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

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March, 2023

Abstract

In this paper, we investigate the effects of implementing an urban toll in São Paulo on road accidents and pollution. Using the Origin and Destination (OD) database for 2017, we employ a nested logit model to estimate transportation demand in São Paulo. Our objective is to analyze the changes in demand resulting from imposing 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 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 36% to 20%. 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$ 191 million annually.

***Keywords*: Car Externalities; Travel Mode demand**

***JEL Codes*: H23, L62, Q42, Q48, Q58.**

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1 Introduction

In this paper, we 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.

Despite road congestion, car usage is still the second most used mean of transportation in the 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 and this congestion imposes a social cost of R$7.3 billion annually (Vale (2018)). Also, car usage is the main responsible for local pollutant emissions in Sâo Paulo (Andrade et al. (2012)) and one of the main responsible for greenhouse gas emissions[2]. Most of these externalities could be reduced by curbing vehicle miles traveled (Parry et al. (2007), Parry (2002)).

From 1967 to 1997, the São Paulo Metropolitan Area population multiplied by 2.5, whereas the motorized vehicle fleet was multiplied by six (De Vasconcellos (2005)). 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 determinate weekday hours. Soon after imposing this system, congestion decreased by 18% in the Expanded Center, CO levels were reduced by 12%, and weekly CO_2 emissions decreased by 17 tons (Hook and Ferreira (2004), Câmara and Macedo (2004)). However, in the following years, congestion began to rise again, mainly due to car fleet growth.[3]

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]

[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-data#Sector

[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.

[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)).

In this matter, an efficient way to discourage car usage in order 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 of internalizing the social costs imposed by car usage properly.

Our results indicate that the imposition of the urban toll per traveled kilometer is capable of reducing the share of individuals choosing car mode from 36% to 20% of our sample. 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$ 191 million annually.

When studying pollution emissions, one can separate them into two parts: global and local pollution. Global pollution regards mainly greenhouse gas (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. NO_x 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 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; 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); Conte Keivabu and 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 and 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 and Walker (2011); Atkinson et al. (2009).

This paper is organized as follows: Chapter 2 describes the econometric model applied; Chapter 3 presents our data set, 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

[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.

remarks.

2 Methodology and Data

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).

Random Utility Models in the context of travel demand are defined as follows. 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, unobservable from the researcher's perspective. It is defined depending on the context, with the purpose of better representing the choice structure.

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 $f(.)$. 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:

$$\exp(-\sum_{k} \sum_{j \in B_k} \exp(-\epsilon_{nj}/\lambda_k)^{\lambda_k}) \tag{2}$$

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. 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:

$$P_{nj} = \frac{\exp(\beta x_{ij}/\lambda_k)(\sum_{i \in B_k} \exp(\beta x_{ij}/\lambda_k))^{\lambda_k - 1}}{\sum_{l=1}^{K}(\sum_{i \in B_l} \exp(\beta x_{ij}/\lambda_l))^{\lambda_l}} \tag{3}$$

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 divided by the marginal utility of income. In that sense, Consumer Surplus is $EC_i = \frac{1}{\alpha_i} max_j(U_{i,j} \quad \forall j \in J)$. Since utility is not observable by the researcher, the expected consumer surplus can be defined as in Train (2009):

$$E(CS_i) = \frac{1}{\alpha_i} ln \sum_{j \in J} exp(V_{ij}) + C \tag{4}$$

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 and Rosen (1981) can be written as:

$$\Delta(CS_i) = \frac{1}{\alpha_i} \left[ln \sum_{j \in J} exp(V_{ij}) \right]_{V_{ij}^0}^{V_{ij}^1} \tag{5}$$

3 Data

3.1 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 Area, including São Paulo city itself.

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. For the purpose of simplification, 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, and others.

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

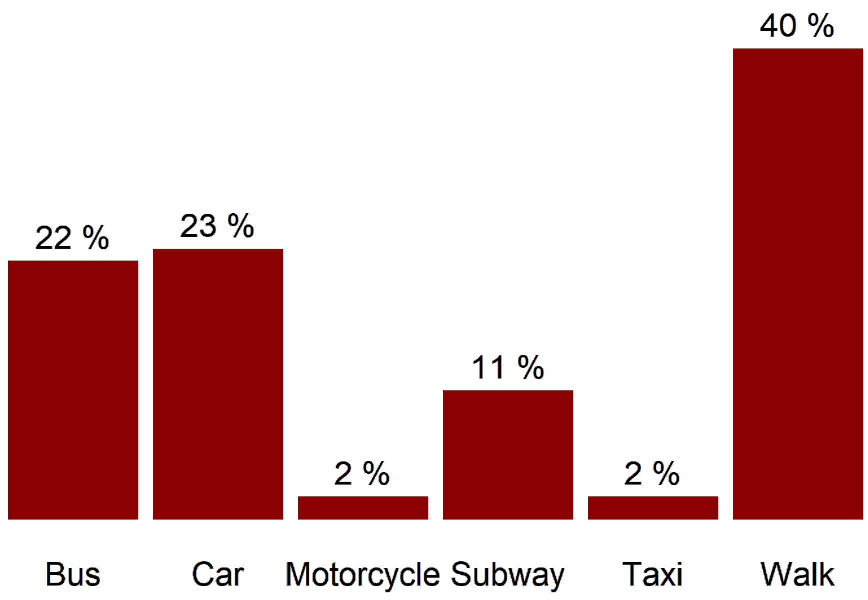

Figure 1: Frequency of trips

Car trips are the second most frequent mode of transportation, behind the aggregate mode of the walk, bicycle, and others. Besides being one of the main means of transportation, car usage is very present in the Expanded Center. Figure 2 shows the number of car trips by hectare by the district. It can be seen that most of the trips made by car are destined for São Paulo's Expanded Center.

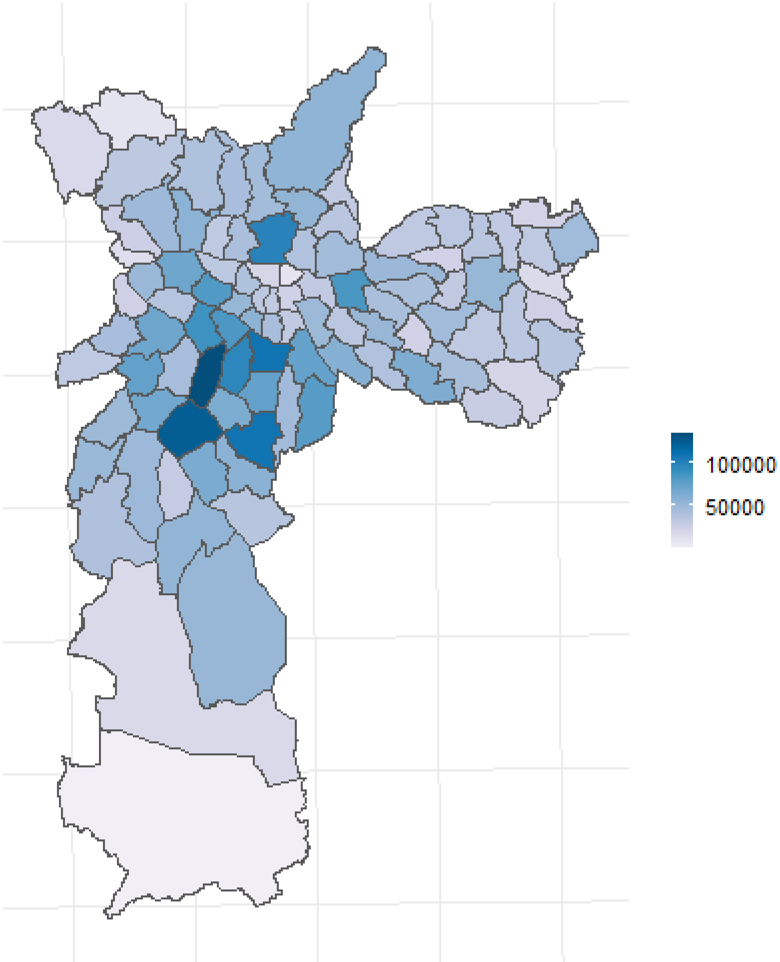

Figure 2: Trips by district

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 with other means of transportation, with the exception of the mode Taxi. Not only do the individuals have a higher income at mean, but they also have higher levels of education. 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	19 %
Car	0.46	5.85	R$ 8,116	4.36	46.81	30 %
Motorcycle	0.40	7.86	R$ 5,121	3.92	36.67	2 %
Subway	1.24	13.65	R$ 5,206	4.08	40.03	13 %
Taxi	0.42	4.66	R$ 8,246	4.38	49.79	2 %
Walk	0.25	1.67	R$ 5,308	3.80	43.26	34 %

The wealthiest families live in the Expanded Center, commute mostly by car, and have a lower time trip. 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 living 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 frequently chosen is walking, whereas in the last five deciles, the most frequent mode is the 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\$ 2,082	11%	0.66	Walk
3	R\$ 2,644	15%	0.65	Walk
4	R\$ 3,186	20%	0.63	Walk
5	R\$ 3,799	20%	0.60	Walk
6	R\$ 4,556	31%	0.57	Car
7	R\$ 5,546	39%	0.53	Car
8	R\$ 7,112	45%	0.50	Car
9	R\$ 9,733	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 and 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. However, 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 – 1.16 kilometers, at the mean.

Finally, regarding pollution, the Expanded Center also concentrates higher levels of externality in comparison to others areas of the city. In figure 3 we can see the daily emission (in kilograms) of Particular Matter (PMs) by district area (in km^2) for the year 2015[7]. PM emissions are originated from combustion and the wear of tires, brakes, and tracks. As expected, in the Expanded Center, the area with a higher volume of car flow,

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

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

Mode	Time	Distance	Income	% of Trips
Bus	0.70	4.40	R$ 6,146	13.86%
Car	0.43	4.85	R$ 10,597	27.55%
Motorcycle	0.33	4.89	R$ 8,453	1.52%
Subway	0.81	6.87	R$ 7,005	14.59%
Taxi	0.40	4.01	R$ 8,887	4.84%
Walk	0.22	1.16	R$ 7,527	37.64%

we observe higher levels of PM emissions.

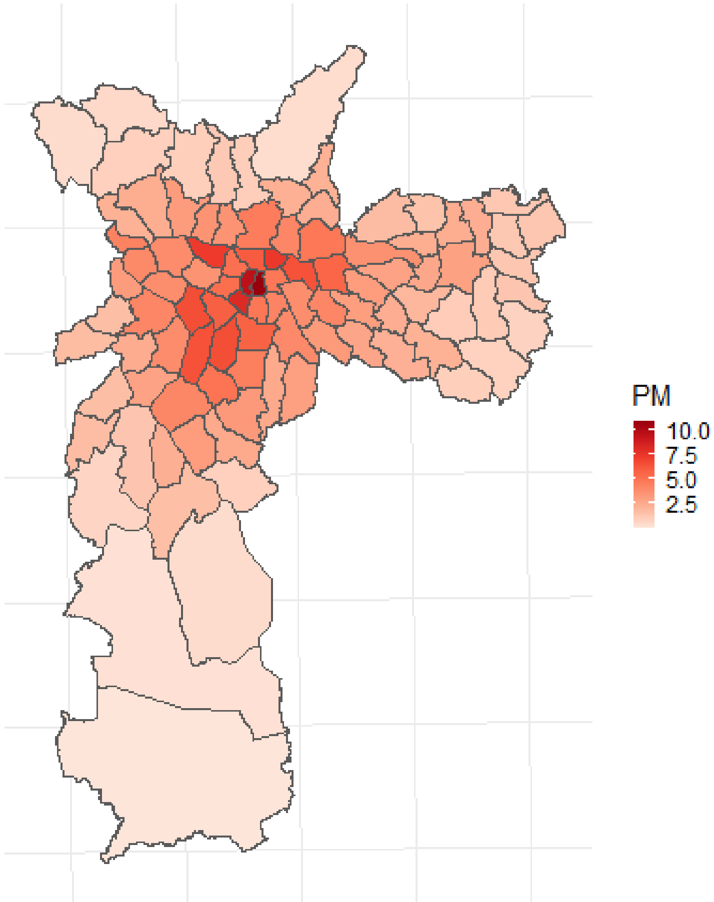

Figure 3: Daily PM emissions (in kg/km^2) by district

3.2 Econometric preparation

In order to perform the discrete choice model for travel demand, we have to adequate our database. The alternative variables in our utility function are: (i) Cost; (ii) Time; (iii) Cost/Income; (iv) Time/Income. The OD survey already has an income variable and a 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).

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

$$C_i = \frac{d_i}{m_c} * p \tag{6}$$

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

$$C_i = \frac{d_i}{m_m} * p \tag{7}$$

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.

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	0
Car	2.93	3.27	2.76	3.62
Subway	3.06	3.07	4	0
Motorcycle	0.786	0.764	0.555	0.718
Táxi	16.1	11.6	18.7	18.0
Walk	0	0	0	0
Time (in hours)				
Bus	0.911	0.534	0.742	0.461
Car	0.455	0.370	0.479	0.317
Subway	1.24	0.639	0.674	0.506
Motorcycle	0.404	0.290	0.362	0.258
Taxi	0.423	0.286	0.495	0.353
Walk	0.248	0.251	0.579	0.399

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

4 Transportation Choice Model

4.1 Model specification

The econometric model estimated is based on the methodology described in section 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 (walking, bicycle, and others). The Private nest includes the others alternative (car, taxi, and motorcycle).

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 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.

$$U_{ij} = \beta_1\, Time + \beta_2\, \frac{Time}{Income} + \beta_3\, Cost + \beta_4\, \frac{Cost}{Income} + Z_{ij}'\, \gamma + \epsilon_{ij} \tag{8}$$

5 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 and Ben-Akiva (1979) we run a third and fourth regression 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 the individuals should present a different Value of Time in comparison to others who do not commute to work. 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	-0.258^{***}	0.013	-0.323^{***}	-0.023
	(0.033)	(0.043)	(0.032)	(0.050)
Time/Income	0.434^{***}	0.308^{***}	0.522^{***}	0.410^{***}
	(0.054)	(0.079)	(0.057)	(0.097)
Cost	-0.578^{***}	-0.937^{***}	-0.752^{***}	-1.409^{***}
	(0.005)	(0.008)	(0.009)	(0.020)
Cost/Income	-0.063^{***}	-0.131^{***}	-0.086^{***}	-0.186^{***}
	(0.005)	(0.011)	(0.005)	(0.010)
IV Public			1.353^{***}	1.691^{***}
			(0.018)	(0.026)
IV Private			0.870^{***}	0.864^{***}
			(0.013)	(0.018)

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

In Appendix A 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. 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 a 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 private nest within the expected range, but the λ of the public 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.

5.1 Elasticities

Table 6 summarises the cost elasticities for each mode, based on the nested logit estimation. 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), 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 and Molnar (2010). We see in our analyses that car mode is the most elastic one, and in the next section when we proceed with the application of the variable urban toll, we will see that demand migration is notable for that mode.

Table 6: Elasticities for the nested logit estimation

	Bus	Car	Subway	Moto	Taxi	Walk
Bus	-0.24	0.10	0.03	0.01	0.01	0.09
Car	0.10	-0.28	0.09	0.02	0.02	0.06
Subway	0.04	0.06	-0.15	0.01	0.01	0.03
Moto	0.00	0.00	0.00	-0.01	0.00	0.00
Taxi	0.06	0.11	0.04	0.00	-0.27	0.06

Table 7 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 lower.

Table 7: Elasticities for the multinomial logit estimation

	Bus	Car	Subway	Moto	Taxi	Walk
Bus	-0.24	0.07	0.04	0.00	0.01	0.11
Car	0.08	-0.23	0.08	0.01	0.01	0.05
Subway	0.05	0.05	-0.14	0.00	0.01	0.04
Moto	0.00	0.00	0.00	-0.01	0.00	0.00
Taxi	0.04	0.07	0.04	0.00	-0.20	0.05

6 Effects of the urban toll

6.1 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 a 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 EC; 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 a traveled kilometer, we are underestimating the urban toll fare for each car trip.[8]. The migration in the transportation demand after the imposition of the urban toll is shown on Table 8. Each row shows the percentage of individuals that remained in their original mode and to where they switched their demand.

Table 8: Demand Migration

	Walk	Bus	Car	Subway	Motorcycle	Taxi	**Total**
Walk	41.6%	0.00%	0.00%	0.00%	0.00%	0.00%	41.56%
Bus	0.00%	11.5%	0.00%	0.00%	0.00%	0.00%	11.51%
Car	7.19%	1.64%	20.22%	5.48%	0.75%	0.55%	35.85%
Subway	0.00%	0.00%	0.00%	8.95%	0.01%	0.00%	8.96%
Motorcycle	0.00%	0.00%	0.00%	0.00%	2.09%	0.00%	2.09%
Taxi	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.02%
Total	48.75%	13.16%	20.22%	14.44%	2.85%	0.57%	100.00%

As seen in Table 8, car trips represented 35.85% of total trips in the sample. That percentage decayed to 20.22% of total trips in the sample after the toll. From this 15.63% reduction in car trips, most of the change was directed to walk mode – 7.19%. Behind walk mode, we observed a 5.48% migration to the subway mode, which culminated in 14.44% of total trips in the sample in this mode. Smaller migrations were accounted for bus, motorcycle, and taxi modes.

In Table 9 we see the demand migration with respect to work-motivated trips. Before the toll application, 31.38% of total trips were made in cars. After the urban toll, that percentage reduced in half, with 15.81% being made in cars. From this 15.57% variation, most of the car trips were relocated to walk trips. Moreover, almost a third of these trips

[8] In order to attenuate this bias, we try to offset this effect by charging all trips that have its origin or destiny in the EC

Table 9: Demand migration for work trips

	Walk	Bus	Car	Subway	Motorcycle	Taxi	**Total**
Walk	38.37%	0.00%	0.58%	0.00%	0.10%	0.01%	39.07%
Bus	0.00%	15.15%	0.01%	0.00%	0.01%	0.02%	15.19%
Car	7.02%	0.92%	15.21%	5.58%	0.97%	1.67%	31.38%
Subway	0.00%	0.00%	0.01%	11.09%	0.01%	0.02%	11.13%
Motorcycle	0.00%	0.00%	0.00%	0.00%	3.21%	0.00%	3.21%
Taxi	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.03%
Total	45.39%	16.08%	15.81%	16.67%	4.30%	1.76%	100.00%

– 5.58% – were assigned to subway trips. 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 usually it 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 section 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 is identified in this model. In Table 10 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 10: Welfare change by decile

Deciles	Mean individual loss	Sum loss
1	-0.58	-22.576
2	-0.57	-33.667
3	-0.61	-59.802
4	-0.64	-93.143
5	-0.68	-128.205
6	-0.68	-158.018
7	-0.68	-202.337
8	-0.70	-229.056
9	-0.74	-258.486
10	-0.90	-319.886
Total	-0.75	-1.505.181

It should be clear that the variation in welfare caused by the urban toll will be 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 road accidents and pollutant emissions.

6.2 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 for reducing 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 it is needed to calculate the average cost per ton of local pollutant emitted, and Parry et al. (2013) do that 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 15 p.p car usage in São Paulo. 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 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 11.

Table 11: Daily pollution averted with urban toll

Pollutant	Emission per km	Km averted with toll	Cost per kg (BRL)	Welfare gain (BRL)
CO_2	190.67 g	23,607,796	0.112	504,145
NO_x	0.056 g	23,607,796	3.264	4,319
$PM_{2.5}$	0.001 g	23,607,796	418.240	9,876

6.3 Impacts on accidents

Another implication of reducing automobile demand is the reduction in road accidents. As a classic example of an externality, when a person decides to take the road, he increases the risk to himself and to others, in that way, 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 and Karaca-Mandic (2006)).[9] 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 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 12.

Table 12: Daily accidents costs averted with urban toll

Km averted with toll	Accidents cost (BRL/KM)	Welfare obtained (BRL)
23,607,796	0.02	1,510,899

6.4 Net welfare change

As we saw in the last subsections, 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, it can already be concluded that the urban toll can be beneficial in terms of social welfare. Table 13 provides a summary of the net social impact of the policy proposed.

[9] 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 13: Net welfare change caused by the urban toll

	Daily	Annually
Urban toll	R$ -1,505,181	R$ -549,390,902
Pollution	R$ 518,340	R$ 189,194,274
Accidents	R$ 1,510,899	R$ 551,478,117
Total effect	**R$ 524,058**	**R$ 191,281,489**

7 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 trip the individual made on a specific day, as well as its 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 and trip cost have the expected negative sign and cost elasticities, especially for car mode choice (-0.28), are in line with other estimations in the literature.

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 almost 16 p.p – from 36% to 20% of our sample. Demand migration was well distributed, with most of it transferring to the walk mode.

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$ 524k 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$ 191 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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8 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 its interpretation are all in respect to the outside option (walk mode).

Table 14: Discrete choice models for case-specific variables

	(1) Multinomial	(2) Multinomial (work only)	(3) Nested	(4) Nested (work only)
Case specific				
Bus				
Income	−0.075***	−0.072***	−0.095***	−0.100***
	(0.003)	(0.004)	(0.003)	(0.006)
Male	−0.185***	−0.327***	−0.275***	−0.576***
	(0.019)	(0.030)	(0.028)	(0.054)
Distance	0.342***	0.382***	0.447***	0.604***
	(0.003)	(0.005)	(0.006)	(0.009)
Age	0.008***	0.006***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.002)
Expanded Center	−0.098***	−0.092***	−0.167***	−0.199***
	(0.021)	(0.032)	(0.030)	(0.056)
Subway				
Income	−0.019***	−0.010***	−0.021***	−0.005
	(0.003)	(0.003)	(0.003)	(0.005)

Male	-0.021	-0.106^{***}	-0.061^{*}	-0.188^{***}
	(0.025)	(0.037)	(0.033)	(0.059)
Distance	0.440^{***}	0.474^{***}	0.560^{***}	0.703^{***}
	(0.003)	(0.005)	(0.007)	(0.009)
Age	-0.001	0.004^{***}	-0.002^{**}	0.004^{*}
	(0.001)	(0.001)	(0.001)	(0.002)
Expanded Center	1.556^{***}	1.475^{***}	1.952^{***}	2.054^{***}
	(0.028)	(0.042)	(0.044)	(0.075)
		Car		
Income	0.033^{***}	0.022^{***}	0.029^{***}	0.018^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Male	0.676^{***}	0.473^{***}	0.659^{***}	0.441^{***}
	(0.017)	(0.024)	(0.019)	(0.028)
Distance	0.632^{***}	0.884^{***}	0.807^{***}	1.298^{***}
	(0.004)	(0.006)	(0.009)	(0.016)
Age	0.016^{***}	0.019^{***}	0.016^{***}	0.019^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Expanded Center	-0.247^{***}	-0.252^{***}	-0.229^{***}	-0.286^{***}
	(0.018)	(0.025)	(0.020)	(0.030)
		Moto		

Income	-0.042^{***}	-0.049^{***}	-0.035^{***}	-0.040^{***}
	(0.006)	(0.006)	(0.005)	(0.006)
Male	2.797^{***}	2.502^{***}	2.592^{***}	2.310^{***}
	(0.076)	(0.091)	(0.073)	(0.090)
Distance	0.424^{***}	0.507^{***}	0.526^{***}	0.728^{***}
	(0.004)	(0.005)	(0.007)	(0.009)
Age	-0.021^{***}	-0.022^{***}	-0.019^{***}	-0.020^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Expanded Center	-0.100^{**}	-0.175^{***}	-0.085^{*}	-0.196^{***}
	(0.051)	(0.059)	(0.050)	(0.061)
		Taxi		
Income	0.027^{***}	0.026^{***}	0.025^{***}	0.021^{***}
	(0.003)	(0.004)	(0.003)	(0.005)
Male	-0.302^{***}	-0.279^{***}	-0.213^{***}	-0.227^{***}
	(0.041)	(0.062)	(0.040)	(0.061)
Distance	1.772^{***}	2.742^{***}	2.303^{***}	4.106^{***}
	(0.013)	(0.020)	(0.027)	(0.055)
Age	0.024^{***}	0.001	0.024^{***}	0.003
	(0.001)	(0.002)	(0.001)	(0.002)
Expanded Center	1.277^{***}	1.543^{***}	1.155^{***}	1.332^{***}
	(0.047)	(0.086)	(0.047)	(0.085)
IV Public			1.353^{***}	1.691^{***}

			(0.018)	(0.026)
IV Private			0.870***	0.864***
			(0.013)	(0.018)
Observations	124,667	76,217	124,667	76,217
R^2	0.355	0.484	0.356	0.491
Note:				*p<0.1; **p<0.05; ***p<0.01