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A socioeconomic analysis of ride-hailing emergence and expansion in São Paulo, Brazil

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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.

1. Introduction

Like in other developing countries, access to cell phones has become ubiquitous in Brazil, with 92.6% of Brazilian households connecting to the internet through these gadgets (IBGE, 2018). 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

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.

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[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.

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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 (SUMC, Shared-Use Mobility Center, 2016; Rayle et al., 2014; Shaheen et al., 2018; Hoffmann et al., 2016), fewer accidents caused by drinking and driving (Dills and Mulholland, 2018; Greenwood and Wattal, 2017; Peck, 2017) and significant shifts in the labor market equilibrium due to the demand for drivers (Cramer and Krueger, 2016; Nie, 2017). Broader economic evaluations are restricted to *ex-ante* studies, such as (ITF-OECD, 2016; Alonso-Mora et al., 2017), 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 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.

3. Method

The integrated framework employed in this paper is summarized by Fig. 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).

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 (van Ommeren and Gutiérrez-i-Puigarnau, 2011), agglomeration economies (captured by accessibility) increase workers' productivity (Graham and Melo, 2009). 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.

[2] The framework is presented and summarized on the methodology session. Additional details are described in (Haddad et al., 2015, 2019). This integrated framework has been used for different policy evaluations in São Paulo, Brazil, including public transit investments (Haddad et al., 2015) and alternative urban transportation policies (Haddad et al., 2019).

[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 (Haddad et al., 2019), Appendix A.

[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.

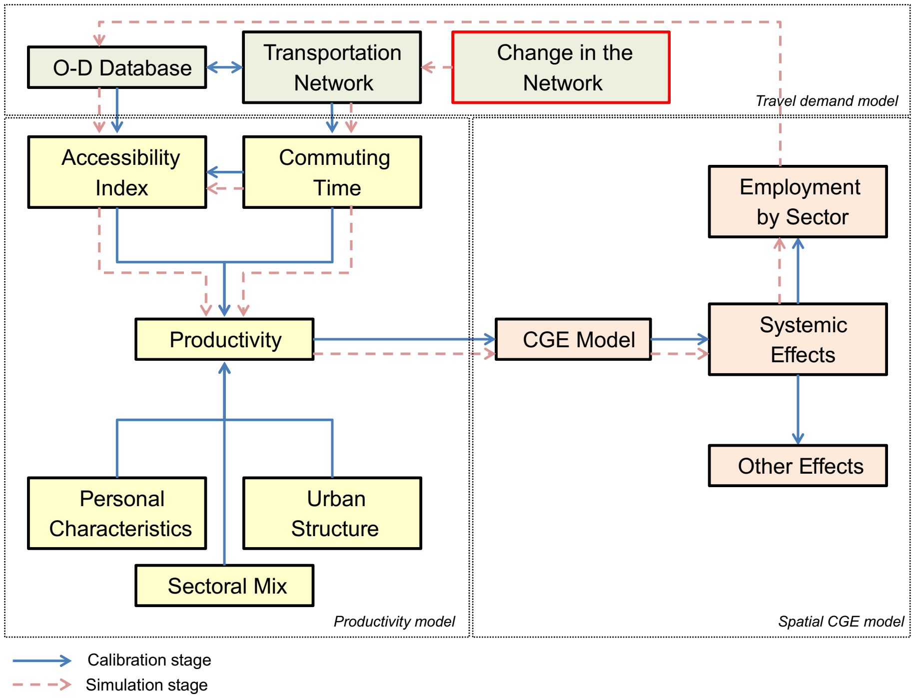

Fig. 1. Integrated framework flowchart. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.) Source: (Haddad et al., 2015).

This estimation can be described by Eq. (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 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 Eq. (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.

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.

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.	9483	2882
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.

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

[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.

Table 2
Transportation model – mode share and average trip characteristics in each scenario.

	Baseline	Scenario A	Scenarios B		
			(E-hailing occupancy increases to 3 pax./veh.)		
	(2018 projection without e-hailing)	(2018 projected with e-hailing)	B1	B2	B3
			(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)
Trips					
Public transit	1,605,276	1,586,239	1,567,737	1,432,605	1,263,690
Private cars	1,695,886	1,623,179	1,564,509	1,023,983	348,326
E-hailing	0	91,744	168,916	844,573	1,689,143
Total	3,301,162	3,301,162	3,301,162	3,301,162	3,301,162
Number of vehicles					
Private cars	1,211,347	1,159,414	1,117,507	731,417	248,804
E-hailing	0	65,531	56,305	281,524	563,048
Total	1,211,347	1,224,945	1,173,812	1,012,941	811,852
Mode share					
Public transit	48.6%	48.1%	47.5%	43.4%	38.3%
Private cars	51.4%	49.2%	47.4%	31.0%	10.6%
E-hailing	0.0%	2.8%	5.1%	25.6%	51.2%
Mean travel time (min)					
Public transit	65.8	65.9	65.7	63.1	58.2
Private cars & e-hailing	31.7	32.1	31.2	27.0	23.4

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.

Table 2 compares the characteristics of each scenario[9] related to the intermediate outcomes of the transportation model such as the number of trips, mode share and the average travel time for each mode.

In the baseline, when there is no e-hailing, public transit and private cars have respectively 48.6% and 51.4% of the motorized mode share. In scenario A, when e-hailing is added to the system, it absorbs 2.8% of trips. Meanwhile, the mode share of public transit and of private cars fall respectively to 48.1% and 49.2%, a decrease that is proportional to the substitution pattern calculated in Section 3.1. In scenario A, the total number of vehicles increases 1.1%, and the average travel time of trips made by car have a similar increase. Meanwhile, travel times by public transit are roughly unaffected.

Scenarios B1–B3 present different patterns. First, as imposed by the criteria used to define these scenarios, there is a large decrease in the mode share of trips made with private cars. The share of trips made by public transit also decreases, but in a much lower ratio. The total number of vehicles observed in each of these scenarios correspond to respectively 96.9%, 83.6% and 67% of the baseline, and the average travel time by car decreases to respectively 98.2%, 85% and 73.8% of the baseline. In the case of trips made by public transit, the mean travel time also goes down, however the decrease is proportionally smaller, corresponding to 99.7%, 95.9% and 88.5% of the travel time observed in the baseline.

In summary, in scenario A we have a slight increase in the number of vehicles and in travel times due to the share of trips that migrate from public transit to e-hailing. Then, on scenarios B1–B3, we have large reductions in the number of vehicles and in the average travel time of trips.

Given these intermediate outcomes from the transportation model, we then proceed to the next step of our integrated framework where we calculate several variables in the final equilibrium of each scenario. The selected output variables evaluated in this step 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.
- *Parking demand (total):* parking spots required by private drivers may be affected by mode switch.

Table 3 shows the results for each of these variables for all the scenarios included in our analysis. The results 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 min. 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

[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/).

[9] The pricing of e-hailing is assumed to remain constant within all simulated scenarios. We note that pricing of e-hailing is not a determinant of e-hailing mode share. Instead, the mode share of e-hailing is exogenously imposed in each scenario.

Table 3
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	6908	6908	6902	6902	7394	7394	7009	7009
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)	1652.9	1653.5	1653.6	1657.8	1658.4	1676.1	1679.8	1680.1	1688.5
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	1223.4	2181.7	2758.7	5062.7
RMSP (% change)		0.007	0.013	0.044	0.078	0.263	0.469	0.593	1089
Brazil (USD million change)		35.1	62.4	212.3	378.1	1279.0	2280.8	2884.0	5292.5
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%

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. Regarding the latter, the SCGE model does not consider household relocation within cities in the SPMR, only taking into consideration potential intercity migration to adjust local labor markets in the long run. 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.

It is important to notice that the findings of this paper face the issue of external validity, i.e. they are not directly transferable to other locations. The causal relationships embedded in the analytical and numerical structures of the SCGE model, in particular, and integrated modeling framework, in general, are valid only in the context of the evaluation of the impacts of the ride-hailing interventions in the environment in which they were implemented. This is the issue of internal validity which only allows identifying the impact of an intervention conducted in a given environment. However, if one wants to forecast comparable impacts of similar ride-hailing interventions implemented in RMSP in other urban environments, one should use a similar modeling structure calibrated, nonetheless, with data for that specific urban area.

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 only tends 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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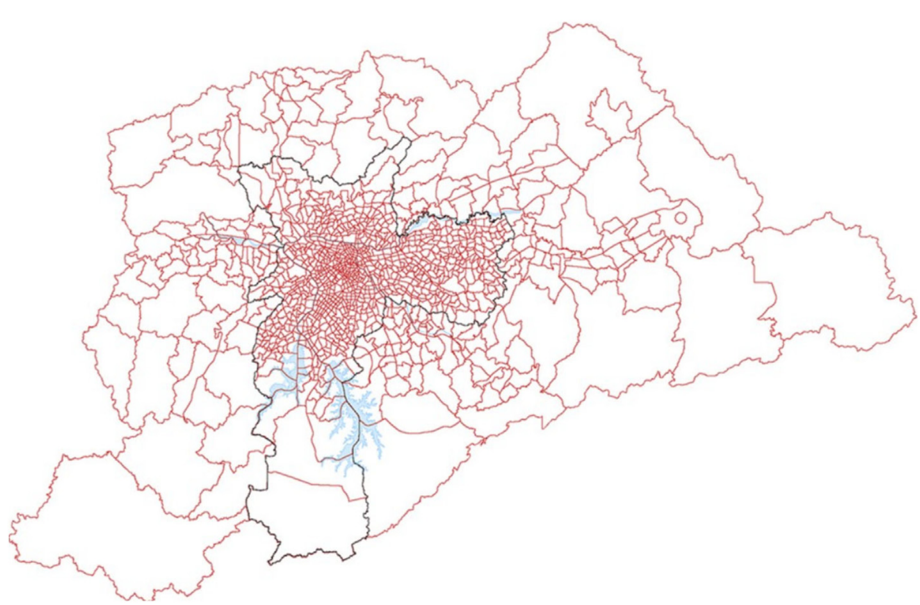
Appendix A. Transport modeling framework (cf. Haddad et al., 2019)

To assess the impacts of changes in the transport system within the SPMR, we used a travel demand model for personal travel developed and implemented by the engineering company TTC– Engenharia de Tráfego e de Transportes, São Paulo, Brazil. The model consists of an aggregated trip-based classical four-step model that takes into account socioeconomic data, survey data, transportation infrastructure characteristics, and operational information to produce trip flows and times. The four steps included in the model are: (i)Trip Generation, which determines the number of trips (by origin and destination from/to each pre-defined zone) within a period of time, by trip purpose; (ii) Trip Distribution, which determines the origin-destination (OD) pairs, based on the total origin and destination trips of each zone; (iii) Mode Choice, which defines the proportion of trips for each OD pair that uses automobiles or public/mass transport modes; and (iv)Assignment, which selects which paths will be used by each OD pair and transport mode.

The variable used to quantify travel time and travel cost is referred to as the generalized cost, which is a linear combination of the weighted components of travel time (walking, waiting, in vehicle, etc.), distance, and monetary costs (fuel costs, public transportation fare, parking costs, etc.) spent on each trip.



The zone system adopted in this study is the same used in the household survey carried out by the São Paulo Metropolitan Company (Metro) in 2007, in which the SPMR was divided into 1895 micro traffic zones, from the original 460 TAZs. Fig. A1.1 illustrates the zone system used for the SPMR (in red), and the city borders of São Paulo (in black).

The first step of the model estimates the total number of trips going out and to every single zone within the study area. This is referred to as the trip generation module. In this stage, regression models are used to relate socioeconomic and geographic variables to travel vectors obtained from the OD 2007 and its 2012 update (METRO, 2013). Two sets of equations are estimated: (i) travel generation equations, which feature the following independent variables: income, self-ownership, population and family structure; and, (ii) travel attraction equations, which use employment and economic sectors as independent variables. These equations are then used to estimate trip generation and attraction for each zone.

In the second step, the vectors of trip generation and attraction obtained in the first step are used in a gravity-type model to estimate the number of trips between origin and destination pairs, creating an O-D matrix using a travel distribution model. Trips for each O-D pair are hence estimated as proportional to the number of trips leaving the origin zone and the number of trips arriving at the destination zone, and inversely proportional to the generalized travel cost between two zones.

The generalized cost between pairs of zones was calculated using a network model for both automobile and mass transit modes. For automobiles, the operational cost of the vehicle, the occupation (people-automobile ratio), travel time, and distance were considered in the calculation. For mass transit, the generalized cost considered the average walking distance, waiting time, travel time, and cost of the fare.

Calibration of the distribution model is made by comparing the travel frequency histogram obtained from the observed OD 2007/2012 surveys with the histogram obtained from the estimated matrix. The distribution model is then adjusted in an iterative manner.

In the third step, travel flows need to be broken down by mode (mass transit and automobile). A mode choice model is estimated employing a binomial logit function which considers as explanatory variables for the probability of using different transportation modes the following variables: reason for travel, income, cost and time of travel, car ownership, travel time, frequency, among others.

Finally, the software Emme4 is used for the assignment of paths by OD pair and mode of transport.[10] As previously mentioned, the simulation model used for this study covers the main roads of the SPMR, in addition to all subway and rail networks. Each link has information attached on length, number of lanes, hierarchical classification, capacity, maximum speed, etc. The simulation model includes the municipal bus lines of São Paulo (regulated by SPTrans) and other 38 cities of the SPMR, intercity bus lines in the SPMR (regulated by EMTU), metropolitan passenger trains operated by the São Paulo Metropolitan Trains Company (CPTM), and the Metro lines. For each of the transit lines there is information on its physical and operational characteristics, such as itinerary, frequency, fare, vehicle type, capacity, etc. A total of 3044 unidirectional transit lines, among municipal, intercity, trains and subway are included in the model.

The simulation model adopts specific travel time functions, or volume delay functions (VDF), for calculating the distribution of automobile demand. The route assignment algorithm for automobiles assumes every car seeks to improve its travel time in each iteration until alternatives routes do not produce improvements in travel time. For mass transport, the transit time of a line at each link is computed considering the automobile time at that link. For links where there are no automobiles, the transit time is computed using a constant speed instead.

Appendix B. Specification of the SCGE Model (cf. Haddad et al., 2019)

In this Annex, we present the analytical, functional and numerical structures of the spatial Computable General Equilibrium model for SPMR. The specification of the linearized form of the model is provided, based on different groups of equations. The notational convention uses uppercase letters to represent the levels of the variables and lowercase for their percentage-change representation. Superscripts *(u)*, $u = 0, 1j, 2j, 3, 4, 5$, refer, respectively, to output *(0)* and to the five different regional-specific users of the products identified in the model[11]: producers in sector *j (1j)*, investors in sector *j (2j)*, households *(3)*, purchasers of exports *(4)*, and government *(5)*; the second superscript *(r)* identifies the domestic region where the user is located. Inputs are identified by two subscripts: the first *(i)* takes the values *1, …, g*, for commodities, $g + 1$, for primary factors; the second subscript identifies the source of the input, being it from domestic region *b (1b)* or imported *(2)*, or coming from labor from domestic region *b (1b)* or capital *(2)*, the two groups of primary factors in the model. The symbol (•) is employed to indicate a sum over an index.

We define the following sets: $G = \{1, \ldots, g\}$, where g is the number of composite goods; $G^* = \{1, \ldots, g, g + 1\}$, where $g + 1$ is the number of composite goods and primary factors, with $G^* \supset G$; $H = \{1, \ldots, h\}$, where h is the number of industries; $U = \{(3), (4b), (5), (kj)\}$ for $k = (1), (2)$ and $j \in H$, is the set of all users in the model; $U^* = \{(3), (5), (kj)\}$ for $k = (1), (2)$ and $j \in H$, with $U \supset U^*$, is the subset of domestic users; $S = \{1, \ldots, r, r + 1\}$, where $r + 1$ is the number of all regions (including foreign); $S^* = \{1, \ldots, r\}$, with $S \supset S^*$, is the subset with the r domestic regions; and $F = \{1, \ldots, f\}$ is the set of primary factors. In the SCGE model for the SPMR, $g = h = 8$, $r = 41$, and $f = 2$.

We model the sourcing of composite goods based on multilevel structures, which enable a great number of substitution possibilities. We employ nested sourcing functions for the creation of composite goods, available for consumption in the regions of the model. We assume that domestic users, i.e. firms, investors, households, and government, use combinations of composite goods specified within two-level CES nests. At the bottom level, bundles of domestically produced goods are formed as combinations of goods from different regional sources. At the top level, substitution is possible between domestically produced and imported goods. Eqs. (B1) and (B2) describe, respectively, the regional sourcing of domestic goods, and the substitution between domestic and imported products.

$$x_{(i(1b))}^{(u)r} = x_{(i(1\bullet))}^{(u)r} - \sigma 1_{(i)}^{(u)r} \left(p_{(i(1b))}^{(u)r} - \sum_{l \in S^*} \left(\frac{V(i, 1l, (u), r)}{V(i, 1\bullet, (u), r)} \right) \left(p_{(i(1l))}^{(u)r.} \right) \right) \qquad \text{(B1)}$$
$$i \in G;\ b \in S^*;\ (u) \in U^*;\ r \in S^*$$

where $x_{(i(1b))}^{(u)r}$ is the demand by user *(u)* in region r for good i in the domestic region *(1b)*; $p_{(i(1b))}^{(u)r}$ is the price paid by user *(u)* in region r for good i in the domestic region *(1b)*; $\sigma 1_{(i)}^{(u)r}$ is a parameter measuring the user-specific elasticity of substitution between alternative domestic sources of commodity i, known as the regional trade Armington elasticity; and $V(i, 1l, (u), r)$ is an input-output flow coefficient that measures purchasers' value of good i from

[10] This Canadian software has been widely used for analytical work in Brazil, and has been the choice of most transit agencies in São Paulo for planning purposes.

[11] We have specified a sixth residual user, *(6)*, to deal with statistical discrepancies in the balancing of the model's absorption matrix based on the SPMR interregional input-output system (IIOS). This procedure deals with the information provided in the IIOS on changes in inventories.

domestic source l used by user *(u)* in region r.

$$x_{(is)}^{(u)r} = x_{(i\bullet)}^{(u)r} - \sigma 2_{(i)}^{(u)r}\left(p_{(is)}^{(u)r} - \sum_{l=1\bullet,2}\left(\frac{V(i,l,(u),r)}{V(i,\bullet,(u),r)}\right)\left(p_{(il)}^{(u)r}\right)\right) \quad i\in G;\ s=1\bullet,2;\ (u)\in U^*;\ r\in S^* \tag{B2}$$

where $x_{(is)}^{(u)r}$ is the demand by user *(u)* in region r for either the domestic composite or the foreign good i; $p_{(is)}^{(u)r}$ is the price paid by user *(u)* in region r for either the domestic composite or the foreign good i; $\sigma 2_{(i)}^{(u)r}$ is a parameter measuring the user-specific elasticity of substitution between the domestic bundle and imports of good i, known as the international trade Armington elasticity; and $V(i,l,(u),r)$ is an input-output flow coefficient that measures purchasers' value of good i from either the aggregate domestic source or the foreign source l used by user *(u)* in region r.

In addition to goods used as intermediate inputs, firms in the model also demand primary factors of production. The equations that describe the industry j's demands inputs are derived under the assumption of Leontief technology with Armington nests (imperfect substitution between inputs of the same type from different sources). In our specification of the nested production functions, we assume firms to use combinations of composite intermediate inputs, formed according to Eqs. (B1) and (B2), and primary factor composites. In the case of the primary factor bundle, substitution is possible among different types of primary factors. Eq. (B3) specifies the substitution between a composite labor input and capital in the model, and is derived under the assumption that industries choose their primary factor inputs to minimize costs subject to obtaining sufficient primary factor inputs to satisfy their technical requirements (nested Leontief/CES specification). We have included technical change variables to allow for factor-specific productivity shocks.

$$x_{(g+1,s)}^{(1j)r} - a_{(g+1,s)}^{(1j)r} = x_{(g+1,\bullet)}^{(1j)r} - \sigma 3_{(g+1)}^{(1j)r}\left(p_{(g+1,s)}^{(1j)r} + a_{(g+1,s)}^{(1j)r} - \sum_{l\in F}\left(\frac{V(g+1,l,(1j),r)}{V(g+1,\bullet,(1j),r)}\right)\left(p_{(g+1,l)}^{(1j)r} + a_{(g+1,l)}^{(1j)r}\right)\right) \quad j\in H;\ s\in F;\ r\in S^* \tag{B3}$$

where $x_{(g+1,s)}^{(1j)r}$ is the demand by sector j in region r for each primary factor; $a_{(g+1,s)}^{(1j)r}$ is the exogenous sector-specific variable of (saving) technical change for primary factor s in region r; $p_{(g+1,s)}^{(1j)r}$ is the price paid by sector j in region r for primary factor s; $\sigma 3_{(g+1)}^{(1j)r}$ is a parameter measuring the sector-specific elasticity of substitution among different primary factors; and $V(g+1,l,(1j),r)$ is an input-output flow coefficient that measures purchasers' value of factor l used by sector j in region r.

In this metropolitan framework, labor inputs are defined by the place of residence. Firms producing at a given region draw their workers from the labor force available in all the municipalities. Eq. (B4) defines the composition of industry j's in region r labor input. In addition to the industry-region-specific expansion in the overall demand for labor, the demand for workers from different locations also respond to changes in the wage of each type relative to the average wage for labor in each regional industry. Notice that, in Eq. (4), technical changes variables associated with labor by place of residence allow imposing productivity shocks that will relate to changes in commuting costs.

We model the combination of intermediate inputs and the value added (primary factors) aggregate in fixed proportions, at the very top of the nested production function, assuming there is no substitution between primary factors and other inputs. The Leontief specification is presented in Eq. (B5). More flexible functional forms have been rarely introduced in multi-regional models, mainly due to data availability constraints. In addition to a technical coefficient in the relation between the sectoral demand for the primary factor composite and the total output, we have also included a scale parameter. This modeling procedure has been based on previous work made by Haddad and Hewings (2005) which allows for the introduction of Marshallian agglomeration (external) economies, by exploring local properties of the CES function.

$$x_{(g+1(1b))}^{(1j)r} = x_{(g+1(1\bullet))}^{(1j)r} - \sigma 4_{(g+1(1\bullet))}^{(1j)r}\left(p_{(g+1(1b))}^{(1j)r} - \sum_{l\in S^*}\left(\frac{V(g+1,1l,(1j),r)}{V(g+1,1\bullet,(1j),r)}\right)\left(p_{(g+1(1l))}^{(1j)r}\right)\right) \quad j\in H;\ i\in G;\ b\in S^*;\ r\in S^* \tag{B4}$$

where $x_{(g+1(1b))}^{(1j)r}$ is the demand by sector *(1j)* in region r for workers living in the domestic region *(1b)*; $p_{(g+1(1b))}^{(1j)r}$ is the wage paid by sector *(1j)* in region r for workers residing in the domestic region *(1b)*; $\sigma 4_{(g+1(1\bullet))}^{(1j)r}$ is a parameter measuring the sector-specific elasticity of substitution between workers living in different locations *(1b)*; and $V(g+1,1l,(1j),r)$ is an input-output flow coefficient that measures labor payments for workers living in region *(1b)* made by firms producing in region r.

$$x_{(i\bullet)}^{(1j)r} = \mu_{(g+1,\bullet)}^{(1j)r} z^{(1j)r} + a_{(i)}^{(1j)r} \quad j\in H;\ i\in G^*;\ r\in S^* \tag{B5}$$

where $x_{(i\bullet)}^{(1j)r}$ is the demand by sector j in region r for the bundles of composite intermediate inputs and primary factors i; $z^{(1j)r}$ is total output of sector j in region r; $a_{(i)}^{(1j)r}$ is the exogenous sector-specific variable of technical change for composite intermediate inputs and primary factors in region r; and $\mu_{(i\bullet)}^{(1j)r}$ is a scale parameter measuring the sector-specific returns to the composite of primary factors in each region.

Units of capital stock are created for industry j, at minimum cost. Commodities are combined via a Leontief function, as specified in Eq. (B6). As described in Eqs. (B1) and (B2), regional, and domestic and imported commodities are combined, respectively, via a CES specification (Armington assumption). No primary factors are used in capital creation. The use of these inputs is recognized through the capital goods producing sectors in the model, mainly machinery and equipment industries, construction, and support services.

$$x_{(i\bullet)}^{(2j)r} = z^{(2j)r} + a_{(i)}^{(2j)r} \quad j\in H;\ i\in G;\ r\in S^* \tag{B6}$$

where $x_{(i\bullet)}^{(2j)r}$ is the demand by sector j in region r for the bundles of composite capital goods i; $z^{(2j)r}$ is total investment of sector j in region r; $a_{(i)}^{(2j)r}$ is the exogenous sector-specific variable of technical change for changing the composition of the sectoral unit of capital in region r.

In deriving the household demands for composite commodities, we assume that households in each region behave as a single, budget-constrained, utility-maximizing entity. The utility function is of the Stone-Geary or Klein-Rubin form. Eq. (B7) determines the optimal composition of household demand in each region. Total regional household consumption is determined as a function of real household income. The demands for the commodity bundles in the nesting structure of household demand follow the CES pattern established in Eqs. (B1) and (B2), in which an activity variable and a price-substitution term play the major roles. In Eq. (B7), consumption of each commodity i depends on two components: first, for the subsistence component, which is defined as the minimum expenditure requirement for each commodity, changes in demand are generated by changes in the number of households and tastes; second, for the luxury or supernumerary part of the expenditures in each good, demand moves with changes in the regional supernumerary expenditures, changes in tastes, and changes in the price of the composite commodity. The two components of household expenditures on the composite commodities are weighted by their respective shares in the total consumption of the composite commodity.

$$V(i,\bullet,(3),\mathrm{r})\left(p_{(i\bullet)}^{(3)r}+x_{(i\bullet)}^{(3)r}-a_{(i\bullet)}^{(3)r}\right)=\gamma_{(i)}^{r}P_{(i\bullet)}^{(3)r}Q^{r}\left(p_{(i\bullet)}^{(3)r}+x_{(i\bullet)}^{(3)r}-a_{(i\bullet)}^{(3)r}\right)+\beta_{(i)}^{r}\left(C^{r}-\Sigma_{j\in G}\gamma_{(j)}^{r}P_{(j\bullet)}^{(3)r}Q^{r}\left(p_{(j\bullet)}^{(3)r}+x_{(j\bullet)}^{(3)r}-a_{(i\bullet)}^{(3)r}\right)\right)\quad i\in G;\, r\in S^{*} \tag{B7}$$

where $p_{(i\bullet)}^{(3)r}$ is the price paid by household in region r for the composite good i; $x_{(i\bullet)}^{(3)r}$ is the household demand in region r for the composite good i; $a_{(i\bullet)}^{(3)r}$ is the commodity-specific variable of regional taste change; Q^r is the number of households in region r; C^r is the total expenditure by household in region r, which is proportional to regional labor income; $\gamma_{(i)}^{r}$ is the subsistence parameter in the linear expenditure system for commodity i in region r; $\beta_{(i)}^{r}$ is the parameter defined for commodity i in region r measuring the marginal budget shares in the linear expenditure system; and $V(i,\bullet,(3),\mathrm{r})$ is an input-output flow coefficient that measures purchasers' value of good i consumed by households in region r.
As noted by Peter et al. (1996), a feature of the Stone-Geary utility function is that only the above-subsistence, or luxury, component of real household consumption, $utility^{(r)}$, affects the per-household utility, as described in Eq. (B8).

$$utility^{(r)}=\left(C^{r}-\Sigma_{j\in G}\gamma_{(j)}^{r}P_{(j\bullet)}^{(3)r}Q^{r}\left(p_{(j\bullet)}^{(3)r}+x_{(j\bullet)}^{(3)r}-a_{(i\bullet)}^{(3)r}\right)\right)-q^{r}-\Sigma_{i\in G}\beta_{(i)}^{r}p_{(i\bullet)}^{(3)r}\quad r\in S^{*} \tag{B8}$$

where q^r is the percentage change in the number of households in each region.
In Eq. (B9), foreign demands (exports) for domestic good i depend on the percentage changes in a price, and three shift variables which allow for vertical and horizontal movements in the demand curves. The price variable which influences export demands is the purchaser's price in foreign countries, which includes the relevant taxes and margins. The parameter $\eta_{(is)}^{r}$ controls the sensitivity of export demand to price changes.

$$\left(x_{(is)}^{(4)r}-fq_{(is)}^{(4)r}\right)=\eta_{(is)}^{r}\left(p_{(is)}^{(4)r}-phi-fp_{(is)}^{(4)r}\right)\quad i\in G;\, r,s\in S^{*} \tag{B9}$$

where $x_{(is)}^{(4)r}$ is foreign demand for domestic good i produced in region s and sold from region r (in the model there is no re-exports, so that $r = s$); $p_{(is)}^{(4)r}$ is the purchasers' price in domestic currency of exported good i demand in region r; phi is the nominal exchange rate; and $fq_{(is)}^{(4)r}$ and $fp_{(is)}^{(4)r}$ are, respectively, quantity and price shift variables in foreign demand curves for regional exports.
Governments consume mainly public goods provided by the public administration sectors. Eq. (B10) shows the movement of government consumption in relation to movements in real tax revenue.

$$x_{(is)}^{(5)r}=taxrev+f_{(is)}^{(5)r}+f^{(5)r}+f^{(5)}\quad i\in G;\, s=1\mathrm{b},2;\, r,b\in S^{*} \tag{B10}$$

where $x_{(is)}^{(5)r}$ is the government demand in region r for good i from region s; $f_{(is)}^{(5)r}$, $f^{(5)r}$ and $f^{(5)}$ are, respectively, commodity and source-specific shift term for government expenditures in region r, shift term for government expenditures in region r, and an overall shift term for government expenditures; and $taxrev$ is the percentage change in real revenue from indirect taxes.
Eq. (B11) specifies the sales tax rates for different users. They allow for variations in tax rates across commodities, and their sources and destinations. Tax changes are expressed as percentage-point changes in the *ad valorem* tax rates.

$$t_{(is)}^{(u)r}=f_{i}+f_{i}^{(u)}+f_{i}^{(u)r}\quad i\in G;\, s=1\mathrm{b},2;\, b,r\in S^{*};\, u\in U \tag{B11}$$

where $t_{(is)}^{(u)r}$ is the power of the tax on sales of commodity (is) to user (u) in region r; and f_i, $f_i^{(u)}$, and $f_i^{(u)r}$ are different shift terms allowing percentage changes in the power of tax.
Eqs. (B12) and (B13) impose the equilibrium conditions in the domestic and imported commodities markets. Notice that there is no margin commodity in the model. Moreover, there is no secondary production in the model. In Eq. (B11), demand equals supply for regional domestic commodities.

$$\Sigma_{j\in H}Y(l,j,r)x_{(l1)}^{(0j)r}=\Sigma_{(u)\in U}B(l,1b,(u),r)x_{(l1)}^{(u)r}\quad l\in G,\, b,r\in S^{*} \tag{B12}$$

where $x_{(l1)}^{(0j)r}$ is the output of domestic good l by industry j in region r; $x_{(l1)}^{(u)r}$ is the demand of the domestic good l by user (u) in region r; $Y(l,j,r)$ is the input-output flow measuring the basic value of output of domestic good l by industry j in region r; and $B(l,1,(u),r)$ is the input-output flow measuring the basic value of domestic good l used by (u) in region r.
Eq. (B13) imposes zero pure profits in importing. It defines the basic price of a unit of imported commodity i – the revenue earned per unit by the importer – as the international C.I.F. price converted to domestic currency, including import tariffs.

$$p_{(i(2))}^{(0)}=p_{(i(2))}^{(w)}-phi+t_{(i(2))}^{(0)}\quad i\in G \tag{B13}$$

where $p_{(i(2))}^{(0)}$ is the basic price in domestic currency of good i from foreign source; $p_{(i(2))}^{(w)}$ is world C.I.F. price of imported commodity i; phi is the nominal exchange rate; and $t_{(i(2))}^{(0)}$ is the power of the tariff. i.e. one plus the tariff rate, on imports of i.
Together with Eqs. (B13), (B14) and (B15) constitute the model's pricing system. The price received for any activity is equal to the costs per unit of output. As can be noticed, the assumption of constant returns to scale adopted here precludes any activity variable from influencing basic prices, i.e., unit costs are

independent of the scale at which activities are conducted. Thus, Eq. (B14) defines the percentage change in the price received by producers in regional industry j per unit of output as being equal to the percentage change in j's costs, which are affected by changes in technology and changes in input prices.

$$\Sigma_{l\in G} Y(l,j,r)\left(p_{(l1)}^{(0)r}+a_{(l1)}^{(0)r}\right)=\Sigma_{l\in G^*,F}\Sigma_{s\in S} V(l,s,(1j),r)p_{(ls)}^{(1j)r} \quad j\in H;\, r\in S^* \tag{B14}$$

where $p_{(l1)}^{(0)r}$ is the basic price of domestic good l in region r; $a_{(l1)}^{(0)r}$ refer to technological changes, measured as a weighted average of the different types of technical changes with influence on j's unit costs; $p_{(ls)}^{(1j)r}$ is the unit cost of sector j in region r; $Y(l,j,r)$ is the input-output flow measuring the basic value of output of domestic good l by industry j in region r; and $V(l,s,(1j),r)$ are input-output flows measuring purchasers' value of good or factor l from source s used by sector j in region r.

Eq. (B15) imposes zero pure profits in the distribution of commodities to different users. Prices paid for commodity i from region s in industry j in region r by each user equate to the sum of its basic value and the costs of the relevant taxes.

$$V(i,s,(u),r)p_{(is)}^{(u)r}=(B(i,s,(u),r)+T(i,s,(u),r))\left(p_{(is)}^{(0)}+t_{(is)}^{(u)r}\right) \quad i\in G;\, s=1b,2;b,r\in S^*;u\in U \tag{B15}$$

where $p_{(is)}^{(u)r}$ is the price paid by user *(u)* in region r for good *(is)*; $p_{(is)}^{(0)}$is the basic price of domestic good *(is)*; $t_{(is)}^{(u)r}$ is the power of the tax on sales of commodity *(is)* to user *(u)* in region r; $V(i,s,(u),r)$ are input-output flows measuring purchasers' value of good i from source s used by user *(u)* in region r; $B(i,s,(u),r)$ is the input-output flow measuring the basic value of good *(is)* used by *(u)* in region r; and $T(i,s,(u),r)$ is the input-output flow associated with tax revenue of the sales of *(is)* to *(u)* in region r.

The theory of the allocation of investment across industries is represented in Eqs. (B16) to (B19). The comparative-static nature of the model restricts its use to short-run and long-run policy analysis. When running the model in the comparative-static mode, there is no fixed relationship between capital and investment. The user decides the required relationship on the basis of the requirements of the specific simulation. Eq. (B16) defines the percentage change in the current rate of return on fixed capital in regional sectors. Under static expectations, rates of return are defined as the ratio between the rental values and the cost of a unit of capital in each industry – defined in Eq. (B17) –, minus the rate of depreciation.

$$r_{(j)}^r=\psi_{(j)}^r\left(p_{(g+1,2)}^{(1j)r}-p_{(k)}^{(1j)r}\right) \quad j\in H;\, r\in S^* \tag{B16}$$

where $r_{(j)}^r$ is the regional-industry-specific rate of return; $p_{(g+1,2)}^{(1j)r}$ is the rental value of capital in sector j in region r; $p_{(k)}^{(1j)r}$ is the cost of constructing units of capital for regional industries; and $\square_{(j)}^r$ is a regional-industry-specific parameter referring to the ratio of the gross to the net rate of return.

Eq. (B17) defines $p_{(k)}^{(1j)r}$ as:

$$V(\bullet,\bullet,(2j),r)\left(p_{(k)}^{(1j)r}-a_{(k)}^{(1j)r}\right)=\Sigma_{i\in G}\Sigma_{s\in S}V(i,s,(2j),r)\left(p_{(is)}^{(2j)r}-a_{(is)}^{(2j)r}\right) \quad j\in H;\, r\in S^* \tag{B17}$$

where $p_{(is)}^{(2j)r}$ is the price paid by user *(2j)* in region r for good *(is)*; $a_{(k)}^{(1j)r}$ and $a_{(is)}^{(2j)r}$ are technical terms; and $V(i,s,(2j),r)$ represents input-output flows measuring purchasers' value of good i from source s used by user *(2j)* in region r.

Eq. (B18) says that if the percentage change in the rate of return in a regional industry grows faster than the national average rate of return, capital stocks in that industry will increase at a higher rate than the average national stock. For industries with lower-than-average increase in their rates of return to fixed capital, capital stocks increase at a lower-than-average rate, i.e., capital is attracted to higher return industries. The shift variable, $f_{(k)}^{(1j)r}$, exogenous in long-run simulation, allows shifts in the industry's rates of return.

$$r_{(j)}^r-\omega=\varepsilon_{(j)}^r\left(x_{(g+1,2)}^{(1j)r}-x_{(g+1,2)}^{(\bullet)r}\right)+f_{(k)}^{(1j)r} \quad j\in H;\, r\in S^* \tag{B18}$$

where $r_{(j)}^r$ is the regional-industry-specific rate of return; ω is the overall rate of return on capital; $x_{(g+1,2)}^{(1j)r}$ is the capital stock in industry j in region r; $f_{(k)}^{(1j)r}$ the capital shift term in sector j in region r; and $\varepsilon_{(j)}^r$ measures the sensitivity of capital growth to rates of return of industry j in region r.

Eq. (B19) implies that the percentage change in an industry's capital stock, $x_{(g+1,2)}^{(1j)r}$, is equal to the percentage change in industry's investments in the period, $z^{(2j)r}$.

$$z^{(2j)r}=x_{(g+1,2)}^{(1j)r}+f_{(k)}^{(2j)r} \quad j\in H;\, r\in S^* \tag{B19}$$

where $f_{(k)}^{(2j)r}$ allows for exogenous shifts in sectoral investments in region r.

In the specification of the labor market, Eq. (B20) defines the regional aggregation of labor prices (wages) across industries by place of production while Eq. (B21) defines aggregate wages by place of residence. Eq. (B22) shows movements in regional wage differentials, *wage_diff*$^{(r)}$, defined as the difference between the movement in the aggregate regional real wage received by workers in region r, and the national real wage.

$$V(g+1,1\bullet,\bullet,r)\left(p_{(g+1,1\bullet)}^{(\bullet)r}-a_{(g+1,1\bullet)}^{(\bullet)r}\right)=\Sigma_{b\in S^*}\Sigma_{j\in H}V(g+1,1b,(1j),r)\left(p_{(g+1,1b)}^{(1j)r}-a_{(g+1,1b)}^{(1j)r}\right) \quad r\in S^* \tag{B20}$$

$$V(g+1,1b,\bullet,\bullet)\left(p_{(g+1,1b)}^{(\bullet)\bullet}-a_{(g+1,1b)}^{(\bullet)\bullet}\right)=\Sigma_{r\in S^*}\Sigma_{j\in H}V(g+1,1b,(1j),r)\left(p_{(g+1,1b)}^{(1j)r}-a_{(g+1,1b)}^{(1j)r}\right) \quad b\in S^* \tag{B21}$$

where $p_{(g+1,1)}^{(1j)r}$ is the wage in sector j in region r, $a_{(g+1,1)}^{(1j)r}$ is a technical term, and $V(g+1,1b,(1j),r)$ represents input-output flows measuring sectoral labor payments to residents in region *1b* working in region *r*.

$$wage\_diff^{(r)} = p^{(\bullet)\bullet}_{(g+1,1r)} - cpi - natrealwage \qquad \underset{r \in S^*}{} \tag{B22}$$

where *cpi* is the national consumer price index, computed as the weighted average of $p^{(3)r}_{(is)}$ across regions *r* and consumption goods *(is)*; and *natrealwage* is the national consumer real wage.

Regional population is defined through the interaction of demographic variables, including interregional migration. Links between regional population and regional labor supply are provided. Demographic variables are usually defined exogenously, and together with the specification of some of the labor market settings, labor supply can be determined together with either interregional wage differentials or regional unemployment rates. In summary, either labor supply and wage differentials determine unemployment rates, or labor supply and unemployment rates determine wage differentials.

Eq. (B23) defines the percentage-point change in regional unemployment rates in terms of percentage changes in labor supply and persons employed.

$$LABSUP(r)del\_unr^{(r)} = EMPLOY(r)\left(labsup^{(r)} - x^{(\bullet)\bullet}_{(g+1,1r)}\right) \qquad r \in S^* \tag{B23}$$

where *del_unr*$^{(r)}$ measures percentage-point changes in regional unemployment rate; *labsup*$^{(r)}$ is the variable for regional labor supply; and the coefficients *LABSUP*(*r*) and *EMPLOY*(*r*) are the benchmark values for regional labor supply and regional employment, respectively, measured in terms of the resident population in the region. The variable *labsup*$^{(r)}$ moves with regional workforce participation rate, proportional to the regional population, and population of working age. Eq. (B24) defines regional population changes in the model as ordinary changes in flows of net regional migration (*d_rm*$^{(r)}$), net foreign migration (*d_fm*$^{(r)}$), and natural population growth (*d_g*$^{(r)}$).

$$POP(r)pop^{(r)} = d\_rm^{(r)} + d\_fm^{(r)} + d\_g^{(r)} \qquad r \in S^* \tag{B24}$$

where *POP*(*r*) is a coefficient measuring regional population in the benchmark year.

Eq. (B25) shows movements in per-household utility differentials, *util_diff*$^{(r)}$, defined as the difference between the movement in regional utility, and the national overall utility (*agg_util*), including a shift variable, *futil*$^{(r)}$.

$$util\_diff^{(r)} = utility^{(r)} - agg\_util + futil^{(r)} \qquad r \in S^* \tag{B25}$$

Finally, we can define changes in regional output as weighted averages of changes in regional aggregates, according to Eq. (B26) below:

$$GRP^r grp^r = C^r x^{(3)r}_{(\bullet\bullet)} + INV^r z^{(2\bullet)r} + GOV^r x^{(5)r}_{(\bullet\bullet)} + \left(FEXP^r x^{(4)r}_{(\bullet\bullet)} - FIMP^r x^{(\bullet)r}_{(\bullet 2)}\right) + \left(DEXP^r x^{(\bullet)s}_{(\bullet(1r))} - DIMP^r x^{(\bullet)r}_{(\bullet(1s))}\right) \qquad r \in S^*;\ s \in S^* \text{ for } s \neq r \tag{B26}$$

where *grp*^{r} is the percentage change in real Gross Regional Product in region *r*; and the coefficients *GRP*^{r} *INV*^{r}, *GOV*^{r}, *FEXP*^{r}, *FIMP*^{r}, *DEXP*^{r} and *DIMP*^{r} represent, respectively, the following regional aggregates: investments, government spending, foreign exports, foreign imports, domestic exports and domestic imports. National output, *GDP*, is, thus, the sum of *GRP*^{r} across all regions *r*. Notice that regional domestic trade balances cancel out.

To close the model, we set the following variables exogenously, which are usually exogenous both in short run and long run simulations: $a^{(1j)r}_{(g+1,s)}$, $a^{(1j)r}_{(i)}$, $a^{(2j)r}_{(i)}$, $a^{(3)r}_{(i\bullet)}, fq^{(4)r}_{(is)}, fp^{(4)r}_{(is)}, f^{(5)r}_{(is)}, f^{(5)r}, f^{(5)}, f_i, f^{(u)}_i, f^{(u)r}_i, p^{(w)}_{(i(2))}$, $t^{(0)}_{(i(2))}$, $a^{(0)r}_{(i1)}$, $a^{(1j)r}_{(k)}$, $a^{(2j)r}_{(is)}$, $a^{(\bullet)r}_{(g+1,1b)}$, $\square, f^{(2j)r}_{(k)}$, $d\_fm^{(r)}$, $d\_g^{(r)}$, and *futil*$^{(r)}$. To complete the short run environment, used in our forthcoming exercises, we also set unchanged current stocks of capital ($x^{(1j)r}_{(g+1,2)}$), the national real wage (*natrealwage*), regional wage differentials, (*wage_diff*$^{(r)}$), and regional population, by keeping regional migration unchanged (*d_rm*$^{(r)}$).[12]

There are other definitions of variables computed by using outcomes from simulations based on the system of Eqs. (B1)–(B26).

B.1. Calibration

The calibration of the model requires two subsets of data to define its numerical structure so that we implement the model empirically. First, we need information from an absorption matrix derived from interregional input-output sources (Table 1) to calculate the coefficients of the model based on the following input-output flows:

- $B(i,1b,(u),r)$, with $i \in G^*$, $(u) \in U$, $b, r \in S^*$
- $T(i,s,(u),r)$, with $i \in G^*$, $s \in S$, $(u) \in U$, $r \in S^*$
- $V(i,s,(u),r)$, with $i \in G^*$, $s \in S, F$, $(u) \in U$, $r \in S^*$
- $Y(i,j,r)$, with $i \in G^*$, $j \in H$, $r \in S^*$

We complete this information with supplementary demographic data from IBGE to calibrate the coefficients *LABSUP*(*r*), *EMPLOY*(*r*) and *POP*(*r*), with $r \square S^{\square}$. Because these estimates are based on snapshot observations for a single year revealing the economic structure of the economic system, this subset of data is denoted "structural coefficients" (Haddad et al., 2002).

The second piece of information necessary to calibrate the model is represented by the subset of data defining various parameters, mainly elasticities. These are called "behavioral parameters". Empirical estimates for some of the parameters of the model are not available in the literature. We have thus relied on "best guesstimates" based on usual values employed in similar models. We set to 1.5 the values for both regional trade elasticities, $\sigma 1^{(u)r}_{(i)}$ in Eq. (B1) and international trade elasticities, $\sigma 2^{(u)r}_{(i)}$ in Eq. (B2). Substitution elasticity between primary factors, $\sigma 3^{(1j)r}_{(g+1)}$ in Eq. (B3), was set to 0.5, and substitution elasticity between labor types, $\sigma 4^{(1j)r}_{(g+1(1\bullet))}$ in Eq. (B4), was set to 0.05. The current version of the model runs under constant returns to scale, so that we set to 1.0 the values of $\mu^{(1j)r}_{(g+1,\bullet)}$ in Eq. (B5). The marginal budget shares in regional household consumption, $\beta^r_{(i)}$ in Eq. (B7), were calibrated from the input-output data, assuming the average budget share to be equal to the marginal budget share, and the subsistence parameter $\gamma^r_{(i)}$, also in Eq. (B7), was associated with a Frisch parameter equal to -3.7. We have set to -2.0 the export demand elasticities, $\eta^r_{(is)}$ in Eq. (B9). The ratio of gross to net rate of return, $\psi^r_{(j)}$ in Eq. (B16), was set to 1.2. Finally, we set to 3.0 the parameter for sensitivity of capital growth to rates of return, $\varepsilon^r_{(j)}$ in Eq. (B18).

[12] In a long run closure, the assumptions on interregional mobility of capital and labor are relaxed by swapping variables $x^{(1j)r}_{(g+1,2)}$, *natrealwage*, *wage_diff*$^{(r)}$ and *d_rm*$^{(r)}$, for $f^{(1j)r}_{(k)}$, *del_unr*$^{(r)}$ and *util_diff*$^{(r)}$.

Table B1
Aggregate flows in the absorption matrix: SPMR, 2008 (values in current BRL millions).

LABELS	User (1j)^r	User (2j)^r	User (3)^r	User (4)^r	User (5)^r	User (6)	TOTAL
i∈G, s∈S*	B(i,1b,(1j),r)	B(i,1b,(2j),r)	B(i,1b,(3),r)	B(i,1b,(4))	B(i,1b,(5),r)	B(i,1b,(6))	B(i,1b,(•),•)
i∈G, s∈S-S*	B(i,2,(1j),r)	B(i,2,(2j),r)	B(i,2,(3),r)	B(i,2,(4))	B(i,2,(5),r)	B(i,2,(6))	B(i,2,(•),•)
i∈G, s∈S	T(i,s,(1j),r)	T(i,s,(2j),r)	T(i,s,(3),r)	T(i,s,(4))	T(i,s,(5),r)	–	T(i,s,(•),•)
s∈F	V(g + 1,s,(1j),r)	–	–	–	–	–	V(g + 1,s,(•),•)
TOTAL	Y(•,•,r)	V(•,•,(2j),r)	V(•,•,(3),r)	V(•,•,(4))	V(•,•,(5),r)	–	V(•,•,(•),•)
BRL	User (1j)^r	User (2j)^r	User (3)^r	User (4)^r	User (5)^r	User (6)	TOTAL
i∈G, s∈S*	2,266,060	473,957	1,503,559	456,070	590,814	17,931	5,308,391
i∈G, s∈S-S*	260,324	63,950	87,709	0	0	6391	418,374
i∈G, s∈S	202,128	41,624	160,585	24,791	0	2517	431,645
s∈F	2,579,879	–	–	–	–	–	2,579,879
TOTAL	5,308,391	579,531	1,751,853	480,861	590,814	26,839	8,738,289

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