Policy Choices and Modeling: An Illustration Using Commuting

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Abstract

We use an agent-based model to illustrate how policymakers may observe the outputs of testing competing policy instruments across various indicators. For example, comparing a housing policy with a social welfare program produces results in inflation, inequality, and total commuting for specific metropolitan regions. Moreover, the comparison is made simultaneously with the application of policy instruments and their absence. The illustration serves as a proof of concept for the use of ABMs to support the understanding of mechanisms and the relevance of capturing varied policy effects on heterogeneous environments. Specifically for our commuting illustration, results suggest that economies of agglomeration, population size, and spatial structure of each metropolitan region may be more relevant to determine total commuting than alternative housing and social welfare policy instruments.

Keywords: Agent-based models, Policymaking, Public Policies, Policy Choices, Methodological Tool

Opciones de política y modelado: ilustración usando desplazamientos

Resumen

Usamos un modelo basado en agentes para ilustrar cómo los formuladores de políticas pueden observar los resultados de probar instrumentos de políticas en competencia a través de una variedad de indicadores. La comparación de una política de vivienda con un programa de bienestar social, por ejemplo, arroja resultados sobre la inflación, la desigualdad y el desplazamiento total para regiones metropolitanas específicas. Además, la comparación se realiza simultáneamente con la aplicación de los instrumentos de política

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y su ausencia. La ilustración sirve como prueba de concepto para el uso de ABM para apoyar la comprensión de los mecanismos y la relevancia de capturar diversos efectos de políticas en entornos heterogéneos. Específicamente para nuestra ilustración de desplazamientos, los resultados sugieren que las economías de aglomeración, el tamaño de la población y la estructura espacial de cada región metropolitana pueden ser más relevantes para determinar el desplazamiento total que los instrumentos alternativos de política de vivienda y bienestar social.

Palabras clave: modelos basados en agentes, formulación de políticas, políticas públicas, opciones de políticas, herramienta metodológica

政策选择与建模：以通勤为例

摘要

我们使用一项基于agent模型(ABM)来阐明决策者如何通过一系列指标来测试和观察不同政策工具的输出。例如，将住房政策与社会福利计划进行比较，可以得出特定大都市地区的通货膨胀、不平等和总通勤量的结果。此外，比较是在“应用和不应用政策工具”这两种情况下同时进行的。该阐述可作为一种概念证明，即ABM的使用能支持理解“描述异质环境下不同的政策效应”的机制和相关性。特别是关于通勤的阐述，结果表明，每个大都市地区的集聚经济、人口规模和空间结构可能比替代性住房和社会福利政策工具更能决定总通勤量。

关键词：基于agent模型，决策，公共政策，政策选择，方法论工具

Introduction

Policy programs affect citizens and businesses heterogeneously across space and time. A specific housing policy instrument may benefit a set of households but may also inadvertently generate a demand for a costly and sparse extension of public infrastructure. A decision to lower taxes on gasoline would please car owners but may result in increased fossil fuel consumption, congestion, and emissions.

Public policy evaluation—when it happens—focuses on indicators produced directly from the instrument. Thus, a housing policy would count the number of houses constructed, and a tax reduction would enumerate the savings to the public, the increase in gasoline sales, or the percentage points in price reduction. This strict, somewhat limited connection between policy instruments and indicators does not happen by chance. Estimating immediate impact is hard. Especially so when the evaluator needs to separate the effect of the policy instrument from all the other contextual, procedural, and historical effects.

Policymaking would benefit more when considering a broader analysis of impacts. Policymakers should quantify the effects of policy by raw indicators, but they should also consider the changes in policy instruments on a wider spectrum of social life, including spillovers and side effects. Moreover, policy should envision a comprehensive view of money expenditure, weighing the best alternatives for the same amount of investment. Policymakers should aim at a better understanding of overall impacts that includes a comparative analysis of each possible decision. However, there have been few methodological tools that fully encompass all of the underpinnings of effects across social themes.

Agent-based modeling—or, to put simply, a computational simulation—is a methodology within the realm of complex systems methods (M. Fuentes, 2015) that emphasizes the heterogeneity of agents (citizens, businesses, households, government) and their interactions. Relying on theory (Arnold et al., 2019) but increasingly on empirical data and validation (Guerini & Moneta, 2017), agent-based modeling incorporates space and time structurally in their modeling. As such, the modeling captures feedback—endogenous effects of agents' actions in the following time steps—and heterogeneous spatial responses.

The main advantage for policymakers is to evaluate effects "ex-ante," to anticipate alternatives, contrast opposing policies, and compare results before having sunk the cost. Not only evaluate before investing but also decide based on an array of indicators across a variety of dimensions.

The objective of this paper is to illustrate the use of alternative policy instruments and their effects on total estimated commuting (and emissions) and other indicators and compare them to a no-policy baseline. We use an agent-based model (ABM) called PolicySpace2 to apply housing and social welfare policy instruments and analyze the results on total commuting, growth, inequality, and quality of life. We also contrast metro regions' total commuting against their population size. The illustration serves to demonstrate the power of ABMs to make across-themes comparisons and to gain a more general perspective on possible effects.

Besides this introduction, we briefly define ABMs and list the advantages and disadvantages for policymakers and analysts in section 2. We then present PolicySpace2 (Alves Furtado, 2022), the possibilities the model entails and the procedures used in the commuting illustration. We conclude with the results, discussion, and final considerations.

Agent-based models and policy

Epstein and Axtell (1996) consolidated ABMs as an adequate modeling tool for the social sciences. ABM is a computational simulation based on theory to design individual agents that interact following explicit rules to generate data. The emphasis is on the construction of the mechanisms that produce phenomena. The method's motto is "If you didn't grow it, you didn't explain it" (Epstein, 1999, p. 43). The authors propose to algorithmically write down the mechanisms of interaction among relevant agents and their environment and then let them evolve to produce a data generation process. The produced simulated data may then be compared to real empirical data. The full cycle evolves from theory to model to data that may be validated and contrasted back with data to generate theory.

More than theory alone, generated data has the very useful attribute of simulating both factual and counterfactual situations. It is as if we had simultaneously the application of the policy and the absence of the application of the policy. As if we had invested in housing, invested in social welfare and not invested in either one at the same time. This process is at the core of causal discussions, which is achieved via experiments, such as randomized control trials (RCT), rigorous analysis of observational data (Pearl, 2009), and also applying an ABM (Arnold et al., 2019).

Besides the contrast between policy and no-policy, Gilbert et al. (2018) argue that ABMs might help to provide an open rationale for the discussion, specifically in complex social mechanisms for which there is no clear theoretical narrative. ABMs function not only as a clear, objective repository of ideas, concepts, and theories, but they also enable scenarios.

Moreover, analysts from different backgrounds and expertise may use a computational and deterministic model as a platform of communication. A canvas to experiment ideas with, in which to measure outputs and compare them with available information. As such, ABMs provide both scenarios but also a scientific process of experimentation that may include stakeholders, practitioners, and researchers. Other advantages include the agility of the process and the relatively low cost of prototype programming.

There are caveats and disadvantages. One is that those modelers do not every time successfully accomplish to translate theory into computational models (Ahrweiler et al., 2015). Parameters, mechanisms, and sequences are unknown. There are no specifics. Moreover, the lack of clarity about parameters and mechanisms implies a lack of existing data to validate aspects of the phenomena. ABMs may also help to identify data that is needed to be produced.

Models are also too flexible. Every author or every group of authors may easily start a new model, a new way to represent phenomena, and thus make it difficult for comparison, cross-validation, and marginal advances, which is the typical pathway of science. The ABM community has responded by trying to implement benchmarking (Dawid & Delli Gatti, 2018) and protocols (Grimm et al., 2020).

A main tool used to measure the accomplishment of a model is the coherence between purpose and model (Edmonds et al., 2019). A model, the authors claim, can only be evaluated in accordance with its proposed objective. When a model promises prediction, then an out-of-sample database—i.e., data that have not been used in the model—is used to demonstrate the accuracy of the model. However, other less ambitious models may promise to explain, describe, explore, illustrate, provide an analogy, or simply be a tool for social learning.

There has been a growing interest in and application of agent-based modeling specifically for policy (M. A. Fuentes et al., 2019; Furtado, 2022b). Kerr et al. (2021) used COVASIM to study people interaction and networking to come up with policy recommendations. His five suggestions, from distancing and masking to testing and isolation, were contrasted with a not-imposing-restrictions scenario. The authors claim the lack of restrictions would have caused a three times higher infection rate.

PolicySpace2 and methods

We use PolicySpace2 (PS2) to construct our illustration. PS2 (Alves Furtado, 2022) is fully documented (Furtado, 2022a) and open source.[1] PS2 generates agents based on census and firm data at the intra-urban scale to compose the municipalities of the 46 largest metropolitan regions of Brazil.

Agents consist of individual workers, households, firms, municipalities' governments, and a bank. Agents interact in the labor, goods, and services, and real estate markets, following benchmarks and rules described in the literature. Additionally, the bank provides credit for the real estate market and remunerates household investments. Municipalities collect taxes on market transactions endogenously and reinvest the funds in quality of life. The model runs from 2010 to 2020 with monthly interactions.

The dynamics imply that workers may change from firm to firm, and households may move to other residences, resulting in mobile workers and households. Distance is also a relevant factor of the model. Households consider either proximity or prices when buying in the goods and services market. Firms consider either qualification (years of study) or proximity to hire new labor, with workers preferring the lower cost of commuting. The model is validated for Brasília, being able to replicate reasonable indicators of unemployment, inflation, and inequality (Alves Furtado, 2022).

PS2 tests and compares the application of three policy instruments. Two refer to housing policy, and one to social welfare. The housing policy instruments consider (a) the municipality buying houses from construction firms (endogenously) and transferring them to the poorest households or (b) paying a rental voucher for a period of 24 months, also to the poorest households. The social welfare policy instrument consists in (c) making a direct equalitarian cash transfer to all households within the lowest quintile of income.

The investment made to each policy alternative is always the same, one-fifth of all the municipalities' investments, although the absolute value may vary as it is endogenously calculated. This means that the effects of the policy instrument may generate more or less economic dynamics and feedback with higher or lower intensity in the following months of the simulation.

PS2 produces monthly data at the level of each individual agent (worker, household, firm, municipality). As a result, the evolution of 66 indicators is produced for every simulation run. Simulation results are presented as the average of many simulation runs. Results of the comparison among the three policy instruments tested and the no-policy baseline consider many simulation runs with each instrument (or its absence) being tested individually.

Procedures for the Illustration

First, we compare the three policies and the no-policy baseline across a few indicators. We use GDP and the Gini coefficient to examine production and inequality, the Average Quality of Life that reflects the investment of municipalities weighted by population, a Price index that encapsulates general inflation, and households' total commuting. Furtado (2022a) makes a more comprehensive analysis across indicators.

Total commuting captures the evolving, dynamic sum of the distance between workers' residences and current firms' addresses.[2] We expect that total commuting is comparatively smaller when there is a more adjusted spatial match—i.e. when the number and qualification of workers available for each firm are within a reasonable distance. We also know that workers and firms engage in longer commuting when the metro regions' spatial structure is large and spread out (Pereira & Schwanen, 2015). Economic dynamics also influence total commuting. When unemployment is high, workers remain at home and do not commute. When firms pay higher salaries, workers penalize proportionally less the commuting cost and may opt for more distant jobs.

Secondly, we regress total commuting against the metropolitan regions, key parameters of the simulation, and the tested policy instruments. We want to capture the correlation between different cities' spatial and economic structures with total commuting and the relative importance of policies. Finally, we regress the metropolitan region coefficients of the first regression against the log of the population, which seems to be the most relevant factor in the correlation between different metro regions and their total commuting.

Results of commuting illustration

Alves Furtado (2022) argues that one of the housing policies (Rent voucher) and the social welfare (Cash transfer) yield the best social results. Indeed, Table 1 shows that all policies increase GDP when compared to the no-policy baseline. However, Property acquisition does so, generating increased inequality and a reduced Quality of Life (QLI), whereas the other two policy instruments provide a reduction in inequality at similar QLI. All three policy instruments produce more inflation and a similar increase in total commuting.

Table 1 *– Output indicators of PolicySpace2 averaged simulation runs for policy instrument alternatives, compared to the no-policy baseline. Following Alves Furtado (2022, p. 2), the best policy instruments seem to be Cash Transfers and Rent Vouchers, which produce higher levels of GDP whilst maintaining lower inequality Gini values, and similar Quality of Life but higher inflation. All of the policy instruments activate the economy and thus produce higher levels of household commuting.*

	GDP index	Gini index	Quality of Life Index	Price index	Households' total commuting
Property Acquisition policy instrument	2973	0.46	0.62	1.64	611.7
No-policy Baseline	2439	0.44	0.8	1.59	573.3
Rent Voucher policy instrument	3036				

0.43

0.78

1.83

611.2

Cash Transfer policy instrument

3226

0.42

0.79

1.99

610.4

We regressed the log of total commuting against three groups of control variables: (a) key parameters of the simulation, (b) dummies of the metropolitan regions using São Paulo—the largest metro region in Brazil—as the default for the comparison, and (c) the three tested policy instruments that compare to the no-policy baseline (see Figure 1). Full results are presented in Appendix 7.1.

Results seem to fit a nice adjustment with high R2 scores (.98). Overall, the factors that correlate higher with total commuting seem to be each individual metro region, reflecting their size, population, spatial structure, and the percentage of the population used in the simulation.

We used four parameters of the simulation in the regression: (a) cost of public transport parameter, (b) hiring by distance parameter, (c) percentage of the population used in the simulation, and (d) percentage of households entering the real estate market. The cost of public transport parameters captures the fact that when the cost is higher, workers penalize long commutes, and total commuting decreases. Hiring by distance is the parameter firms use to weigh their hiring decision and consider more workers based on qualification or proximity criteria. Results suggest that when firms hire based on distance (higher parameter), total commuting is smaller, so local labor spatial adjustments are preferred.

The percentage of the population used in the simulation is a parameter that non-linearly includes economies of agglomeration in the model. Furtado (2022a) explains that the model was built, calibrated, and validated considering the default configuration of the metro region of Brasília and a percentage of the population of 1% of citizens. The sensitivity analysis performed (2022a, pp 116 e ss.) suggests that indicators vary proportionally more than twice when doubling the population, for example. This phenomenon is in accordance with the literature (Bettencourt, 2013).

The percentage of households entering the real estate market—which in the sensitivity analysis proved to be relevant for the increase in economic dynamics of the model—seemed to have a relatively small correlation with commuting compared to each individual metro.

The three policy instruments suggest a small increase in total commuting, comparatively to the no-policy baseline. Probably, they reflect the increase in production (and inflation), therefore enabling firms to pay higher salaries and hire workers with enough premiums to afford the longer and costlier commute. This effect, however, seems to be of small proportion when considering the relevance of the characteristics of each individual metropolitan region.

We used the coefficients of our first regression and plotted them against the log of the population of each metro region (see Appendix 7.2 and Figure 2). More populous metro regions have higher total commuting. However, they differ quite a lot depending on the city. Rio de Janeiro and Brasília both are much higher compared to the typical response of the other metro regions. Probably, because Rio de Janeiro is a spread-out city dotted with natural rock formations and uninhabited areas, whereas Brasília has an extremely low density, with urbanized areas spread out kilometers apart from each other. [3] Maceió e Fortaleza, on the other end of the spectrum, is denser, more contiguous metro regions, whereas Belo Horizonte seems to settle right on the average across the metro regions.

Discussion

We provided a simple illustration of how ABMs enable analysis across policy themes. The ABM—PolicySpace2—is an economic spatial simulation that describes empirical market interactions at the intra-urban level. Policy instruments coming from two different domains (Housing and Social Welfare) produce results that are comparable across 66 indicators.

Theory supported the construction of the rules of the model. Empirical data provided quantitative and spatially detailed information, and the simulation generated the data for analysis. Depending on the original design (the markets), the purpose, and the validation of the model, policymakers may gather different perspectives, comparisons, and insights.

We show that ABMs are tools that incorporate theory and empirical data and organize them to help foster an understanding of mechanisms as well as responses to specific research questions. The advantages when compared to other methodologies are that ABMs play the role of the process—the construction of the model, the discussion of the mechanisms—and the role of prognostics. Besides, there is enough literature, journals, and conferences to guide policymakers and scientists in the necessary steps of developing, validating, and experimenting with models (Crooks & Heppenstall, 2012; Edmonds & Meyer, 2017; Gilbert et al., 2018; Wilensky & Rand, 2015).

Two other aspects of ABMs are relevant for policymakers. First is that ABMs do not exclude other methods of tools. Developing and using ABMs benefits from other scientific processes (Arnold et al., 2019; Lamperti et al., 2018). Secondly, responses can be specific. ABMs can be made to mimic the time series of an entire country (Poledna et al., 2020) or how diseases evolve into pandemics (Epstein, 2009).

Final Considerations

We illustrated how an agent-based model could be used to account for outputs on different indicators, from inequality and inflation to total commuting time, across specific metropolitan regions. Moreover, these results come from the application of policy instruments from different domains. Our illustration also used what-if counterfactual analysis to compare and contrast the application of the policy with its absence. That in itself strengthens the comparison, given that the modeling mechanism is exactly the same. Specifically for our illustration, we showed that the relative importance of which city receives the policy instruments matters more than the instrument itself, with relevant different magnitudes. The analysis also suggests that intrinsic factors within each metro region—its population, but also other factors—conform to heterogeneous results.

We also conceptualize and list the pros and cons of agent-based modeling. Although there is plenty of literature and material across different disciplines, ABMs are still not that much used in policymaking. An essential feature that this text brings to the surface is the unique ability of ABMs to cover side effects, spillovers, and indirect effects of policy within different domains. We have shown that the researcher may ask a question about housing and collect outputs in inflation, inequality, or total commuting. Ask a question about the firm's hiring process and collect data on production or tax collection and investments.

A more specific response about the determinants of total commuting for each metro region would demand more data and analysis. PS2 calculates commuting as a simple Euclidean distance between the coordinates of the worker's residence and the firm. A more rigorous analysis could benefit from the modularity of ABM modeling. The modeler would be able to use the original available code and add specific detailing to answer different research questions and attend to different purposes.

Francis Tseng produced an empirical routing process for trips generated by PolicySpace (Furtado, 2018b, 2018a). The prototype model, also open and available[4], uses the output from standardized GTFS data on transit systems, routes, and schedules to simulate actual routes and times from residences to firms. Outputs of public and private transit can be visualized on a map.

The coupling of the two models makes the hard connection between monthly economic processes and minute simulation of daily commutes. The routing project was done for PolicySpace, but it is compatible with Policy-

Space2, which demonstrates the modularity of ABMs. However, no results have been produced from the model. The increase in quality and availability of GTFS data (before restricted to the municipality of Belo Horizonte only and with chunks of missing data)[5] associated with adequate funding may push the project forward.

We have only scratched the possibilities posed by PolicySpace2. Given that the model is based on empirical intra-urban data of households and it already contains three markets, a number of research questions are easy to implement. We intend to investigate: (a) endogenous household investments on workers' qualifications, (b) improved real estate forecasting by including urban amenities and land-use regulation, (c) private and public mobility choices, and, possibly, (d) firm innovation.

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Appendix

7.1 Regression results for Commuting against metro regions and simulation parameters

Dep. variable: Log total commuting	Averaged Simulation Runs	All Simulation Runs
const	7.72***	7.71***
	(0.06)	(0.02)
Property Acquisition policy instrument	0.02	0.03***
	(0.01)	(0.00)
Cash Transfer policy instrument	0.01	0.02***
	(0.01)	(0.01)
Rent Voucher policy instrument	0.02	0.04***
	(0.01)	(0.01)
Cost of Public Transport	-0.10	-0.10***
	(0.08)	(0.03)
Parameter of hiring by distance	-0.29***	-0.29***
	(0.10)	(0.03)
Perc. Pop. used in simulation	0.49***	0.48***
	(0.09)	(0.02)
Perc. Households entering real estate market	-0.04	-0.04
	(0.08)	(0.02)
Aracaju	-1.98***	-1.98***
	(0.06)	(0.02)
Belém	-1.01***	-1.01***
	(0.06)	(0.02)
Belo Horizonte	-0.58***	-0.58***
	(0.06)	(0.02)
Brasília	-0.18***	-0.17***
	(0.05)	(0.02)
Campina Grande	-2.68***	-2.68***
	(0.06)	(0.03)
Campinas	-0.88***	-0.88***
	(0.06)	(0.02)
Campo Grande	-2.08***	-2.08***
	(0.06)	(0.03)
Campos	-1.69***	-1.68***
	(0.06)	(0.03)
Caxias do Sul	-2.39***	-2.39***
	(0.06)	(0.02)
Crato	-2.49***	-2.48***
	(0.06)	(0.03)
Cuiabá	-2.17***	-2.17***
	(0.06)	(0.02)
Curitiba	-0.86***	-0.86***
	(0.06)	(0.02)
Feira de Santana	-2.51***	-2.51***
	(0.06)	(0.02)
Florianópolis	-1.91***	-1.91***

	(0.06)	(0.02)
Fortaleza	-1.02***	-1.01***
	(0.06)	(0.02)
Goiânia	-1.13***	-1.13***
	(0.06)	(0.02)
Ilhéus-Itabuna	-2.40***	-2.40***
	(0.06)	(0.03)
Ipatinga	-2.65***	-2.64***
	(0.06)	(0.03)
João Pessoa	-1.94***	-1.94***
	(0.06)	(0.02)
Joinville	-1.88***	-1.86***
	(0.09)	(0.07)
Juiz de Fora	-2.18***	-2.17***
	(0.06)	(0.02)
Jundiaí	-2.17***	-2.16***
	(0.06)	(0.03)
Londrina	-2.03***	-2.02***
	(0.06)	(0.03)
Macapá	-1.76***	-1.76***
	(0.06)	(0.03)
Maceió	-2.00***	-1.99***
	(0.06)	(0.02)
Manaus	-1.10***	-1.09***
	(0.06)	(0.02)
Maringá	-2.45***	-2.45***
	(0.06)	(0.03)
Natal	-1.62***	-1.62***
	(0.06)	(0.02)
NH-SL	-2.34***	-2.34***
	(0.06)	(0.03)
Pelotas	-1.92***	-1.93***
	(0.06)	(0.02)
Petrolina-Juazeiro	-1.66***	-1.66***
	(0.06)	(0.03)
Porto Alegre	-0.92***	-0.92***
	(0.06)	(0.02)
Recife	-0.74***	-0.74***
	(0.06)	(0.02)
Ribeirão Preto	-1.97***	-1.97***
	(0.06)	(0.02)
Rio de Janeiro	-0.05	-0.04**
	(0.06)	(0.02)
Salvador	-0.89***	-0.89***
	(0.06)	(0.02)
Santos	-1.25***	-1.25***
	(0.06)	(0.02)
SJRP	-2.76***	-2.76***

	(0.06)	(0.02)
SJC	-1.09***	-1.09***
	(0.06)	(0.02)
São Luis	-1.55***	-1.54***
	(0.06)	(0.02)
Sorocaba	-1.47***	-1.47***
	(0.06)	(0.02)
Teresina	-1.56***	-1.55***
	(0.06)	(0.02)
Uberlândia	-2.69***	-2.68***
	(0.06)	(0.02)
Vitória	-1.26***	-1.26***
	(0.06)	(0.02)
Volta Redonda	-2.09***	-2.09***
	(0.06)	(0.03)
R-squared	0.99	0.98
R-squared Adj.	0.99	0.98
No. observations	554	4740

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01
Observations.
NH-SL: Novo Hamburgo/Sao Leopoldo.
SJRP: Sao Jose do Rio Preto.
SJC: Sao Jose dos Campos

7.2 Regression results for Coefficients of commuting regression against Metro regions' population

	Averaged Simulation Runs	All Simulation Runs
const	-348.41***	-378.96***
	(22.30)	(21.88)
Log Pop.	19.55***	21.79***
	(1.61)	(1.57)
R-squared	0.78	0.82
R-squared Adj.	0.77	0.81
No. observations	44	45

Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01

[1] https://github.com/bafurtado/policyspace2

[2] Commuting in the simulation is only calculated for worker—firm trips.

[3] See Pereira, R. H., Parga, J. P., Saraiva, M., Bazzo, J. P., Tomasiello, D., Silva, L. P., Nadalin, V., & Barbosa, R. (2022). Forma urbana e mobilidade sustentável: Evidências de cidades brasileiras (Publicação Preliminar). *Discussion Papers*, 65 [http://repositorio.ipea.gov.br/handle/11058/11343], for more details.

[4] https://github.com/frnsys/transit_demand_model

[5] See https://ipeagit.github.io/intro_access_book/4_dados_gtfs.html#tbl-gtfs_brasil Pereira, R. H. M., & Herszenhut, D. (2022). *Introdução à acessibilidade urbana: Um guia prático em R*. Institututo de Pesquisa Econômica Aplicada.