	0.00%	15.82%	0.04%	0.00%	0.00%	0.01%	15.87%
Car	2.91%	2.40%	17.31%	6.99%	0.93%	0.48%	31.01%
Subway	0.00%	0.00%	0.01%	11.66%	0.01%	0.01%	11.68%
Motorcycle	0.02%	0.00%	0.00%	0.01%	3.06%	0.00%	3.09%
Taxi	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.03%
Total	41.10%	18.23%	17.50%	18.66%	3.99%	0.53%	100.00%

In Table 11 we see the demand migration concerning work-motivated trips. Before the toll application, 31.01 % of total trips were made in cars. After the urban toll, that percentage reduced in half, with 17.50 % being made in cars. From this 13.51 p.p variation, most of the car trips were also relocated to subway trips. Moreover, after the Subway mode, most of the change was directed to Walk Mode. As in total trip migration, smaller changes were observed in bus, motorcycle, and taxi trips.

The advantage of implementing an urban toll lies in the fact that it usually impacts individuals progressively with respect to their income in comparison with other forms of mitigating car usage ((Lucinda et al. (2017), Parry (2002)).

As described in Chapter 2, discrete choice models enable a straightforward welfare analysis. Because of the integration constant in the Consumer Surplus formula (equation 13) only the welfare variation can be identified in this model. In Table 12 we show the welfare variation by decile induced by the urban toll application. This analysis considers only those individuals who were impacted by the toll. As income grows, the average individual loss also grows. Not only that but more individuals are affected by the toll as we ascend on the deciles.

Table 12 – Welfare variation

Deciles	Average trip loss (in R$)	Welfare loss (in R$)
1	-0.60	-23,975
2	-0.58	-34,091
3	-0.66	-67,216
4	-0.59	-83,538
5	-0.65	-133,276
6	-0.66	-154,139
7	-0.64	-193,891
8	-0.69	-227,766
9	-0.74	-262,550
10	-1.03	-367,822
Total	**-0.77**	**-1,548,263**

It should be clear that the variation in welfare caused by the urban toll is negative simply because we are only imposing costs on the individuals, without accounting for the positive externalities that can emerge from this policy. In the next subsection, we will detail some – but certainly not the only – positive externalities derived by the application of an urban toll: the reduction in pollutant emissions and road accidents.

Impacts on pollution

The straightforward implication of reducing car usage in São Paulo is the reduction in pollution that could come with it. To estimate this reduction, it should be clear that pollution can be separated into two parts: local pollution and global pollution.

Pricing global pollution is easier since the effort to reduce climate change presupposes the mitigation of CO_2 emission and its pricing has been done by several institutions. The one used in this work is the same as the one used in Parry et al. (2013) and IAWG (2013) which fixes the CO_2 emission price at \$35/ton.

Pricing local pollution is a lot harder given that despite having many harmful environmental effects, premature death is the prominent one. Determining the cost of local pollution implies determining the health costs local pollution imposes on society. To assess this damage we need to calculate the average cost per ton of local pollutants emitted by proceeding with the following steps.

1. Determining the intake fractions, i.e how people are exposed to pollution.
2. Assessing how this exposure translates to premature mortality, given the population characteristics.
3. Monetizing the health impacts. This stage takes into account the mortality valuation presented in OECD (2012).

Thus, we have the estimated cost by a ton of emissions of global pollutants – CO_2 – and local pollutants – NO_x and $PM_{2.5}$. We also know that the imposition of the urban toll reduces car usage from 33.1% to 23.9% of our sample. In that way, what we have to calculate is the pollution that is no longer emitted with the urban toll. To proceed with the analysis we calculated the sum of car traveled kilometers averted with the urban toll. The last information required is the emission factors, i.e the amount of pollutant by traveled kilometer produced. We use the estimation factors calculated by CETESB (2017). The welfare obtained in monetary terms given the pollution averted are shown in Table 13.

Table 13 – Daily pollution averted with urban toll

Pollutant	Emission per km	Km averted with toll	Cost per kg	Welfare gain
CO_2	190.67 g	18,783,745	R$ 0.116	R$ 415,454
NO_x	0.056 g	18,783,745	R$ 3.369	R$ 3,544
$PM_{2.5}$	0.001 g	18,783,745	R$ 431.396	R$ 8,103

Note: Cost per kg and Welfare gains are calculated in BRL. Since (PARRY et al., 2013) estimated the cost of pollutants in dollars, we used the mean exchange rate reported in 2017 by the Time Series Management System of the Brazilian Central Bank.

Impacts on accidents

Another implication of reducing automobile demand is the reduction in road accidents. A classic example of an externality is, when a person decides to take the road, he increases the risk to himself and to others, therefore accident externalities are positively correlated with the number of drivers (Vickrey (1968)). Some authors estimate that this relationship exceeds unity, i.e. a 1% increase in aggregate driving would rise aggregate accident costs by more than 1% (Edlin & Karaca-Mandic (2006)).[14] As in the case of pollution, an urban toll can be used to diminish the negative impacts of these externalities on society.

In order to measure the economic costs of accident externalities, we make use of the same source presented in the pollution section. Parry et al. (2013) develop estimates for accident cost by traveled kilometer for several countries including Brazil. Social costs for road accidents include fatal and non-fatal injury costs, medical costs and property damage.

Injury costs embrace injuries related to pedestrians, cyclists, and occupants in single-vehicle collisions and occupants in multi-vehicle collisions. Medical and property damage costs include all costs incurred by government and insurance companies related to road accidents.

Traffic fatalities data are taken from IRF (2012) which compiles road deaths in 2010 per country. There is no data regarding nonfatal injuries, medical costs and property damage in Brazil. However, authors manage to estimate its cost based on observable data for other countries. Mortality values per country are based on OECD (2012), the same used for computing pollution costs. The welfare obtained by the reduction in car usage is presented in Table 14.

[14]The riskiness of accidents can decrease when driving demand increases since more cars on road imply less traffic speed. However, in this work, we assume this effect does not exceed the reduction in accidents.

Table 14 – Daily accidents costs averted with urban toll

Km averted with toll	Accidents cost per km	Welfare gain
18,783,745	R$ 0.082	R$ 1,540,267

Note: Accidents cost per km and Welfare gains are calculated in BRL. Exchange rate conversion was carried out in a similar way to that presented in Table 12.

Net welfare change

As we saw in the last sections, the reduction in social welfare caused by the imposition of a new type of tax can be offset by the gains provided by the reduction in externalities. Even though we only considered a few types of pollutants and only two sources of externalities, we can already conclude that the urban toll can be beneficial in terms of social welfare. Table 15 provides a summary of the net social impact of the policy proposed.

Table 15 – Net welfare change caused by the urban toll

	Daily	Annually
Urban toll	R$ -1,548,263	R$ -565,115,995
Pollution	R$ 427,101	R$ 155,891,865
Accidents	R$ 1,540,267	R$ 562,197,445
Total effect	**R$ 419,105**	**R$ 152,973,325**

6 Conclusion

In this article we studied the impacts of a kilometer-based urban toll in São Paulo, calculating its influences on social welfare and in externalities reduction, in particular pollution and accidents. The data used was provided by the Origin and Destiny Survey carried out by São Paulo's Subway Company in 2017, which aims to register every individual trip made on a specific day, as well as individual socioeconomic characteristics.

The estimations consisted of discrete choice models, in particular a Nested and a Multinomial Logit to assess transportation mode choice. The estimated coefficients for trip time, trip cost, trip cost over income and trip time over income have the expected sign. Car cost elasticities (-0.38 for work-motivated trips and -0.18 for all trips) are in line with other estimations in the literature. Value of time estimations suggests that individuals price their time in transit by R$6.03 per hour on average, which corresponds to 41% of the average individual hourly wage.

In our policy simulations, we applied the urban toll proposed by the PITU 2025, which is based on an R$ 0.47 charge for a traveled kilometer inside the Expanded Center. This policy was able to reduce car mode choice by 9.2 p.p – from 33.1% to 23.9% of our sample. Demand migration was well distributed, with most of it transferring to the Subway and Bus modes.

With the demand migration arising from the urban toll imposition, we were able to calculate the social welfare impact of the policy. Tax imposition reduced social welfare by R$ 1.5 million daily. However, we were also able to estimate the externalities reduction provided by the reduction in car usage. For that, we relied on Parry et al. (2013) pricing estimation for pollutant emissions and road accidents. We were able to calculate car emission factors using CETESB (2017) database.

In conclusion, we find that the imposition of the urban toll increases social welfare by R$ 419k daily. That increase comes from pollutant emission reduction

– CO_2, NO_x and $PM_{2.5}$ –, and road accidents reduction. Annual impacts on social welfare sum up to R$ 153 million. Moreover, we need to state we assessed the impacts of the reduction in car usage only on pollution and road accidents, not considering many other negative externalities such as traffic congestion, noise, and oil dependency (Parry et al. (2007)) in a way that our results must be interpreted as a lower bound for this policy impacts.

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Appendix A. São Paulo's Expanded Center

São Paulo's Expanded Center is displayed below. The area comprises 24 districts of the city.

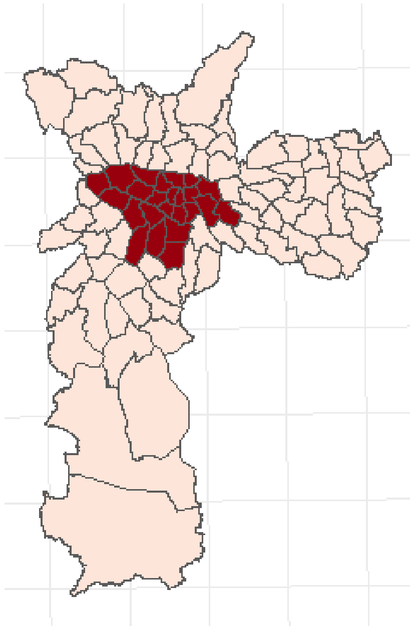

Figure A.1 – São Paulo's Expanded Center

Appendix B. Discrete choice models using different nest structures

We present the alternative-specific estimates of the discrete choice models addressed using several nests definitions. The coefficients of interest all have the expected sign, providing robustness to our main results.

Table B.1 – Robustness Check

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time	-3.392^{***}	-4.188^{***}	-4.387^{***}	-4.025^{***}	-3.581^{***}	-3.217^{***}	-3.878^{***}
	(0.025)	(0.033)	(0.033)	(0.029)	(0.028)	(0.030)	(0.019)
Cost	-0.643^{***}	-1.077^{***}	-1.097^{***}	-0.745^{***}	-0.664^{***}	-0.524^{***}	-0.856^{***}
	(0.006)	(0.011)	(0.011)	(0.006)	(0.005)	(0.006)	(0.008)
Cost/ Income	-0.026^{***}	-0.105^{***}	-0.104^{***}	-0.010^{**}	-0.059^{***}	-0.053^{***}	-0.110^{***}
	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)	(0.006)
Time/ Income	0.196^{***}	-0.021	0.010	0.288^{***}	0.207^{***}	0.216^{***}	0.014
	(0.013)	(0.059)	(0.059)	(0.015)	(0.013)	(0.017)	(0.031)
IV 1	0.431^{***}	2.592^{***}	2.643^{***}	0.580^{***}	0.628^{***}	0.800^{***}	1.522^{***}
	(0.005)	(0.048)	(0.048)	(0.006)	(0.007)	(0.009)	(0.016)
IV 2	1.269^{***}	1.429^{***}	1.199^{***}	1.844^{***}	1.761^{***}	1.061^{***}	0.167^{***}
	(0.033)	(0.034)	(0.015)	(0.016)	(0.015)	(0.015)	(0.0004)
IV 3	2.646^{***}	0.466^{***}	0.560^{***}				
	(0.089)	(0.008)	(0.017)				
Nests							
Walk	1	3	3	1	1	1	2
Bus	1	1	1	1	1	1	1
Car	2	2	2	2	2	2	2
Moto	2	2	3	1	1	1	1
Subway	3	1	1	2	2	1	1
Taxi	3	3	2	2	1	2	1
Observations	124,667	124,667	124,667	124,667	124,667	124,667	124,667
R^2	0.478	0.475	0.473	0.481	0.476	0.457	0.483

Appendix C. Estimations of case-specific variables

We present the case-specific estimates of the discrete choice models addressed in section 4. Most of the coefficients have the expected sign and their interpretation are all in respect to the outside option (walk mode).

Table C.2 – Discrete choice models for case-specific variables

	(1) Multinomial	(2) Multinomial (work only)	(3) Nested	(4) Nested (work only)
		Bus		
Income	-0.087^{***}	-0.086^{***}	-0.073^{***}	-0.090^{***}
	(0.003)	(0.004)	(0.002)	(0.005)
Male	-0.298^{***}	-0.425^{***}	-0.238^{***}	-0.478^{***}
	(0.022)	(0.034)	(0.022)	(0.044)
Distance	-0.027^{***}	0.010^{**}	-0.031^{***}	0.018^{***}
	(0.004)	(0.005)	(0.004)	(0.006)
Age	0.008^{***}	0.005^{***}	0.007^{***}	0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.002)
Expanded Center	-0.241^{***}	-0.270^{***}	-0.179^{***}	-0.305^{***}
	(0.024)	(0.036)	(0.024)	(0.047)

		Subway		
Income	-0.036^{***}	-0.024^{***}	-0.030^{***}	-0.024^{***}
	(0.003)	(0.004)	(0.002)	(0.004)
Male	-0.205^{***}	-0.246^{***}	-0.160^{***}	-0.267^{***}
	(0.028)	(0.041)	(0.025)	(0.048)
Distance	0.073^{***}	0.101^{***}	0.059^{***}	0.109^{***}
	(0.004)	(0.004)	(0.004)	(0.006)
Age	-0.001	0.002	-0.0001	0.002
	(0.001)	(0.002)	(0.001)	(0.002)
Expanded Center	1.410^{***}	1.245^{***}	1.163^{***}	1.364^{***}
	(0.031)	(0.045)	(0.031)	(0.059)
		Car		
Income	0.030^{***}	0.017^{***}	0.033^{***}	0.016^{***}
	(0.002)	(0.002)	(0.002)	(0.003)
Male	0.604^{***}	0.419^{***}	0.620^{***}	0.410^{***}
	(0.019)	(0.027)	(0.021)	(0.034)
Distance	0.259^{***}	0.534^{***}	0.202^{***}	0.601^{***}
	(0.004)	(0.006)	(0.004)	(0.009)

Age	0.018***	0.019***	0.018***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)
Expanded Center	−0.337***	−0.331***	−0.339***	−0.365***
	(0.020)	(0.028)	(0.022)	(0.036)
		Motorcycle		
Income	−0.046***	−0.059***	−0.051***	−0.078***
	(0.006)	(0.007)	(0.006)	(0.007)
Male	2.897***	2.643***	3.012***	2.963***
	(0.079)	(0.094)	(0.082)	(0.107)
Distance	−0.001	0.084***	0.002	0.094***
	(0.005)	(0.006)	(0.005)	(0.007)
Age	−0.021***	−0.023***	−0.022***	−0.028***
	(0.002)	(0.002)	(0.002)	(0.003)
Expanded Center	−0.238***	−0.298***	−0.233***	−0.320***
	(0.054)	(0.062)	(0.055)	(0.074)
		Taxi		
Income	0.024***	0.023***	0.026***	0.016***
	(0.003)	(0.004)	(0.004)	(0.006)
Male	−0.387***	−0.331***	−0.437***	−0.525***

	(0.042)	(0.064)	(0.046)	(0.075)
Distance	1.476***	2.560***	1.152***	2.912***
	(0.014)	(0.022)	(0.015)	(0.036)
Age	0.026***	−0.001	0.026***	−0.005*
	(0.001)	(0.002)	(0.001)	(0.003)
Expanded Center	1.203***	1.469***	1.298***	1.787***
	(0.049)	(0.088)	(0.052)	(0.102)
Observations	124,667	76,217	124,667	76,217

Note: *p<0.1; **p<0.05; ***p<0.01