Policy comparisons and causality in an agent-based model

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Abstract. This paper explores the use of social simulation with an open source agent-based model (ABM) as a mechanistic and counterfactual approach to causality and policy comparison. We argue that ABMs can explicitly capture both the dynamics of the factual and the counterfactual scenarios. In addition to discussing the relevant literature, we simulate identical agents, in the same context and timeframe, with and without treatment in different urban frameworks to highlight distinct policy outcomes. The objective is to use an ABM that implements social welfare and housing policy instruments as interventions, to explain how policy instruments (the causes) affect production and inequality across heterogeneous cities (the effects). Furthermore, we use *ex post* directed acyclic graphs (DAGs) to identify the paths that affect policy responses, and recover the ABM's *ex ante* causal mechanisms. We provide recommendations of best policy instruments across different cities. Our study demonstrates how ABMs can be utilised as a mechanism-based approach to identify and quantify complex causal relationships in public policy applications.

Keywords: Causality · Agent-based models · Public policies · Cities · Directed acyclic graphs (DAGs)

1 Introduction

In today's rapidly changing world, policymakers face immense pressure to address complex societal problems quickly. However, limited resources and the potential for unforeseen outcomes from their decisions make this a challenging task. In this context, computational modelling and agent-based models (ABMs) have emerged as powerful tools for decision-making [4,9]. Not only do ABMs serve the purpose of communication [11], but they also make assumptions and uncertainties explicit, providing a more comprehensive understanding of the underlying processes. Moreover, ABMs can help scientists establish causal relationships between variables [10], a critical factor in the complex urban socioeconomic context, where identifying who benefits and who bears the costs of actions is essential.

In this paper, our aim is to highlight the potential of ABMs in guiding urban policymakers' decision-making. Specifically, we demonstrate that, despite utilising the same policy instruments, mechanisms, and component entities (such as workers, households, and firms), different policy outcomes can result from the distinct urban frameworks of each city. ABMs offer a unique solution to the fundamental problem of causal inference, where we cannot observe both the treated and untreated outcomes for the same individual simultaneously. By simulating both factual and counterfactual trajectories for the same entity, ABMs allow for the recovery of causal mechanisms and the identification of the total direct effects of policies on different cities.

Accordingly, we demonstrate the causal features of ABMs and illustrate their practical application in measuring the simulated heterogeneous outcomes of policy instruments across cities. We use an open-source agent-based model to show that ABMs can be used to establish causality by simultaneously observing the mechanisms and behaviour of agents, the application of policy instruments, and their effects on different cities. We elaborate on the model mechanisms using directed acyclic graphs (DAGs) to capture the effects of policy instruments and to help identify causation.

The informed regression results provide reliable quantitative evidence of policy effects, while controlling for covariates and considering the model structure. The goal is to separate the endogenous effects of the model from the city-specific effects. By doing so, we can isolate the single effect of the policy instrument itself, purging all the differences in outcomes. We observe that each policy instrument affects each city differently, and ultimately aim to demonstrate which policy instrument is most suitable for each city along two dimensions: production and income inequality, measured by GDP and the Gini coefficient, respectively.

From a practical perspective, the results of this exercise should provide valuable insights to the federal government of Brazil regarding the optimal level of expenditure for specific policy programs, namely the "Bolsa Família" (a social welfare payment to households) and "Minha Casa, Minha Vida" (a program that finances the construction and distribution of houses by the central government). By identifying which policy instruments are most effective for which city, policymakers can make informed decisions on how to allocate resources and tailor policies to local conditions, ultimately leading to better outcomes for citizens.

2 Causality, ABMs, and policymaking

Many democratic governments strive for evidence-based policies to enhance policy performance and mitigate the impact of ideological biases on decision-making [13]. In pursuit of *ex ante* evaluation of public policies, the field of causal inference is of significant interest since randomised controlled trials, which are the standard method for recovering causal effects, may not be a practical option in this context.

The potential outcome approach, which provides theoretical support for randomisation, aims to estimate causal effects by comparing outcomes that would have been observed under different treatment conditions. This approach involves defining potential outcomes for each individual under every possible treatment condition, with the assumption that only one potential outcome can be observed. The difference between the observed outcomes under different treatment conditions is then used to estimate the treatment effect [16].

In economics, outside of the randomisation framework, causal claims have traditionally been made using the instrumental variables approach or the "natural experiments" framework, relying on an exogenous source of variation to identify causal effects [2]. However, it may not always be feasible to find valid instruments or natural experiments for the situations in question. Robins and colleagues [19] have emphasised the use of causal inference methods to draw conclusions about cause and effect relationships in observational studies, which are inherently limited by confounding and other sources of bias.

ABMs can be defined as a computational model environment in which agents engage among themselves and the environment in silico, following formal rules[6]. Agent-based modelling (ABM) is a powerful tool for analyzing the impact of public policies on social systems. Unlike traditional numerical simulations, ABMs incorporate known or theorised mechanisms, and the interactions among entities to derive outcomes. This makes ABMs well suited for causal inference as it provides a more accurate representation of the real world. ABMs offer an effective way to evaluate the impact of policy decisions on complex systems, making them a valuable tool for policymakers and researchers.

Gianluca [10] distinguishes between two types of causality, dependence and production, which differ in how they conceptualise mechanisms. Dependence aligns with the horizontal view of mechanisms, which sees them as chains of intervening variables, consistent with regularity, counterfactual, and experimental approaches described by Little [14]. In contrast, production aligns with the vertical view, which understands mechanisms as complex systems of interacting lower-level units that trigger higher-level outcomes. This view emphasises entities and processes, and it aligns with the "generative" approach advocated by Epstein [6].

Not all ABMs are appropriate for causal analysis. According to Gianluca [10], for an ABM to convey causality convincingly, it must be theoretically sound and based on a descriptive rather than simplistic approach (see also [5]). In addition, two other essential criteria for applying ABMs to causality are input realism and output validation. Input realism refers to designing the model based on actual data, space, and parameters, while output validation refers to the model's ability to replicate observed outcomes and be compared to data and stylised facts. Thus, to use ABMs as a tool for causal inference, it is crucial to have a theoretically based model that incorporates input realism and output validation.

To ensure the robustness of ABMs, basic checks and procedures should be implemented. Sensitivity analysis is essential to confirm that slight changes in parameters do not drastically alter or disrupt the results. Structural sensitivity analysis is also helpful for checking the model's internal details, rules, and mechanisms for robustness [12,8]. In addition, dispersion analysis requires a reasonably large number of runs to ensure that typical results are not fortuitous. It is also important to have a model that is both cognitively plausible and understandable [10]. By incorporating these checks and procedures, ABMs can be more reliable and better suited for causal analysis.

ABMs can simulate interventions in complex systems, similar to those discussed by Pearl [18]. As such, ABMs can focus on both the effects of causes and the causes of effects. In the former case, ABMs simulate the results after a treatment, intervention, or policy has been applied, thus conforming a "what-if", forward approach [10]. This approach is complemented by the "why" view of causes, which looks at the causal factors that produce an effect [20].

3 Methods

3.1 Baseline agent-based model, data

PolicySpace2 (PS2) [1] is a framework used to analyse policy questions. The focus is on comparing social welfare and housing alternatives. Within PS2, various agents interact in markets like labour, goods, services, housing, rentals, and credit. The model runs monthly from 2010 to 2020, based on census tract-level demographic and spatial data for Brazilian metropolitan regions. Agents explicitly interact in local markets, with sellers determining house prices based on neighbourhood characteristics, vacancy rates, and time on the market. Buyers make offers based on their financial holdings. Workers consider proximity to potential firms, and bank loans factor in household assets, wages, and intended mortgages.

We chose to use PS2 as our model for this causality application due to its theoretical basis in microeconomics, well-documented support in the literature, and detailed mechanisms. It relies on empirical input, specifically census data on households, geolocation of firms, and spatial neighbourhoods, and has been validated based on cumulative macroeconomic indicators and reasonable real estate price configurations [8]. The model also presents a sensitivity analysis of parameters and a structural analysis of rules, and the results have been averaged over multiple runs. Therefore, we believe that PS2 fulfills the necessary requisites for an ABM model, suited for causal analysis as suggested by [10].

We directly downloaded the open-source ABM named PolicySpace2 from its public repository here. We then ran simulations with the original default parameters, exclusively varying the cities and the policy instruments. The simulation ran from 7 December 2022 to 18 January 2023. We used an average of 5 runs, 30 times for each pair city–policy, generating a total of 34 GB of output. This database is available upon request. The code for data preparation, the summarised data, along with the figures, dags, regressions, and total effect tables is here.

3.2 Policy instruments

The three contrasting alternative policy instruments embedded in PolicySpace2 refer to two housing and one social welfare instruments. The policy instruments and the default procedure of no-policy baseline are funded via endogenous collection of taxes. Taxes come from all markets of the model and encompass taxes on goods and services, and housing transactions, firms' profits, workers' salaries, house financing, and house property.

These endogenously collected funds regularly fuel the per capita increase of municipalities' Quality of Life (QLI) index. Although the model is stock-flow consistent, taxes are linearly transformed when invested to improve per capita Quality of Life. QLI will also later in the model influence the house prices of each neighbourhood, given their quality. When policies are in effect, a percentage of these municipal funds goes to the policy instrument instead of altering QLI. Thus, a percentage of funds collected within the model environment is reinvested in specific policies when in effect. The baseline scenario can be viewed as an "intervention" in which the full investment goes to QLI [8]. We will discuss each policy instrument separately. The same percentage is applied to all policy instruments, but the actual amount invested may vary due to the endogenous collection of taxes.

1. Property acquisition: This instrument is modelled after the federal program Minha Casa Minha Vida. In the model, municipalities hire contractors (represented as construction firms in the model) to build houses and maintain a list of registered low-income households that do not own any properties. The model reproduces the house construction process and the eligibility of households using the endogenous distribution of household income.
2. Rent vouchers. This instrument of housing policy uses municipal funds to provide rent vouchers for low-income households, which cover the cost of their specific rent for a period of 24 months. The aid is only valid for the current house arrangement. Note that if a household remains eligible and funding is available, they may reenter the program after the initial period ends for as long as it is deemed necessary.
3. Monetary aid. This instrument focuses on a non-spatial policy that equally distributes all available funding to the lowest quintile of households each month, similar to the Bolsa Família program in Brazil. The aid is provided as a cash transfer to eligible households, which must remain within the program's eligibility criteria to continue receiving the aid.

3.3 Causality: Direct Acyclic Graph (DAG)

The use of DAGs in modelling helps to make assumptions explicit and guide decision-making in selecting which variables to include in regressions. DAGs provide a visual tool that aids in understanding the causal relationships between variables and identifying confounding variables that need to be controlled for, as well as colliders that should not be considered as covariates.

In our application, we use DAGs to clarify the organisation of the mechanisms of PS2, allowing us to accurately quantify the results of policy instruments and eliminate any endogenous influence from our model. The DAG synthesises the evolution of the model's mechanisms and informs the panel regression, which estimates the causal effect of the instruments on the outcome. Our main interest is in observing the total effect of the policy instruments, comparing them among themselves and against the no policy baseline case, and across heterogeneous metropolitan regions. This approach enables us to make valid policy recommendations based on rigorous empirical analysis.

We analyze the relationship between covariates within the model to determine the need for controlling variables for both the GDP and Gini coefficient outcomes. Figures 1 and supplemental material Figure 1 (here) provide visual representations of the inner workings of the model, which are the same for both outcomes, but differ slightly for the policy instruments. We will provide an explanation of each mechanism.

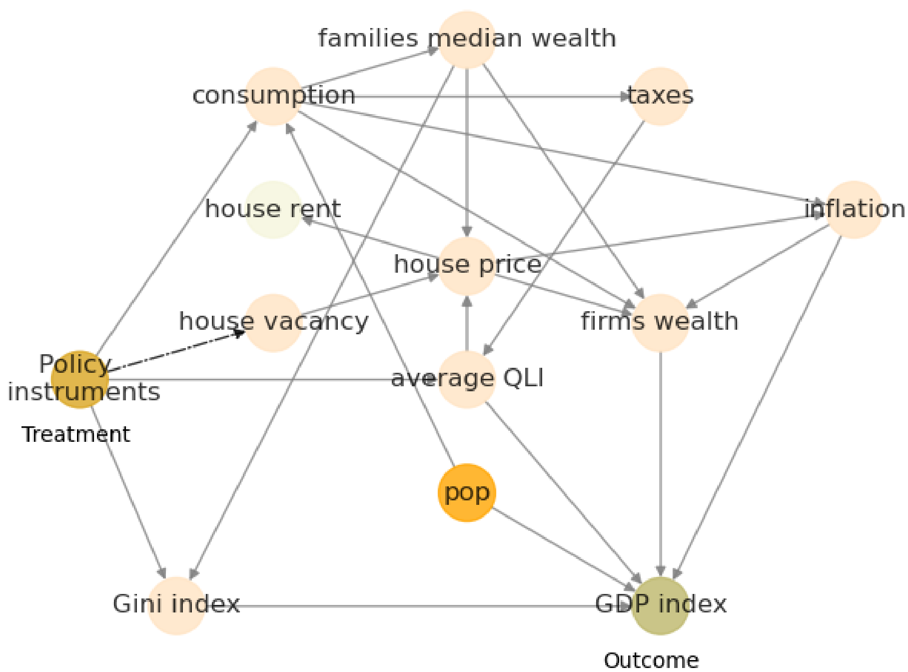

Fig. 1. Proposed DAG illustrating the inner workings of the model when GDP index is the outcome of interest and policy instruments are the treatment. Policy instruments directly affect consumption, average QLI, and the Gini index. Population, which is mostly exogenous, influences consumption and GDP index and, as a confounder, should be controlled for in the regression. The dashed arrow indicates that only Property acquisition affects House vacancy, which the other instruments do not. The analysis controls for population effects and aims to estimate the total causal effect of the policy instruments on GDP.

According to the model equations [1] and the DAG in Figure 1, the three policy instruments directly affect consumption, average Quality of Life Index (QLI), and the Gini index. Monetary aid directly affects consumption, while the other two instruments reduce the burden on households' budgets by subsidising rent payments. The fact that some households receive subsidies while others do not also directly affects the Gini index. However, investments in policy instruments cannot be used for infrastructure improvements, which are typically measured by an increased QLI. Specifically, when the policy instrument is "Property acquisition," house vacancy is directly affected, while this is not the case for the other instruments.

These direct connections give rise to other indirect connections within the model. For instance, changes in consumption affect the level of inflation, as firms update prices in response to changes in the level of stocks. Consumption also affects firms' wealth, as profits from sales increase. House vacancy levels explicitly affect house prices, which are negotiated based on the size of demand and the availability of resources from households (i.e., families' median wealth). Population affects both consumption and total output, and house rent levels are negotiated around a percentage of the base house price. Moreover, consumption helps maintain firms' demand, thereby sustaining levels of employment and families' median wealth. Taxes, which fund the infrastructure and amenities captured by QLI, are also affected by changes in consumption. QLI, in turn, reflects the quality of the neighbourhood and brings spatial influences to house prices. Finally, consumption, families' wealth, inflation, and house prices (for construction firms) all influence firms' wealth and thus total GDP.

To evaluate the effects of policy instruments on both total production and income inequality, we included the household income Gini coefficient as an outcome of interest. Figure 1 in supplemental material (here) represents the inner workings of the model when the Gini index is the outcome of interest, and policy instruments are the treatment. In this scenario, population acts as a confounder and should be controlled for in the regression. It is important to note that when Gini is the outcome of interest, many of the variables in the model act as successors, indicated by lighter coloring in the figure, and do not directly affect the total effect.

3.4 Panel regression

The construction of DAGs provides clarity regarding the need to control for population as the only exogenous variable that could confound the results. In addition, we utilise the panel structure of the data to investigate the heterogeneity of each city and measure the causal effects of various policies. This approach yields more precise and informative outcomes for policymakers than the original timeline indicators presented in [1].

If the data were observed rather than simulated, the methodology would be akin to that of an observational study utilising differences-in-differences, with covariates selected based on a DAG. However, the simulated data meets the parallel worlds assumption. The primary difference lies in the absence of a treated and untreated group; instead, the same individuals are treated before and after. The unit of analysis for the regression is the cities themselves, with errors being clustered at the city level, taking into account their unique paths based on the policies being implemented. The policies were initiated in 2011, which represents the second observation in the dataset. The first observation for each city represents its pre-treatment value, which is the same for all cities across the various policy paths.

At the start of the model in 2010, actual spatial data from the Brazilian Census is inputted into the model. The real-world spatial structure of the cities influences the model's evolution because its mechanisms rely on the intra-urban location of families and jobs. This real-world spatial structure is the primary source of heterogeneity in the variables considered in the regressions, as they are evaluated at the city level. The panel regression framework is utilised to implement a differences-in-differences model, which considers the causal effect of policies as an average of all the post-treatment periods. The unmeasured initial conditions of each city may have an influence on all periods, as well as differences in the average effect for the period. Some of the influence of the spatial structure is fixed in time, and is accounted for by the cities' dummy variables.

4 Results

Based on the regression results presented in Table 1 (see supplemental material here), the effectiveness of the three policy instruments in stimulating economic growth can be compared. Figure 2 shows that most coefficient values for Property acquisition at the city level are not significant and have higher standard-deviation. Nevertheless, on average their contribution to GDP is lower than that of the other two instruments. Specifically, Property acquisition reduces GDP by about 50 points compared to the no policy baseline. In contrast, Rental vouchers and Monetary aid both present positive and significant values, increasing GDP by around 70 and 112 points respectively. These findings suggest that Rental vouchers and Monetary aid may be more effective policies for promoting economic growth.

Figure 2 of the supplemental material (here) confirms that the Property acquisition instrument is less effective in reducing income inequality, as it clearly increases the Gini coefficient when comparing across cities. Rent vouchers and Monetary aid are the two most effective instruments in reducing the Gini coefficient, with a slightly higher number of non-significant Monetary aid coefficients. Overall, according to Table 1 (here), Property acquisition does not significantly alter Gini values, whereas Rent vouchers reduce the indicator by approximately 0.05 and Monetary aid by a little over 0.01.

The total effect values for all cities are represented by the summation of the coefficients of each city, plus the coefficient of interaction between the city and the instrument and the value of the average instrument. The results for GDP and Gini coefficient are presented in Figures 3 and 4 (here), respectively. For GDP, the total effect is positive for most cities, with higher results for more

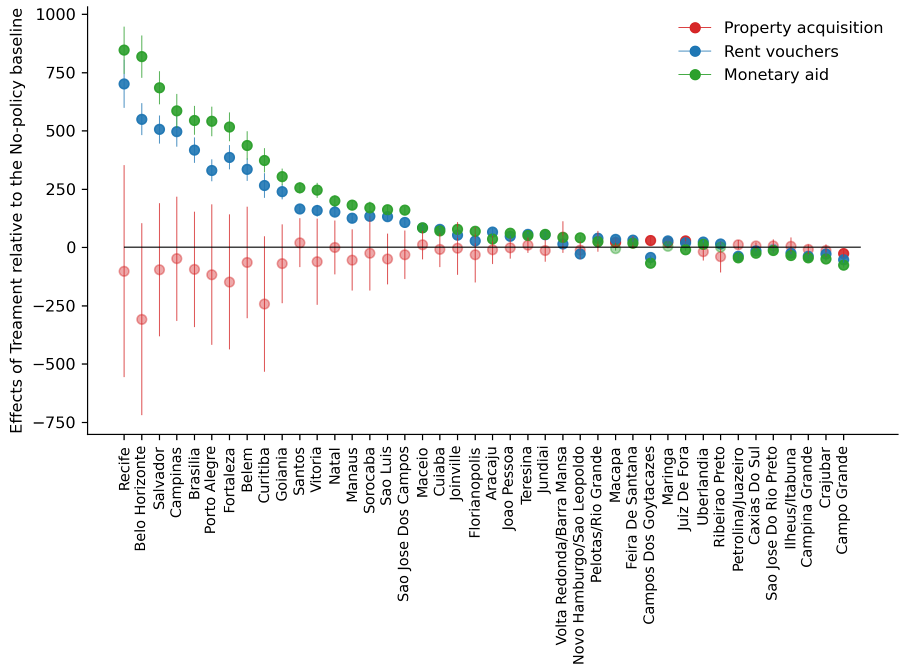

Fig. 2. Treatment effects of policy instruments on GDP controlling for population and excluding São Paulo and Rio de Janeiro (see full total effect for all cities in Figure 3 of the supplemental material (here). The policy instrument of Monetary aid appears to be the most effective for the most populous cities, but loses its advantage as population diminishes. Property acquisition contributes less to GDP gains and provides more uncertain results with larger variation. Markers are transparent for p-values not significant at 10%, and the line represents standard deviations. Despite controlling for population, scale still seems to play a role as cities are broadly ordered by population from left to right. Londrina is the reference city, and the no policy instrument is the reference group. Total effects tables are included in the code link in section 3.1.

populous cities. Only three cities had total negative results for GDP: Campos dos Goytacazes (in Rio de Janeiro state), Campo Grande (the capital of Mato Grosso do Sul), and Teresina for the Property acquisition policy instrument. All of the other 42 cities showed increases in GDP. Campo Grande was also the only city that did not respond with a decrease in inequality with the application of policy instruments, along with Campos dos Goytacazes for (again) the Property acquisition policy instrument. All of the other cities showed significant gains in reducing the Gini coefficient, ranging from a 0.2 decrease for São Paulo and Rio de Janeiro to smaller reductions between 0.05 and 0.1 for most other cities.

Overall, the results suggest that policy instruments have a positive impact on the economy and income distribution. The Property acquisition policy instrument seems to have a less beneficial impact on both GDP and inequality, while

Rent vouchers and Monetary aid appear to be the most effective instruments, with some variation depending on the specific city.

5 Discussion

The analysis using Directed Acyclic Graphs (DAGs) helped to identify that the exogenous population influence was the confounding variable that needed to be controlled for in the model. However, it was surprising to find that even after controlling for this variable, the GDP results (refer to figure 2) still appeared to be roughly ordered by population. In fact, we had to exclude the two largest Brazilian macro metropolises, São Paulo and Rio de Janeiro, from the graph to make it easier to compare the other cities.

This finding indicates that, despite controlling for population, production still exhibits scaling properties, which has been previously discussed by several authors [3,15]. It appears that economies of agglomeration [7] play a significant role in this phenomenon, confirming the scaling analysis that suggests doubling a city's size leads to more than a doubling of its specialisation, diversity, and production levels.

Despite the observed phenomenon of scaling in other aspects of the city, it seems that this scaling does not apply to the inequality that arises from the implementation of policy instruments. This suggests that other spatial factors within the city may be contributing to the inequality. These spatial factors are unique to each city and are the only source of variability in our simulated data. While we cannot identify the specific mechanisms behind these factors, we can see that Rent vouchers and Monetary aid, which originate from different social domains (namely welfare and housing), are more effective than Property acquisition in reducing inequality.

The results from this study offer informative and diverse insights for policymakers, tailored to the specific context of their city. For instance, a policymaker from Uberlândia or Santos would notice that Rent vouchers perform comparatively better than Monetary aid in these cities. However, when considering the total effect across all cities, Property acquisition consistently generates less production and more inequality.

It is worth noting that the model used in this study is designed to be stock-flow consistent [8]. Therefore, the No-policy baseline refers to the *default* scenario in which all collected taxes are allocated to the Quality of Life Indicator (QLI), which, in turn, impacts the infrastructure and amenities of the neighbourhoods and affects house prices. In the case of Campo Grande, for instance, investing in QLI (i.e., No-policy baseline) would be the most beneficial in terms of both production and inequality. Similarly, for Campos dos Goytacazes, investing in QLI would be more advantageous in terms of production. However, Rent vouchers and Monetary aid would be more effective in reducing inequality than the No-policy baseline for Campos dos Goytacazes.

Based on the results of our analysis, we are confident in making policy recommendations. In terms of maximising social benefits, characterised by higher production and smaller inequality with the same amount of investment, Monetary aid appears to be the most effective instrument out of the four alternatives tested. Rent vouchers performed similarly well, both options vastly outperformed Property acquisition. This finding is primarily due to the fact that Property acquisition, which involves municipalities purchasing and transferring homes to low-income households, benefits a significantly smaller number of families while not contributing to the long-term economic dynamics [1].

However, we should emphasise that policy recommendations must be made in consideration of the specific circumstances of each city, and other factors should be taken into account when deciding on the most appropriate policy instrument to adopt. Campos dos Goytacazes and Campo Grande may benefit more from investments in infrastructure and amenities, rather than in any of the proposed policy instruments.

It is important to acknowledge the limitations of our study. Despite ongoing debates, it is crucial to keep in mind that causal claims should always be considered provisional, and require background theories and substantial evidence to support them [14]. Therefore, our illustration implicitly depends on the reliability of the original model [1,8]. However, we have employed additional methodological strategies, such as DAG analysis and Panel regression methods, to scrutinise the analysis. This aligns with the view that consensus-building is facilitated by employing multiple models [17,10]. By utilising a variety of methods to examine our results, we can have greater confidence in the robustness of our findings.

6 Final considerations

We have utilised an ABM model to showcase its potential for providing a causal argument. In doing so, we have highlighted the literature that outlines the considerations and criteria necessary for using ABMs as a causal analysis tool. We have also used a causal DAG and panel regression analysis to inform our results. By using a sound ABM and regression mechanism, we believe that we have accurately compared the policy alternatives. Our study has demonstrated the power of comparing policies both intra-model and across policies, where all states remain the same except for the policy change. Additionally, we have shown that policies across domains and spatial units can be quantitatively compared.

Overall, we hope that this paper will encourage the use of ABMs that meet the necessary criteria for studying causal relationships. We believe that our results can encourage policymakers and scientists with an illustration of quantitative means of assessing the effects of various policies and mechanisms.

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