A Socioeconomic Analysis of Ride-Hailing Emergence and Expansion in São Paulo, Brazil

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Eduardo Amaral Haddad
NEREUS – IPE/USP
Av. Prof. Luciano Gualberto, 908, FEA2, sala C122
Cidade Universitária, São Paulo-SP, Brazil. 05508-010
ehaddad@usp.br

Renato Schwambach Vieira (corresponding author)
NEREUS – IPE/USP
Av. Prof. Luciano Gualberto, 908, FEA2, sala C122
Cidade Universitária, São Paulo-SP, Brazil. 05508-010
renato.sv.1988@gmail.com

Miguel Stevanato Jacob
99 Tecnologia Ltda.
R. Sansão Alves dos Santos, 400
Brooklin Paulista, São Paulo-SP, Brazil. 04571-090
miguel.jacob@99app.com

Ana Waksberg Guerrini
99 Tecnologia Ltda.
R. Sansão Alves dos Santos, 400
Brooklin Paulista, São Paulo-SP, Brazil. 04571-090
ana.guerrini@99app.com

Eduardo Germani
TTC – Engenharia de Tráfego e de Transportes
R. Marcondes de Andrade, 262
Ipiranga, São Paulo-SP, Brazil. 04265-040
eduardo.germani@ttc.com.br

Fernando Barreto
TTC – Engenharia de Tráfego e de Transportes
R. Marcondes de Andrade, 262
Ipiranga, São Paulo-SP, Brazil. 04265-040
fbarreto@ttc.com.br

Miguel Luiz Bucalem
Escola Politécnica da USP
Av. Prof. Almeida Prado, trav. 2, 271
Cidade Universitária, São Paulo-SP, Brazil. 05508-900
mlbucale@usp.br

Pedro Levy Sayon
NEREUS – IPE/USP
Av. Prof. Luciano Gualberto, 908, FEA2, sala C122
Cidade Universitária, São Paulo-SP, Brazil. 05508-010
pedro.sayon@usp.br

Abstract

This paper estimates the socioeconomic impacts of the emergence and expansion of e-hailing services in São Paulo, Brazil. Combining data from a major service provider, individual level data from a representative travel diary survey and a structural traffic network simulation, we evaluate the impact of e-hailing on commuters' travel time and accessibility. We then estimate the effect of these changes on workers' productivity. Finally, using a Spatial Computable General Equilibrium (SCGE) model, we estimate the effect of these productivity shocks on broader economic outcomes. Our main results indicate that 83% of current e-hailing trips derived from trips that were previously made by traditional motorized private modes. We also find that the current e-hailing supply has mostly negligible effects on travel times and congestion; however, some individuals experienced important accessibility gains due to the emergence of this alternative mode. We then simulate e-hailing expansion and development scenarios, including the case of larger vehicle occupancy. Total economic activity expands by 1.089% if average vehicle occupancy reaches 3 passengers per trip and all motorized private trips are substituted by e-hailing.

Keywords: E-Hailing; Computable General Equilibrium; Impact Evaluation; Urban Economics; São Paulo, Brazil

1. Introduction

Like in other developing countries, access to cell phones have become ubiquitous in Brazil, with 92.6% of Brazilian households connecting to the internet through these gadgets [1]. Because of that, innovative services related to urban transportation became easily available to individuals such as real time geo-positioning, online mapping, routing apps and multi-mode scheduling. More recently, a new type of urban transportation arrangement known as e-hailing became available with the peer-to-peer connection between passengers and drivers who own a private vehicle. This market expanded quickly, becoming one of the most vibrant and dynamic sectors of the sharing economy.[1] This new transport alternative changed the range of possibilities faced by urban residents, who now have an easier and cheaper option for traveling by a private car without the necessity and costs of owning a vehicle. Moreover, e-hailing travelers do not need to assume the responsibility for driving and parking.

However, the broader socioeconomic impacts of this technological revolution are not completely clear. While e-hailing shares similar negative externalities with traditional private vehicles, there are important specific aspects of the new service that might have important consequences to urban transportation and the urban economy. For example, e-hailing requires fewer parking areas if compared to traditional private modes. However, the period that e-hailing drivers circulate searching for passengers may impose an additional burden on congested roads and an increase in gas emissions. Additionally, the availability of e-hailing services may provide important accessibility gains to poorer individuals who were transit dependent. These factors, which do not cover all possible channels of impacts, point to a range of effects in different and sometimes opposing directions. Because of that, and considering the complexity of the transport system, computing the total net socioeconomic impacts of e-hailing emergence and expansion is not a trivial task. One additional challenge for carrying this type of analysis is that the e-hailing sector is relatively new, and it is operated by private companies, so that detailed operational data are not commonly available to researchers.

Hence, the literature investigating the socioeconomic impacts of the emergence of this service is still incomplete. The existing ex-post impact evaluations are usually focused on a narrow range of effects; other works rely mainly on data from surveys mostly run in specific situations, thus stated behavior of individuals might differ from reality. Among the results from these analyses, we highlight a still ambiguous effect on mode substitution from public transit [2], [3], [4], [5], fewer accidents caused by drinking and driving [6] [7] [8] and significant shifts in the labor market equilibrium due to the demand for drivers [9] [10]. Broader economic evaluations are restricted to *ex-ante* studies, such as [11] and [12], which simulated the substitution of private mode trips by shared e-hailing systems with varying passenger capacity. The results of these extreme simulations indicate a potential impact of completely eliminating both congestion and parking demand. The results also indicate large reductions in emissions. The literature still lacks *ex-post* evaluations of the broader socioeconomic impacts of e-hailing emergence and

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List of abbreviations:
- OD07: 2007 Origin Destination Survey of the São Paulo Metropolitan Region.
- SCGE: Spatial Computable General Equilibrium;
- SPMR: São Paulo Metropolitan Region
- TZ: Traffic Zone

[1] This type of service is usually referred as e-hailing or commercial peer-to-peer ridesharing. In the decade of 2010, several companies started offering this type of service in Brazil, including 99, a Brazilian company founded in 2012 that is the main provider of data for this paper. Other major companies operating in this sector in São Paulo, Brazil, include Uber (USA) and Cabify (Spain), among other smaller players.

expansion based on real demand data. This gap is particularly relevant in the case of cities from the developing world, where congestion and accessibility impacts are likely to be amplified.

This paper aims to address this issue by carrying a detailed impact evaluation of e-hailing emergence in a major city of the developing world. Based on operational data from a leading e-hailing provider and a large representative household travel survey, we estimate the transfer of motorized trips to e-hailing. With this result, we employ an integrated framework[2] to calculate the socioeconomic impacts of the current e-hailing market. Next, we extend our analysis to a set of ex-ante simulations where we calculate the impact of alternative expansion scenarios of this market.

The remaining of this paper is structured as follows: Section 2 details the data used in the different steps of our integrated framework. Section 3 summarizes our methodology. Section 4 presents our main results and Section 5 concludes.

2. Data

The integrated framework used in this paper employs information gathered from different sources related to the transport network and the commuting patterns of the São Paulo Metropolitan Region (SPMR). The baseline data source is the 2007 Origin Destination Survey (OD07), a household survey designed to be representative of the travel patterns observed in a regular weekday in the SPMR.[3] The OD07 divides the metropolitan region into 460 traffic zones (TZs), and for each trip included in the survey, it has information about the zones of origin and destination, the departure and arrival time, trip motivation and travel mode. It is important to notice that the survey was carried in 2007, thus before the emergence of e-hailing services in São Paulo. Therefore, e-hailing is not reflected as a specific mode in the survey.

To overcome that limitation, we also included in our analysis operational information provided by 99, a leading e-hailing company in SPMR. The information supplied by 99 included the number of trips taken by TZ pair in two typical weeks of operation between 2017 and 2018.[4]

The transport network of São Paulo was simulated by TTC, a traffic engineering company specialized in transportation analysis for the SPMR. They use a 4-step model that provided our integrated framework with travel time and mode demand equilibria given different scenario simulations.[5]

Finally, the SCGE model is calibrated by combining data from the OD07 and the 2008 input-output tables of Brazilian municipalities. The SCGE model is specified with eight economic sectors. It is divided into 41 regions that correspond to the 39 municipalities of the SPMR, the rest of the state of São Paulo, and the rest of Brazil. Furthermore, the model maps industrial connections by place of production, and in the case of the labor market, wages are assigned to the location of firms, however, household consumption is based on workers municipality of residence. Therefore, the pendular movements of the labor market and of the economic activity are fully accounted for.

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[2] The framework is presented and summarized on the methodology session. Additional details are described in [13] and [16]. This integrated framework has been used for different policy evaluations in São Paulo, Brazil, including public transit investments [13] and alternative urban transportation policies [16].

[3] The survey was carried by the subway company of São Paulo (METRO). It interviewed 29,957 households asking about all trips taken by all family members in the day immediately before the survey. Besides information about trips, the survey also collected sociodemographic characteristics of individuals and households.

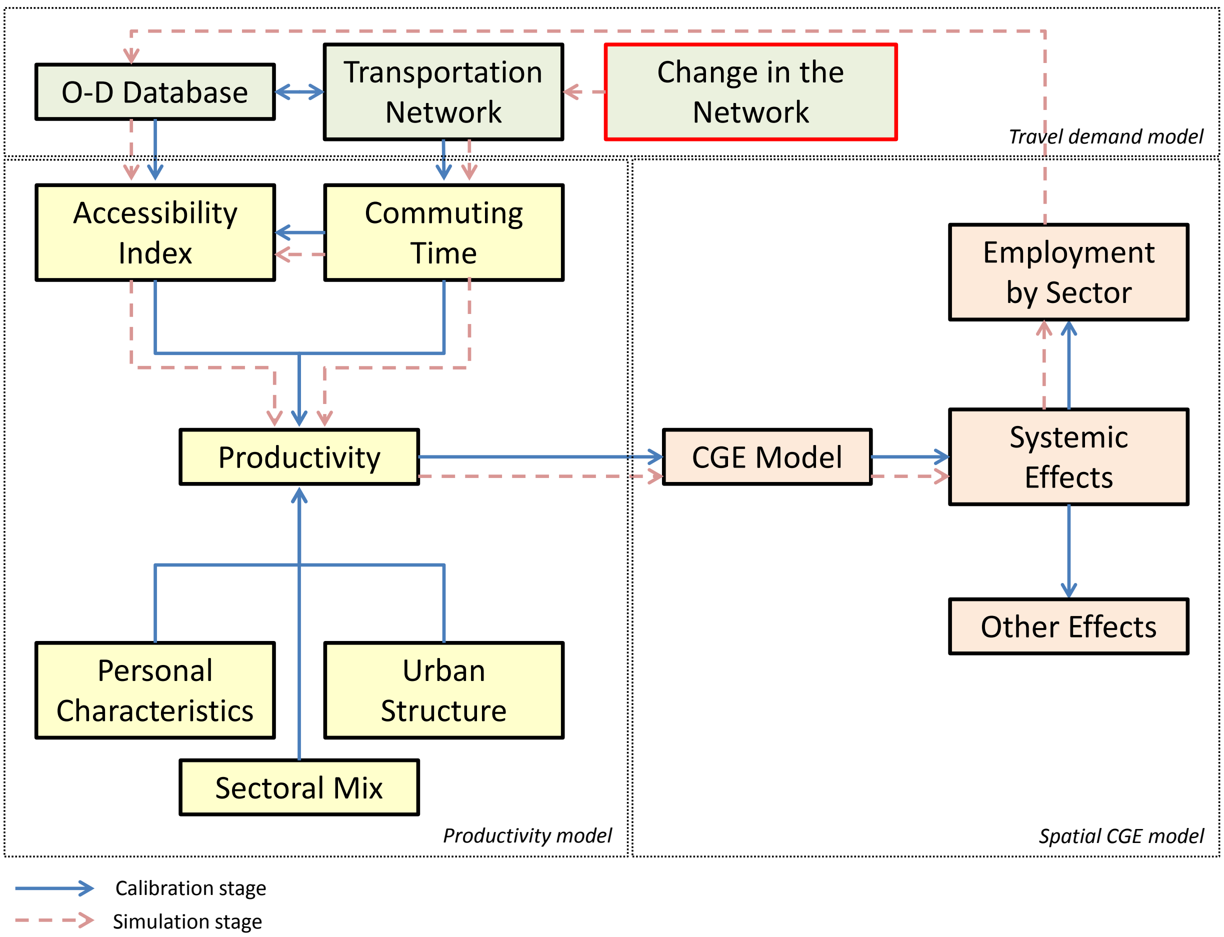
[4] Because of the competitive nature of the e-hailing market and the proprietary ownership of the information, we are not allowed to disclosure further details about the data provided by 99.

[5] For the reader interested in additional details about the TTC model, we refer to [16], appendix 1.

3. Method

The integrated framework employed in this paper is summarized by Figure 1, and it can be separated into two main phases, that are the calibration of the baseline (represented by the blue flows) and the simulated scenarios (dashed red flows).

Figure 1: Integrated Framework Flowchart



Source: Haddad et al., 2013. [13]

The calibration phase is based on the travel patterns and workers' data observed in the OD07. Using commuters travel time and accessibility as explanatory variables, we estimate a wage equation relating these variables to workers' productivity. While longer commutes are expected to decrease productivity [14], agglomeration economies (captured by accessibility) increase workers' productivity [15]. Worker's productivity is the linkage variable between the productivity model and the SCGE model.

After the calibration phase, simulated scenarios can be explored, including changes in transport structure (e.g. new modes, new transit lines, different travel speeds) or in commuters' characteristics (e.g. income, employment, access to private vehicles). In the case of this paper, we will simulate the emergence of the e-hailing market (a new transport mode) and possible scenarios for its expansion and development.

3.1 Calibrating the current e-hailing market

The main challenge to incorporate e-hailing in the integrated model is that this transport mode did not exist when the OD07 survey was carried in 2007. Meanwhile, we do observe the number of e-hailing trips in the data provided by 99. However, we cannot simply add up the two datasets. It is necessary to consider that the observed e-hailing trips are most likely trips that were previously made by traditional modes. So, the number of trips from traditional modes needs to be reduced accordingly.[6] However, a question that remains is: how much of each mode should be reduced to accommodate the new e-hailing trips? In other words, what was the substitution pattern from each traditional mode to e-hailing?

To answer this question, and since the OD07 is not a panel dataset where we can observe specific behavior alterations, we propose to exploit the heterogeneity of traditional mode shares by TZ pair observed in the OD07 survey. Using a linear regression, we combine the number of observed e-hailing trips nowadays with the travel patterns observed in 2007, and estimate how the later predicts the former, thus estimating the average substitution ratio between each traditional mode to e-hailing. This estimation can be described by Equation (1), below:

$$Y_{OD} = \alpha X_{OD}^{pub} + \beta X_{OD}^{pri} + \gamma X_{OD}^{act} + \varepsilon_{OD} \quad (1)$$

Where:

- Y_{OD}: number of trips by e-hailing by TZ pair in 2017-2018[7]
- X_{OD}^{pub}: number of trips by public transportations by TZ pair in 2007
- X_{OD}^{pri}: number of trips by traditional motorized private modes by TZ pair in 2007
- X_{OD}^{act}: number of trips by active modes by TZ pair in 2007
- α: mode substitution coefficient from public transit to e-hailing
- β: mode substitution coefficient from private modes to e-hailing
- γ: mode substitution coefficient from active modes to e-hailing
- ε_{OD}: error term that captures unobserved covariates

The coefficients of the above specification indicate the average substitution from each traditional mode to e-hailing. To facilitate the interpretation of results, we multiply the coefficients by 100. So, for example, if the coefficient α for private modes is estimated to be equal to 2, it means that for every 100 trips by

[6] Due to the static nature of the household travel survey and the absence of information about potential trips that were not taken, one restriction of our integrated framework is that the total number of trips has to be kept constant, so induced trips cannot be modeled.

[7] Our dataset only includes trips made by 99, which is only one of the e-hailing companies operating in São Paulo. So, to calculate the total number of e-hailing trips, we used 99 internal estimations of total market size and assumed that the travel pattern of their competitors was the same to their own.

traditional private modes observed in 2007, we now have 2 trips that are made by e-haling in 2017-18, indicating an average substitution ratio of 2% from traditional private modes to e-hailing.

Table 1 presents the results for the estimation of Equation 1 using two alternative specifications. Model (1) includes motorized modes only, and Model (2) adds active modes (walking and biking) to the covariates. The regressions were estimated using OLS method and observations were weighted by the total number of trips observed by TZ pair in 2007. TZ pairs with no trips by any of the modes were excluded from the analyses.

Table 1: Regression Results – Mode Substitution from Traditional Modes to E-Hailing

	Dependent Variable: E-Hailing Trips (2017-2018)	
	(1)	(2)
Private Trips 2007 (x100)	1.395 ***	1.346 ***
	(0.043)	(0.053)
Public Trips 2007 (x100)	0.235 ***	0.316 ***
	(0.047)	(0.053)
Active Trips 2007 (x100)		0.007
		(0.013)
Obs.	9,483	2,882
Adj. R^2	0.58	0.55

Notes: *** $p < 0.001$, ** $p<0.01$, * $p<0.05$. Standard errors in parenthesis. Coefficients indicate the number of trips that migrate from each traditional mode to e-hailing for every 100 trips observed in 2007.

Results from both models were consistent for the cases of private and public modes. The inclusion of non-active trips in Model (2) indicates that the substitution from walking and biking to e-hailing was not statistically different from zero at a 5% confidence level. Therefore, we take the estimates from model (1) as our preferred set of results. According to this model, for every 100 trips by private modes observed in 2007, we now have 1.395 trips by e-hailing, and for every 100 trips made by public transportation we must add 0.235 trips to that e-hailing total.

According to the OD07, private modes accounted for about 44.7% of motorized trips observed on a regular weekday of 2007, while public modes were responsible for the remaining 55.3%. Therefore, given our preferred set of coefficients, we can calculate that approximately 83% of e-hailing trips observed in 2017-18 derived from trips that were originally made by private modes, and the remaining 17% are trips that were originally made by public transportation.

4. Discussion of Results

Next, we proceed to our integrated framework to evaluate the economic impacts of the current e-hailing market and alternative expansion scenarios. All scenarios are compared to the original calibration of TTC for the year of 2018. This baseline scenario was based on a projection of the OD07 to 2018 given changes in the transportation infrastructure (new subway lines and roads) and changes in the socioeconomic composition of the population. Given that baseline, we then compared it with the following scenarios:

A – The Current e-hailing market, added to the model according to the substitution patterns estimated in the previous session

B1 – An increase in the average occupancy of e-hailing to 3 passengers per vehicle and an additional migration of 10% of trips from traditional private modes to e-hailing

B2 – Same as B1, however with a migration of 50% of trips made by traditional private modes to e-hailing.

B3 – Same as B1, however with a migration of 100% of trips made by traditional private modes to e-hailing.

The set of scenarios B1-B3 are in line with the current tendency of e-hailing companies to invest on shared rides and larger vehicles. While most e-hailing companies already offer shared ride services on regular automobiles, leading companies are investing on shared e-hailing trips using vehicles with larger capacity, particularly in cities in the developing world.[8] The expansion and development of these services is likely to promote an increase in the average occupancy of vehicles per trip.

The selected output variables evaluated in the final equilibrium of each scenario include:

- *Changes in the commuting time of workers (mean and inequality)*: in each scenario, given the mode distribution of trips, we have different levels of congestion. Additionally, individuals who substitute between different modes might experience dramatic changes in commuting times given the structural differences observed in the SPMR.

- *Workers' accessibility to the labor market (mean)*: the changes in travel time affect the potential equivalent labor pool available to each worker; general equilibrium effects can also affect the spatial distribution of employment in the metropolitan region.

- *Real wages (mean and inequality)*: given the shocks in workers' productivity and employment, the labor market adjusts at new levels of wages and local prices.

- *Spatial distribution of employment and economic activity (spatial inequality)*: given the shocks in workers' productivity and the changes in the spatial arrangement of the economic activity, each scenario will end up in a new labor market equilibrium.

- *GDP changes (economic efficiency)*: total economic activity is also affected by the new labor market equilibrium and spatial arrangement under new productivity levels.

[8] Some examples include the Didi buses and shuttles offered in Beijing (https://www.didiglobal.com/travel-service/bus) and Uber Bus, currently under test in Cairo (https://www.uber.com/en-EG/blog/introducing-uber-bus-a-new-way-to-commute/).

- *Parking demand (total):* parking spots required by private drivers may be affected by mode switch.

Table 2 shows the results for each of these variables for all the scenarios included in our analysis.

Table 2: Results of Scenarios Simulation

	Baseline	Scenario A		Scenarios B (e-hailing occupancy increases to 3 pax./veh.)					
				B1		B2		B3	
	(2018 projection without e-hailing)	(2018 projected with e-hailing)		(10% of private mode trips migrate to e-hailing)		(50% of private mode trips migrate to e-hailing)		(100% of private mode trips migrate to e-hailing)	
		Short Term	Long Term	Short Term	Long Term	Short Term	Long Term	Short Term	Long Term
Travel Time									
Mean (min.)	45.00	45.02	45.02	42.98	42.98	36.84	36.84	34.55	34.55
Delta baseline		0.04%	0.04%	-4.49%	-4.49%	-18.13%	-18.13%	-23.22%	-23.22%
Gini	0.35792	0.35745	0.35745	0.36147	0.36147	0.38443	0.38443	0.38184	0.38184
Delta baseline		-0.13%	-0.13%	0.99%	0.99%	7.41%	7.41%	6.68%	6.68%
P90/P10	7.000	6,908	6,908	6,902	6,902	7,394	7,394	7,009	7,009
Delta baseline		-1.31%	-1.31%	-1.40%	-1.40%	5.63%	5.63%	0.13%	0.13%
Job Market Accessibility									
Equivalent job market (million)	2.989	2.997	2.997	3.010	3.010	3.098	3.099	3.187	3.188
Delta baseline		0.25%	0.25%	0.69%	0.69%	3.65%	3.67%	6.63%	6.66%
Wages									
Mean (BRL)	1,652.9	1,653.5	1,653.6	1,657.8	1,658.4	1,676.1	1,679.8	1,680.1	1,688.5
Delta baseline		0.03%	0.04%	0.30%	0.33%	1.40%	1.62%	1.64%	2.15%
Gini	0.40785	0.40779	0.40779	0.40797	0.40797	0.40835	0.40835	0.40584	0.40583
Delta baseline		-0.01%	-0.01%	0.03%	0.03%	0.12%	0.12%	-0.49%	-0.50%
P90/P10	7.003	6.988	6.988	7.003	7.003	7.027	7.027	7.022	7.022
Delta baseline		-0.21%	-0.21%	0.00%	0.00%	0.34%	0.34%	0.27%	0.27%
Employment (Spatial Gini)									
Equal weights	0.7796	0.7796	0.7796	0.7795	0.7795	0.7789	0.7789	0.7793	0.7792
Delta baseline		0.00%	0.00%	-0.01%	-0.01%	-0.09%	-0.09%	-0.04%	-0.05%
Pop. Weights	0.018	0.018	0.018	0.0178	0.0178	0.017	0.0169	0.0175	0.0174
Delta baseline		0.00%	0.00%	-1.11%	-1.11%	-5.56%	-6.11%	-2.78%	-3.33%
GDP									
RMSP (USD million change)		33.6	59.6	203.1	361.7	1,223.4	2,181.7	2,758.7	5,062.7
RMSP (% change)		0.007	0.013	0.044	0.078	0.263	0.469	0.593	1,089
Brazil (USD million change)		35.1	62.4	212.3	378.1	1,279.0	2,280.8	2,884.0	5,292.5
Brasil (% change)		0.001	0.002	0.008	0.014	0.049	0.087	0.110	0.201
Parking (morning-peak)									
Demand (million)	1.195	1.150	1.150	1.107	1.107	0.724	0.724	0.246	0.246
Delta baseline		-3.8%	-3.8%	-7.4%	-7.4%	-39.4%	-39.4%	-79.4%	-79.4%

The results, shown in Table 2, may be divided into four different groups of variables. The first group concerns the average commuting travel time in SPMR, for which the baseline value is 45 minutes. In Scenario A, this value shows a small increase of 0.04%. We have run our simulations assuming the same average occupancy rate of private vehicles as estimated in the OD07, 1.4 passengers per vehicle. A sensitivity analysis has shown that an occupancy of at least 2 passengers per trip for e-hailing would be required to mitigate this increase on travel times. That is, the introduction of e-hailing replacing those trips made by private or public transport modes is beneficial up to a certain point, after which ridesharing becomes necessary to avoid negative impacts on average travel time in the city. The inequality indicators, Gini and P90/P10, fall, respectively, by 0.13% and 1.31%. The reduction in inequality can be explained by the substitution of some trips from public modes to e-hailing. This substitution represents significant time savings to individuals who were taking some of the longest trips in the region Hence, e-hailing practically does not affect average travel time in the SPMR; it does affect inequality in travel time though, which diminished to a greater extent.

Can on-demand trip sharing, in the form of private individual transport, benefit cities? Scenarios B1-B3 simulate what the effects of a mass ridesharing system would potentially be. Average travel time in the SPMR would be expected to decrease by 4.49%, 18.13% and 23.22%, respectively, in the case of 10%, 50% and 100% of trips currently made by private cars (owned, not intermediated by apps) were made by sharing vehicles with an average occupancy of three passengers. That would represent, in the most extreme scenario, over ten minutes less, on average, per trip. The effect on inequality is less linear: for Scenarios B1 and B2, Gini would rise (0.99% and 7.41%), falling Scenario B3 (6.68%). The P90/P10 indicator would fall in Scenario B1 (-1.40%), rising more strongly in B2 (5.63%) than in B3 (0.13%) in relation to the baseline.

The second group of results packs variables related to the labor market, namely wages and access to jobs. As mentioned in Section 3, gains in accessibility can lead to increases in workers' productivity. Results point that the emergence of e-haling services may have increased the average number of jobs a worker can reach, given their time constraints and transport mode choices. In Scenario A, our indicator of accessibility to jobs increased by 0.25%, while in the ridesharing scenarios (B1-B3) it scales up to a high of 6.66%, reaching 3.188 million jobs in B3.

It is also estimated that the emergence of e-hailing services in the SPMR has generated a positive effect on wages. This impact could have reached 0.04% in the long term equilibrium of Scenario A; the extreme scenario in which 100% of trips made by traditional private modes migrate to ride-hailing, B3, of the second set of scenarios could generate a potential increase of workers' real wage of 2.15%. Inequality indicators are diffuse for the ridesharing scenarios, just like travel time indicators. However, the reduction of wage inequality could already be verified with the entry of on-demand app-based riding services: the P90/P10 indicator shows a decrease of -0.21% in Scenario A. The improvement in the distribution of workers' income would be associated with a slightly higher average wage level, reflecting small aggregate productivity gains due to the increase in accessibility.

The third group of results relates to economic efficiency (growth) and the spatial distribution of economic activity. With the potential democratization of access to the labor market, there would be also a deconcentration of economic activity from the core municipality of São Paulo, generating more job opportunities in other municipalities of the SPMR and promoting decentralization of the economic activity within the SPMR, which can be verified by the results for the spatial Gini coefficient for employment.

In terms of economic efficiency, the aggregate productivity, associated with increases in accessibility to jobs, would generate positive impacts on the regional GDP of the SPMR as well as on national GDP, especially in the long run. In monetary terms, accessibility gains associated with current e-hailing services in SPMR would have made the national (regional) GDP in 2017 larger than the baseline in be USD 62.4 million (USD 59.6 million), while the extreme-case scenario of ridesharing would potentially increase GDP in the long run above 1%.

Finally, the last output of our model is the demand for parking in the SPMR, represented here by the morning-peak values. The analysis shows that the current e-hailing market has already reduced parking demand by -3.8%, and in the expansion scenarios the demand would decrease by respectively -7.4%, -39.4% and -79.4%. These are very substantial reductions, and the total impact of this change may extrapolate our integrated framework as we are still not accounting for changes in real-estate values.

5. Conclusion

This paper has shown that the emergence and expansion of e-hailing services has had a positive net impact in the economy of a large city of the developing world, São Paulo, Brazil. E-hailing takes away passengers from both public transit and traditional private modes, but most of the e-hailing market expansion was derived from trips that were previously made by the latter. Therefore, the net impacts on congestion are small. However, the emergence of e-hailing increased the travel possibility of individuals, facilitating the access of workers to labor markets and dramatically reducing the travel time of commuters who were previously transit dependent. Because of that, our results indicate that not only e-hailing led to an increase in the economic efficiency, but also reduced the overall economic and spatial inequality observed in São Paulo. Our future scenario simulations have shown that with the increase in the average occupancy of e-hailing vehicles, the economic impacts of e-haling can be largely increased.

As it happens with all models, our analysis faces important limitations. For example, we still cannot identify the effect of e-hailing on multimode trips, limiting our capacity to evaluate the effects of e-haling emergence on the first/last mile mode choice. This can be a relevant neglected problem as trip segments previously made by active modes may now be made by automobiles. Our analysis also does not touch longer term impacts of e-haling on individuals' decisions, such as the possession of automobiles and household location. We also do not explore the reductions in emissions associated with the shorter life-cycle of e-hailing vehicles if compared to privately owned automobiles. Further research to address these limitations is recommended.

With the same speed that e-hailing markets have emerged, they are now evolving and expanding. With the advance of technology, the impact of this market on the welfare of individuals is only going to increase. Previous decisions and regulations are likely to quickly become obsolete. With the results and insights presented in this study, we hope to inform the public debate and the decisions of policy makers about this dynamic and important market.

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