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Agent-Based Modelling of Battery Electric Vehicle Adoption in Portugal

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Abstract

This paper develops an agent-based model to analyse Battery Electric Vehicle (BEV) adoption across Portuguese municipalities. The model combines heterogeneous agents, spatial interactions, charging infrastructure dynamics, and an inverse Matthew mechanism designed to favour municipalities with lower levels of adoption. Charging infrastructure evolves according to a stochastic logistic diffusion process, allowing for uncertainty in infrastructure expansion over time. The model is calibrated using municipality-level data and validated out-of-sample. Results indicate that income is the most robust determinant of BEV adoption, while spatial interactions improve the representation of local diffusion patterns. The analysis also shows that parsimonious specifications combining income, spatial interactions, and compensatory mechanisms outperform more complex behavioural configurations in out-of-sample validation. Policy simulations indicate that, under the calibrated scenarios, expanding charging infrastructure increases adoption and reduces spatial concentration, whereas additional fiscal incentives generate only limited effects under the current Portuguese policy framework. The findings highlight the importance of infrastructure investment for both electric mobility diffusion and territorial cohesion.

Keywords: Battery electric vehicles, agent-based modelling, spatial diffusion, charging infrastructure, inverse Matthew effect, Portugal, stochastic infrastructure dynamics.
JEL Codes: R12, R48, H23, Q58, C21

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1 Introduction

The transport sector is one of the largest contributors to greenhouse gas emissions in Portugal, with road transport accounting for a large share of transport-related emissions. It is also an important source of fiscal revenue through vehicle taxation, fuel taxation, and circulation-related charges (ACAP, 2025).

In response to climate and sustainability objectives, public policy has increasingly promoted the adoption of Battery Electric Vehicles (BEVs). These policies include fiscal incentives, exemptions from vehicle-related taxes, national purchase subsidies, and local municipal incentives. In Portugal, fully electric vehicles benefit from exemption from Vehicle Registration Tax (ISV) and Annual Circulation Tax (IUC), while additional support schemes have been implemented through national programmes and municipal policies.[0]

Although BEV adoption has expanded over time, adoption is unlikely to occur uniformly across space. It may depend on local income, charging infrastructure, accessibility conditions, local policy incentives, and interaction mechanisms between municipalities. From a computational and evolutionary perspective, economic behaviour can emerge from decentralised interactions between heterogeneous agents, generating clustering, concentration, and self-organised spatial patterns rather than homogeneous diffusion (Banish and Araújo, 2012).

Despite the growing adoption of BEVs, relatively little is known about how fiscal incentives interact with local conditions and spatial networks to shape the concentration of BEVs across Portuguese municipalities. Existing studies on electric vehicle adoption emphasise the importance of incentives, infrastructure, consumer characteristics, and social diffusion (Sierzchula et al., 2014; Peres et al., 2010; Eppstein et al., 2011; Kangur et al., 2017). However, the interaction between fiscal policy, municipal heterogeneity, network effects, and behavioural adoption mechanisms remains underexplored in the Portuguese case.

This paper addresses the following research question:

> *How do fiscal incentives, local conditions, and network interactions affect the spatial concentration of BEV adoption across Portuguese municipalities?*

The paper contributes to the literature in three ways. First, it develops a municipality-level agent-based model of BEV adoption in Portugal. Second, it incorporates a filtered spatial network based on a minimum spanning tree connectivity threshold, allowing adoption decisions to depend on neighbouring municipalities. Third, it introduces an inverse Matthew effect mechanism together with a redistributive incentive mechanism, allowing the model to evaluate whether fiscal incentives reduce or reinforce spatial inequalities in BEV adoption.

2 Literature Review

This section reviews the main concepts related to BEV adoption, fiscal incentives, agent-based modelling, network diffusion, and cumulative advantage mechanisms.

[0] See MOBI.E, "Benefits and Incentives": https://www.mobie.pt/en/mobility/benefits-incentives. See also the European Alternative Fuels Observatory overview for Portugal: https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road/portugal/incentives-legislations.

2.1 Fiscal Incentives and BEV Adoption

Fiscal incentives reduce the relative cost of BEV adoption and may therefore increase the probability that households and firms choose electric vehicles. These incentives can take several forms, including purchase subsidies, tax exemptions, circulation tax reductions, and local benefits such as free or discounted parking.

Sierzchula et al. (2014) show that financial incentives can support electric vehicle adoption, although they are not sufficient by themselves. Charging infrastructure and socioeconomic factors also play an important role. This suggests that fiscal incentives must be analysed together with local conditions, rather than as isolated policy instruments.

Innovation diffusion studies also show that adoption depends on social and spatial interactions. Peres et al. (2010) argue that incentives can accelerate adoption, but diffusion depends on network structure, communication, and interaction between adopters and potential adopters. In this sense, incentives may change the initial attractiveness of adoption, while the subsequent diffusion process depends on endogenous interactions.

From a computational economics perspective, incentives do not operate independently from the structure of the system. Araújo (2011) and Araújo and Weisbuch (2010) emphasise that local interactions and system structure can generate aggregate patterns that differ from what would be expected from isolated individual decisions.

2.2 Agent-Based Models and Technology Adoption

Agent-based models are useful for analysing complex systems composed of heterogeneous agents who interact locally and generate aggregate outcomes (Bonabeau, 2002; Tesfatsion and Judd, 2006). In the context of technology adoption, ABMs allow researchers to model individual decision rules, heterogeneity in preferences and resources, social influence, and spatial interactions.

Previous studies have used ABMs to analyse the diffusion of electric and plug-in hybrid vehicles. Eppstein et al. (2011) develop an agent-based model of plug-in hybrid electric vehicle market penetration, showing how consumer heterogeneity and social influence affect adoption. Kangur et al. (2017) also use an ABM framework to study electric vehicle diffusion, emphasising the role of behavioural heterogeneity and policy interventions.

The ABM approach is particularly appropriate for the present study because BEV adoption is not only a function of average municipal characteristics. It also depends on the behaviour of heterogeneous agents, their economic resources, their exposure to local and neighbouring adoption, and the evolution of infrastructure and incentives over time.

2.3 Network Effects and Spatial Diffusion

Spatial diffusion processes are often shaped by network structure. Municipalities are not isolated units: they are connected through roads, commuting patterns, geographic proximity, infrastructure networks, and social interaction. As a result, adoption in one municipality may influence adoption in nearby or connected municipalities.

In this paper, the municipal network is used to capture spatial spillovers in BEV adoption. The network allows the model to include neighbouring adoption as part of the behavioural

payoff of agents. This is important because BEV visibility, social learning, infrastructure familiarity, and perceived feasibility may spread across connected municipalities.

2.4 Matthew Effects and Cumulative Advantage

The inverse Matthew effect captures a compensatory mechanism whereby agents and municipalities with weaker initial conditions receive a stronger adoption stimulus (Merton, 1968). In the context of BEV adoption, wealthier agents may have greater purchasing capacity, lower sensitivity to price barriers, and better access to information. Similarly, municipalities with higher prior adoption may benefit from greater visibility, stronger charging demand, and stronger social normalisation of electric mobility.

However, public policy can also work in the opposite direction. If incentives are designed or modelled so that they are more effective in disadvantaged municipalities, they may partially compensate for initial inequalities. This paper therefore combines two compensatory mechanisms: an inverse Matthew effect and a redistributive incentive mechanism designed to offset initial disadvantage.

3 Data

The empirical analysis uses municipality-level data for Portugal, combining information from multiple sources:

- BEV-in-use data from ACAP;
- fiscal incentive data, including ISV and IUC tax benefits as well as national subsidy schemes;
- municipality-level parking incentives for electric vehicles, including free or discounted parking policies;
- socioeconomic indicators from INE;
- road network and geographic data from OpenStreetMap and official GIS sources;
- charging infrastructure data from MOBI.E.

These data sources allow the construction of both standard explanatory variables and network-based measures of spatial connectivity. In particular, the combination of municipal coordinates, road accessibility, and infrastructure data enables the representation of municipalities as nodes in a connected spatial system.

3.1 Institutional Framework of BEV Incentives in Portugal

The Portuguese policy framework for electric mobility combines national tax benefits, purchase subsidies, and local municipal incentives. Fully electric vehicles benefit from exemption

from Vehicle Registration Tax (ISV) and Annual Circulation Tax (IUC), reducing both acquisition and ownership costs.

In addition to tax exemptions, Portugal has implemented purchase incentive schemes for zero-emission vehicles, usually administered through national programmes. These schemes vary across years in terms of eligible beneficiaries, subsidy amounts, budget limits, and vehicle price caps.

At the municipal level, some municipalities provide additional incentives, including free or discounted parking for electric vehicles. These local incentives reduce the operating cost of BEV ownership and may be particularly relevant in urban municipalities, where parking costs and restrictions are more important.

In this study, national incentives are treated as part of the common policy environment affecting all municipalities, while local parking incentives are used to capture municipal-level policy variation.

4 Methodology

This study develops a calibrated agent-based model to analyse the adoption of BEVs across Portuguese municipalities. The model combines municipality-level data with a synthetic population of agents in order to simulate adoption dynamics under heterogeneous local conditions.

The behavioural parameters of the model are calibrated rather than statistically estimated. Parameter values are selected to ensure stable simulation dynamics and realistic adoption trajectories while preserving consistency with observed municipal-level BEV adoption patterns. The parameters governing the stochastic charging infrastructure process are also treated as calibration parameters and their influence is subsequently evaluated through sensitivity analysis using alternative volatility scenarios.

The modelling strategy proceeds in five stages. First, municipality-level panel data are organised into a structured state space by year. Second, a spatial municipal network is constructed using a minimum spanning tree connectivity threshold. Third, a synthetic population of agents is allocated across municipalities proportionally to population. Fourth, adoption behaviour is simulated annually through a probabilistic decision rule. Fifth, the model is calibrated and evaluated out-of-sample by comparing simulated and observed BEV shares.

4.1 Data and State Variables

Let $m = 1, \ldots, M$ index municipalities and $t = 1, \ldots, T$ index years. The core municipality-level variables included in the simulation are:

- **Population** ($POP_{m,t}$);
- **Income** ($INC_{m,t}$);
- **Observed BEV share** ($BSH_{m,t}$);
- **Charging density** ($CD_{m,t}$);

- **Number of charging stations** ($CS_{m,t}$);
- **Fiscal incentive per vehicle** ($FI_{m,t}$);
- **Local parking incentive** ($PI_{m,t}$);
- **Observed number of BEVs** ($BEV_{m,t}$);
- **Municipal area** ($AREA_{m,t}$).

The dataset is arranged into municipality-by-year matrices so that each municipality evolves under time-varying local conditions. Missing observations are replaced by year-specific means, while missing parking incentives are set to zero.

4.2 Spatial Network Construction Using a Minimum Spanning Tree

The ABM incorporates a spatial municipal network. Each municipality is represented as a node, and the edges represent spatial proximity between municipalities. The initial network is defined as a complete weighted graph, where every municipality is connected to every other municipality. The weight of each edge corresponds to the distance between municipalities.

Let $G = (V, E)$ denote the complete weighted graph, where V is the set of municipalities and E is the set of all possible pairs of municipalities. The distance between municipalities m and n is denoted by d_{mn}.

A minimum spanning tree is computed from the complete weighted graph. The minimum spanning tree is the subset of edges that connects all municipalities while minimising the total distance and avoiding cycles:

$$T^{MST} = \arg\min_{T \subset E} \sum_{(m,n) \in T} d_{mn}. \tag{1}$$

The maximum distance among the edges of the minimum spanning tree is used as the connectivity threshold:

$$\delta = \max_{(m,n) \in T^{MST}} d_{mn}. \tag{2}$$

The final filtered network is obtained by keeping all edges in the complete network whose distance is lower than or equal to this threshold:

$$A_{mn} = \begin{cases} 1, & \text{if } d_{mn} \leq \delta \text{ and } m \neq n, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

This procedure filters the complete network while ensuring that all municipalities remain connected. Therefore, δ represents the minimum distance cut-off required to preserve full network connectivity. The resulting adjacency matrix is used to compute spatial peer effects in the agent-based model.

4.3 Synthetic Agent Population

The model assumes a total population of 1,000 synthetic agents. Agents are allocated across municipalities proportionally to population in the base year:

$$N_m = 1000 \cdot \frac{POP_{m,0}}{\sum_{j=1}^{M} POP_{j,0}}. \tag{4}$$

where N_m is the number of synthetic agents allocated to municipality m and $POP_{m,0}$ denotes the municipality population in the base year.

Each agent i is characterised by:

- a home municipality m;
- an endowment level E_i;
- an adoption status;
- an adoption year.

Initial endowment is linked to municipality-level income and an idiosyncratic stochastic term:

$$E_i = 0.5 + 0.5\widetilde{INC}_{m,0} + \sigma_E \varepsilon_i, \tag{5}$$

where E_i denotes the endowment of agent i, $\widetilde{INC}_{m,0}$ is normalised municipal income in the base year, σ_E is the standard deviation of endowment heterogeneity, and $\varepsilon_i \sim \mathcal{N}(0,1)$.

This formulation allows agents located in wealthier municipalities to begin with higher purchasing capacity while preserving within-municipality heterogeneity.

4.4 Initial Set-up of Agents

At the beginning of the simulation, a synthetic population of 1,000 agents is created. Each agent is assigned to one Portuguese municipality according to the municipality's population share in the base year. This procedure ensures that larger municipalities contain more synthetic agents, while keeping the total number of agents computationally manageable.

Each agent is initially characterised by municipality of residence, endowment, adoption status, and adoption year. The municipality of residence remains fixed during the simulation. The endowment variable captures the agent's relative capacity to adopt a BEV and is partly determined by the income level of the municipality where the agent lives, plus an idiosyncratic random component.

At the start of the simulation, agents are treated as potential adopters. Their adoption status is updated endogenously during the simulation when they are selected to reconsider adoption and their probabilistic adoption decision is evaluated.

4.5 Incremental Model Specifications

To avoid over-specification and evaluate the contribution of different behavioural and spatial mechanisms, the model is estimated under five incremental specifications.

The baseline specification includes only the core economic determinants of BEV adoption: endowment, fiscal incentives, and charging infrastructure.

The social specification additionally incorporates local peer effects.

The spatial specification further includes network spillovers between neighbouring municipalities.

The redistribution specification introduces the redistributive incentive mechanism.

Finally, the full specification combines all behavioural, spatial, and redistributive mechanisms, including parking incentives, metropolitan heterogeneity, and the inverse Matthew effect.

The baseline specification therefore captures the core economic adoption dynamics with a parsimonious behavioural structure.

The social specification evaluates whether local imitation mechanisms improve the diffusion dynamics of the model.

The spatial specification additionally evaluates the contribution of inter-municipal spillovers through the municipal network structure.

The redistribution specification evaluates whether compensatory fiscal incentives improve adoption diffusion in disadvantaged municipalities.

Finally, the full specification incorporates all mechanisms simultaneously in order to evaluate the interaction between behavioural, spatial, and redistributive dynamics.

This incremental structure allows the analysis to assess whether additional mechanisms improve the simulation of observed BEV adoption patterns or mainly increase model complexity.

4.6 Metropolitan Heterogeneity

The model includes a metropolitan dummy to capture spatial differences not fully explained by income or infrastructure:

$$METRO_m = \begin{cases} 1, & \text{if municipality } m \text{ belongs to a metropolitan area,} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

where $METRO_m$ is a metropolitan dummy variable equal to one for municipalities belonging to metropolitan areas and zero otherwise.

This term captures additional urban externalities, such as higher market visibility, stronger social diffusion, and denser economic interactions (Lohrey and Creutzig, 2016).

4.7 Inverse Matthew Effect

The model includes an inverse Matthew effect mechanism to counteract cumulative advantage in BEV adoption. This techniques is the opposite of Matthew Effect, argued by Merton (1968). Agents with lower endowment living in municipalities with lower previous BEV adoption receive a larger compensatory effect.

The Inverse Matthew effect term is defined as:

$$IMAT_{i,m,t} = (1 - E_i) \times (1 - SSHR_{m,t}). \tag{7}$$

where $IMAT_{i,m,t}$ denotes the inverse Matthew effect component for agent i, E_i is the agent's endowment, and $SSHR_{m,t}$ is the simulated BEV adoption share in municipality m at time t.

This mechanism increases the adoption potential of agents located in municipalities with lower previous BEV adoption, helping to counteract cumulative advantage and reduce excessive spatial concentration.

4.8 Stochastic Charging Infrastructure Dynamics

The expansion of charging infrastructure is subject to uncertainty arising from investment timing, policy implementation, local demand conditions, and technological factors. To account for this uncertainty, charging density is modelled as a stochastic logistic diffusion process.

Let $DEN_{m,t}$ denote charging density in municipality m at time t. Its evolution is given by:

$$dDEN_{m,t} = rDEN_{m,t}\left(1 - \frac{DEN_{m,t}}{K}\right)dt + \sigma DEN_{m,t}dW_t, \tag{8}$$

where r is the diffusion rate, K is the carrying capacity of charging infrastructure, σ is the volatility parameter, and W_t denotes a standard Wiener process.

The deterministic component captures the gradual expansion of charging infrastructure towards a long-run saturation level, while the stochastic component captures uncertainty associated with infrastructure deployment.

For simulation purposes, the continuous-time process is approximated using the Euler–Maruyama discretisation:

$$DEN_{m,t+1} = DEN_{m,t} + rDEN_{m,t}\left(1 - \frac{DEN_{m,t}}{K}\right) + \sigma DEN_{m,t}\varepsilon_t, \tag{9}$$

where $\varepsilon_t \sim N(0, 1)$.

The resulting charging density enters the disadvantage index and therefore affects both agent selection probabilities and the redistributive incentive mechanism.

Charging density is interpreted as an aggregate measure of charging infrastructure availability and accessibility. The stochastic process therefore captures uncertainty in the overall evolution of local charging infrastructure.

4.9 Redistributive Incentive Mechanism

The model also includes a redistributive incentive mechanism. While the inverse Matthew effect provides a compensatory behavioural mechanism, the redistributive mechanism captures the possibility that fiscal incentives are more effective in disadvantaged municipalities.

First, all relevant municipality-level variables are normalised to the interval $[0, 1]$. Then a disadvantage index is defined as:

$$DIS_{m,t} = \frac{(1 - \widetilde{INC}_{m,t}) + (1 - \widetilde{SHR}_{m,t}) + (1 - \widetilde{DEN}_{m,t})}{3}. \tag{10}$$

where $DIS_{m,t}$ is the municipal disadvantage index, $\widetilde{INC}_{m,t}$ is normalised income, $\widetilde{SHR}_{m,t}$ is the normalised observed BEV share, and $\widetilde{DEN}_{m,t}$ is the normalised charging density.

The effective fiscal incentive is then given by:

$$EFIN_{m,t} = \widetilde{FIN}_{m,t} \left(1 + \theta DIS_{m,t}\right). \tag{11}$$

where $EFIN_{m,t}$ denotes the effective fiscal incentive, $\widetilde{FIN}_{m,t}$ is the normalised fiscal incentive, $DIS_{m,t}$ is the municipal disadvantage index, and $\theta > 0$ controls the strength of the redistributive adjustment.

This formulation implies that municipalities with lower income, lower prior BEV penetration, and weaker charging infrastructure receive relatively stronger incentive effects within the simulated adoption process.

For example, municipalities with lower income and weaker charging infrastructure obtain a larger disadvantage index. As a result, the same nominal fiscal incentive generates a stronger effective incentive in disadvantaged municipalities than in already advantaged municipalities.

4.10 Selection of Agents by Timestep

Time is modelled in annual steps. In each year, only a subset of agents is selected to reconsider adoption. Specifically, 50 non-adopting agents are selected per year.

The probability of being selected is not uniform. Instead, it depends on municipal conditions, with higher probability assigned to agents located in municipalities with weaker charging coverage and lower BEV penetration. The municipal selection weight is defined as:

$$SEL_{m,t} = 0.5 + 0.5 \cdot \frac{(1 - \widetilde{DEN}_{m,t}) + (1 - \widetilde{SHR}_{m,t})}{2}. \tag{12}$$

where $SEL_{m,t}$ denotes the municipality selection weight, $\widetilde{DEN}_{m,t}$ is normalised charging density, and $\widetilde{SHR}_{m,t}$ is the normalised observed BEV share.

These weights are assigned to all non-adopting agents residing in municipality m, and weighted sampling without replacement is used to choose the set of agents who re-evaluate adoption in year t.

4.11 Behavioural Payoff

For each selected agent i living in municipality m, the latent utility associated with BEV adoption is defined as:

$$\begin{aligned} U_{i,t} = {} & E_i \cdot EFIN_{m,t} \cdot INF_{m,t} \\ & + PEER_{m,t} \cdot PAR_{m,t} \cdot NPEER_{m,t} \\ & + IMAT_{i,m,t} \cdot \widetilde{INC}_{m,t} \cdot METRO_m \cdot \eta_i. \end{aligned} \tag{13}$$

where $U_{i,t}$ is the latent utility associated with BEV adoption, E_i is the agent's endowment, $EFIN_{m,t}$ is the effective fiscal incentive, $INF_{m,t}$ is the infrastructure component, $PEER_{m,t}$ is the local peer effect, $PAR_{m,t}$ is the parking incentive indicator, $NPEER_{m,t}$ is the network peer effect, $IMAT_{i,m,t}$ is the inverse Matthew effect component, $\widetilde{INC}_{m,t}$ is normalised municipal income, $METRO_m$ is the metropolitan dummy, and $\eta_i \sim \mathcal{N}(0, \sigma_\eta^2)$ is an idiosyncratic shock.

The infrastructure term varies across model specifications:

$$INF_{m,t} = \begin{cases} \widetilde{DEN}_{m,t}, & \text{Density specification,} \\ \widetilde{STA}_{m,t}, & \text{Stations specification,} \\ \widetilde{DEN}_{m,t} + \widetilde{STA}_{m,t}, & \text{Combined specification.} \end{cases} \tag{14}$$

where $INF_{m,t}$ denotes charging infrastructure, $\widetilde{DEN}_{m,t}$ is normalised charging density, and $\widetilde{STA}_{m,t}$ is the normalised number of charging stations.

For example, a municipality with more charging stations and higher charging density generates a larger infrastructure term, increasing the latent payoff from adoption and therefore increasing the probability of BEV adoption.

4.12 Adoption Probability and Adoption Threshold

Adoption is probabilistic and follows a logistic decision rule, a standard approach in discrete choice and agent-based adoption models (Train, 2009):

$$P(Adopt_{i,m,t} = 1) = \frac{1}{1 + \exp\left[-s\left(U_{i,t} - \tau\right)\right]}. \tag{15}$$

where s is the slope parameter and τ is the adoption threshold.

The parameter τ represents the minimum perceived net benefit required for BEV adoption to become more likely than non-adoption. When $U_{i,t} = \tau$, the adoption probability is equal to 0.5. When $U_{i,t} > \tau$, adoption becomes more likely than non-adoption.

4.13 Infrastructure Specifications

In addition to the incremental behavioural specifications, the model is also estimated under alternative infrastructure specifications.

Three infrastructure specifications are considered:

- **Density**: infrastructure is represented by charging density only;
- **Stations**: infrastructure is represented by the absolute number of charging stations only;
- **Both**: both charging density and charging stations are included simultaneously.

This comparison allows the analysis to assess whether BEV adoption responds more strongly to relative charging coverage, to absolute infrastructure scale, or to both jointly.

4.14 Training and Out-of-Sample Validation

The model is calibrated using the years 2021–2023 and tested on the hold-out year 2024:

$$\mathcal{T}_{train} = \{2021, 2022, 2023\}, \qquad \mathcal{T}_{test} = \{2024\}. \tag{16}$$

For each specification, the model is evaluated using:

- Root Mean Squared Error;
- Mean Absolute Error;
- correlation between simulated and observed BEV shares;
- average prediction bias.

The preferred model is selected according to the lowest out-of-sample test RMSE.

Because the model contains several stochastic components, including agent endowment, agent selection, adoption decisions, and charging infrastructure dynamics, each specification was evaluated using repeated Monte Carlo simulations. The number of replications was determined through a convergence analysis in which the out-of-sample RMSE was monitored for increasing replication levels (10, 25, 50, 100, 250, and 500). The results indicated that prediction errors stabilised beyond approximately 250 replications, with only marginal improvements thereafter. Consequently, all reported performance measures are based on averages computed over 500 Monte Carlo replications[1].

4.15 Outputs

The model produces both agent-level and municipality-level outputs. At municipality-year level, the main outcomes are:

- simulated BEV share;
- observed BEV share;
- adopted agents in each year;
- cumulative adopted agents;
- effective fiscal incentives;
- disadvantage index;
- local peer effect;
- network peer effect.

At agent level, the model records:

[1]The convergence analysis is presented in Appendix A

- municipality of residence;
- latent payoff;
- adoption probability;
- year of adoption.

4.16 Interpretation

The model is designed to examine how BEV adoption emerges from the interaction between local resources, infrastructure, incentives, peer effects, and network spillovers. The inverse Matthew effect captures a compensatory mechanism whereby agents and municipalities with weaker initial conditions receive a stronger adoption stimulus. The redistributive incentive mechanism captures a similar compensatory force by increasing the effectiveness of fiscal incentives in municipalities with lower income, lower BEV penetration, and weaker charging infrastructure.

The main behavioural mechanism of the model is therefore the tension between cumulative advantage and policy compensation. If underlying spatial and socioeconomic advantages dominate, BEV adoption becomes more spatially concentrated. If redistributive incentives and network spillovers are strong enough, adoption may spread more evenly across municipalities.

5 Results

The results compare alternative model specifications in order to evaluate how behavioural, spatial, and redistributive mechanisms contribute to reproducing observed BEV adoption patterns across Portuguese municipalities.

The simulations suggest that BEV adoption is primarily shaped by the interaction between local economic conditions, spatial interactions, and behavioural mechanisms. While infrastructure availability and fiscal incentives remain important drivers of adoption, their effects are conditioned by municipal heterogeneity and network position.

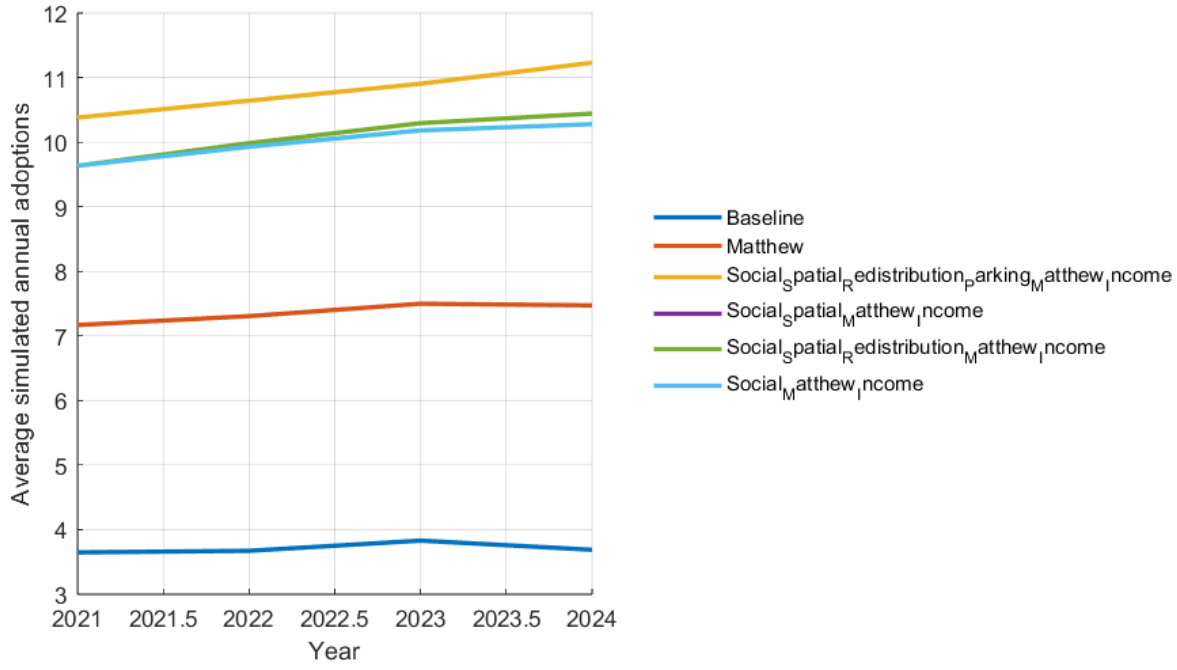


Figure 1: Average annual simulated adoptions for selected model specifications

Figure 1 presents the average annual number of simulated adoptions generated by selected model specifications.

The baseline model, represented by the blue line, produces the lowest adoption levels, indicating that fiscal incentives and charging infrastructure alone are insufficient to reproduce the observed diffusion of BEVs across municipalities.

The inclusion of the inverse Matthew effect increases adoption relative to the baseline specification, suggesting that cumulative advantages and local inequalities influence the diffusion process. Municipalities with more favourable initial conditions tend to accumulate adoption more rapidly, reinforcing existing disparities.

The full model generates the highest number of simulated adoptions, indicating that behavioural, spatial and redistributive mechanisms reinforce each other within the simulation framework. However, generating a larger number of adoptions does not necessarily imply superior predictive performance.

An important result emerges from the comparison of model specifications. The best-performing calibrated models are not the most complex ones. Instead, the highest validation scores are obtained by models combining income, spatial interactions, and the inverse Matthew mechanism. This finding suggests that parsimonious behavioural structures may reproduce observed adoption patterns more effectively than highly parameterised specifications.

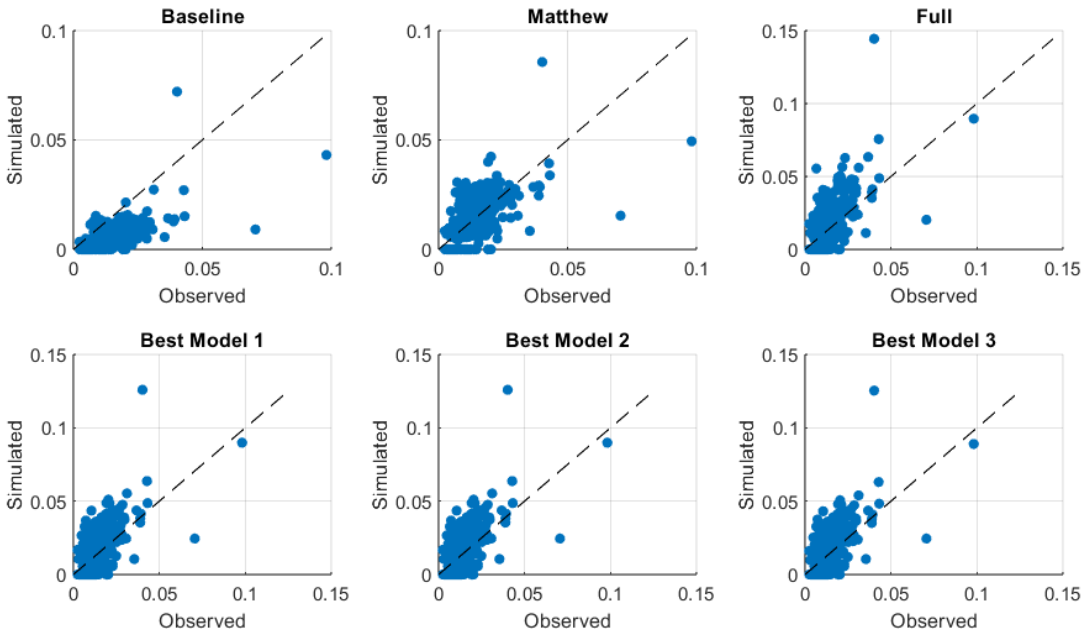


Figure 2: Observed versus simulated BEV shares in 2024

Figure 2 compares observed and simulated BEV shares in 2024. Points located closer to the 45-degree line indicate municipalities where the model reproduces observed adoption levels more accurately.

The baseline model exhibits considerable dispersion, reflecting limited explanatory power. The incorporation of the inverse Matthew effect improves the correspondence between observed and simulated values, although substantial variation remains.

The full model achieves a stronger overall fit but continues to display some degree of dispersion. In contrast, the best-performing specifications exhibit a tighter concentration around the diagonal and fewer extreme deviations, indicating a more accurate representation of municipal-level adoption patterns.

Table 1: In-sample and out-of-sample performance of benchmark, behavioural and top-performing ABM specifications

Specification	Train RMSE	Train MAE	Train Corr	Test RMSE	Test MAE	Test Corr
Baseline	0.00660	0.00496	0.532	0.01175	0.00960	0.599
Matthew	0.00629	0.00442	0.553	0.01038	0.00777	0.544
Full Model	0.00858	0.00573	0.600	0.01452	0.01027	0.612
Best Model 1	0.00781	0.00536	0.609	0.01300	0.00956	0.618
Best Model 2	0.00785	0.00538	0.610	0.01319	0.00974	0.618
Best Model 3	0.00780	0.00536	0.609	0.01307	0.00963	0.618

Table 1 reports the performance of benchmark and top-performing specifications selected from the full factorial design comprising $2^6 = 64$ possible combinations of behavioural mechanisms.

The results show that predictive performance does not increase monotonically with model complexity. Although the full model achieves relatively strong correlations between observed and simulated adoption levels, simpler specifications combining income, spatial interactions and the inverse Matthew mechanism obtain the highest validation scores.

A second important finding concerns the role of income. Variables associated with local economic conditions appear in all top-performing specifications, indicating that income remains the most robust determinant of BEV adoption across municipalities. By contrast, the redistributive mechanism generates only marginal differences under the current calibration, suggesting that its influence on adoption outcomes is limited within the analysed period.

Overall, the results indicate that BEV diffusion is best explained by a combination of economic resources, spatial interaction effects, and cumulative adoption dynamics rather than by the simultaneous inclusion of all available behavioural mechanisms.

5.1 Sensitivity Analysis of Infrastructure Uncertainty

To evaluate the role of stochastic infrastructure dynamics, a sensitivity analysis was conducted by varying the volatility parameter of the charging infrastructure diffusion process (σ_{DEN}). Three scenarios were considered: deterministic infrastructure dynamics ($\sigma_{DEN} = 0$), moderate volatility ($\sigma_{DEN} = 0.10$), and high volatility ($\sigma_{DEN} = 0.25$).

Under deterministic infrastructure dynamics, the Income specification achieved the highest performance score, suggesting that local economic conditions alone explain a substantial part of observed adoption patterns. When moderate volatility was introduced, specifications combining spatial interactions, income effects, and the inverse Matthew mechanism outperformed simpler alternatives. Under high volatility, spatial effects remained important, while the contribution of the inverse Matthew mechanism weakened.

These findings indicate that infrastructure uncertainty affects the relative importance of behavioural and spatial mechanisms. While income remains a robust predictor of BEV adoption across all scenarios, stochastic infrastructure dynamics increase the explanatory relevance of local interaction effects and spatial heterogeneity.

Table 2: Sensitivity analysis with respect to infrastructure volatility

σ_{DEN}	Best Specification	Score
0.00	Income	0.24263
0.10	Spatial_Matthew_Income	0.24043
0.25	Spatial_Income	0.24031

5.2 Policy Experiments

To illustrate the policy relevance of the proposed framework, three counterfactual scenarios were simulated for the period 2025–2026 using the best-performing specification (*Social_Spatial_Matthew_Income*).

The first scenario corresponds to the continuation of current policies (*Status Quo*). The second scenario assumes an accelerated expansion of charging infrastructure across municip-

alities (*Infrastructure Expansion*). The third scenario assumes stronger fiscal incentives for BEV adoption while maintaining the existing infrastructure trajectory (*Higher Incentives*).

Table 3 summarises the main results.

Table 3: Policy scenario comparison

Scenario	Relative Adoption Change	HHI 2026	ΔHHI	Interpretation
Status Quo	0.0%	0.0321	+0.0002	Concentration increases
Infrastructure Expansion	+3.9%	0.0310	-0.0008	Concentration decreases
Higher Incentives	0.0%	0.0321	+0.0002	Concentration increases

The results indicate substantial differences between infrastructure-oriented and incentive-oriented policies. While the infrastructure expansion scenario increases total BEV adoption by approximately 3.9% relative to the status quo, the higher incentive scenario generates virtually no additional adoption under the current calibration.

More importantly, infrastructure expansion alters the spatial distribution of adoption. Under the infrastructure scenario, the Herfindahl–Hirschman Index (HHI) decreases between 2025 and 2026, suggesting a reduction in municipal concentration and a partial convergence between leading and lagging municipalities. By contrast, both the status quo and higher incentive scenarios continue to exhibit increasing concentration.

These findings suggest that charging infrastructure may operate not only as a direct adoption driver but also as a territorial equalisation mechanism. Additional fiscal incentives appear to have limited marginal effects once the existing incentive structure is already relatively generous.

Overall, the simulations indicate that infrastructure investment may be more effective than additional fiscal incentives in simultaneously increasing adoption and reducing territorial disparities in BEV diffusion.

6 Discussion

The model provides a behavioural framework for analysing BEV adoption across Portuguese municipalities. Rather than treating adoption as a purely aggregate process, the agent-based approach represents BEV diffusion as the outcome of heterogeneous individual decisions shaped by local economic conditions, infrastructure availability, social interactions, and spatial influences.

A central finding of the analysis is the importance of income as a determinant of BEV adoption. Income-related mechanisms appear in all top-performing specifications, indicating that local economic resources remain the most robust predictor of adoption patterns across municipalities. This result is consistent with the relatively high acquisition costs associated with electric vehicles and suggests that socioeconomic disparities continue to play an important role in shaping the transition to electric mobility.

The results also provide evidence that spatial interactions contribute to explaining observed adoption patterns. The best-performing specification combines income, spatial effects and the inverse Matthew mechanism, suggesting that adoption decisions are influenced not

only by local characteristics but also by conditions in neighbouring municipalities. This finding supports the view that electric mobility diffusion exhibits a spatial dimension that extends beyond municipal administrative boundaries.

The role of the inverse Matthew mechanism is more nuanced. While the mechanism does not consistently improve predictive performance across all specifications, it appears in the highest-performing model under the baseline calibration. This suggests that cumulative adoption dynamics may contribute to explaining observed diffusion patterns when combined with economic and spatial mechanisms. However, its contribution is conditional rather than universal, indicating that the importance of cumulative advantages depends on the broader behavioural and spatial environment.

By contrast, the redistributive mechanism produces only marginal differences under the current calibration. In several specifications, models with and without redistribution generate virtually identical performance indicators. This suggests that the redistributive adjustment, as currently parameterised, has a limited effect on aggregate adoption outcomes. Future research may explore alternative formulations or stronger redistributive incentives to evaluate whether more pronounced effects emerge.

An additional contribution of the study concerns the incorporation of stochastic charging infrastructure dynamics. The sensitivity analysis shows that the relative importance of behavioural mechanisms depends on the degree of infrastructure uncertainty. Under deterministic infrastructure dynamics, income emerges as the dominant explanatory factor. Under moderate infrastructure volatility, specifications combining income, spatial interactions and the inverse Matthew mechanism achieve the best performance. Under higher volatility levels, spatial effects remain important, while the contribution of the inverse Matthew mechanism becomes weaker. These findings suggest that infrastructure uncertainty influences the behavioural structure required to reproduce observed adoption patterns.

Another important result is that the full model does not outperform all alternative specifications. Although the full model generates the highest number of simulated adoptions, its predictive performance is lower than that of several more parsimonious models. This finding highlights the importance of model selection and calibration within agent-based modelling frameworks and suggests that additional behavioural mechanisms do not necessarily improve predictive accuracy.

Overall, the results indicate that BEV diffusion across Portuguese municipalities is best explained by a combination of local economic conditions, spatial interactions and, under some circumstances, cumulative adoption dynamics. The findings further suggest that infrastructure uncertainty influences the relative importance of these mechanisms and should therefore be explicitly considered when analysing the diffusion of electric mobility.

An additional contribution emerges from the policy experiments. The scenario analysis suggests that infrastructure expansion generates both higher adoption and lower spatial concentration of BEV ownership. In contrast, stronger fiscal incentives produce almost no additional adoption under the current calibration and do not alter the concentration dynamics. This result may indicate that, once fiscal incentives reach a sufficiently high level, infrastructure availability becomes the binding constraint for further diffusion. Consequently, policies focused on expanding charging networks may achieve larger territorial and adoption gains than additional purchase incentives.

7 Conclusion

This paper developed a spatial agent-based model to analyse Battery Electric Vehicle (BEV) adoption across Portuguese municipalities. The model combines municipality-level socioeconomic and infrastructure characteristics with a synthetic population of heterogeneous agents whose adoption decisions depend on income, fiscal incentives, charging infrastructure, parking incentives, social interactions, spatial spillovers, and compensatory policy mechanisms.

The proposed framework contributes to the literature on electric mobility by integrating behavioural decision-making, spatial interactions, and infrastructure dynamics within a unified simulation environment. Unlike approaches based exclusively on aggregate relationships, the model explicitly represents adoption as the outcome of individual decisions embedded in heterogeneous local contexts and interconnected municipal networks.

The results indicate that local economic conditions constitute the most robust determinant of BEV adoption. Income-related mechanisms appear consistently in the highest-performing specifications, highlighting the importance of economic resources in shaping the transition towards electric mobility. Spatial interactions also play a relevant role, suggesting that adoption patterns are influenced not only by local characteristics but also by neighbouring municipalities.

The inverse Matthew mechanism produces more nuanced results. Although it does not uniformly improve predictive performance across all specifications, it appears in the highest-performing model under the baseline calibration, indicating that cumulative adoption dynamics may contribute to explaining observed diffusion patterns when combined with economic and spatial mechanisms. By contrast, the redistributive mechanism has only a limited effect under the current calibration, producing results that are often indistinguishable from equivalent specifications without redistribution.

An important contribution of the study is the incorporation of stochastic charging infrastructure dynamics. The sensitivity analysis demonstrates that the relative importance of behavioural mechanisms depends on the degree of infrastructure uncertainty. Under deterministic infrastructure expansion, income emerges as the dominant explanatory factor. Under moderate infrastructure volatility, specifications combining income, spatial interactions, and the inverse Matthew mechanism achieve the strongest validation performance. Under higher volatility levels, spatial effects remain important while the contribution of the inverse Matthew mechanism becomes weaker. These findings suggest that infrastructure uncertainty conditions the behavioural structure required to reproduce observed adoption patterns.

The comparison across model specifications further reveals that greater complexity does not necessarily imply better predictive performance. The full model generates the highest levels of simulated adoption but is outperformed by several more parsimonious specifications. This finding highlights the importance of model selection and calibration within agent-based modelling frameworks and suggests that a limited set of mechanisms may be sufficient to reproduce observed BEV diffusion patterns.

From a policy perspective, the results emphasise the importance of reducing economic barriers to adoption and expanding charging infrastructure, particularly in municipalities with weaker market conditions. The findings also suggest that policies should account for spatial interdependencies, since adoption dynamics extend beyond individual municipal boundaries.

Beyond its explanatory role, the proposed framework can also be used as a policy simulation laboratory. Once calibrated, the model allows decision-makers to evaluate alternative fiscal and infrastructure scenarios before implementation. For example, policymakers may simulate future adoption paths under the continuation of current BEV tax exemptions combined with alternative charging infrastructure expansion strategies. Such counterfactual experiments make it possible to assess not only expected adoption levels but also the spatial distribution of adoption across municipalities and the potential emergence of territorial inequalities. The framework therefore provides a flexible tool for ex-ante policy evaluation in the transition towards electric mobility.

The policy simulations provide an additional insight. While Portugal currently relies heavily on fiscal incentives such as ISV and IUC exemptions, the model suggests that further increases in incentives may generate limited additional adoption. By contrast, charging infrastructure expansion produces both higher adoption rates and a more balanced spatial distribution of BEVs across municipalities. These results highlight the importance of infrastructure investment as a complementary policy instrument capable of supporting both market growth and territorial cohesion.

Future research could extend the framework by introducing technological competition between internal combustion vehicles, hybrid vehicles and BEVs, endogenous infrastructure investment decisions, alternative incentive schemes, and richer behavioural decision rules. Such extensions would provide a more comprehensive representation of the long-run transition towards sustainable mobility and further enhance the policy relevance of agent-based approaches to electric vehicle adoption.

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A Monte Carlo Convergence

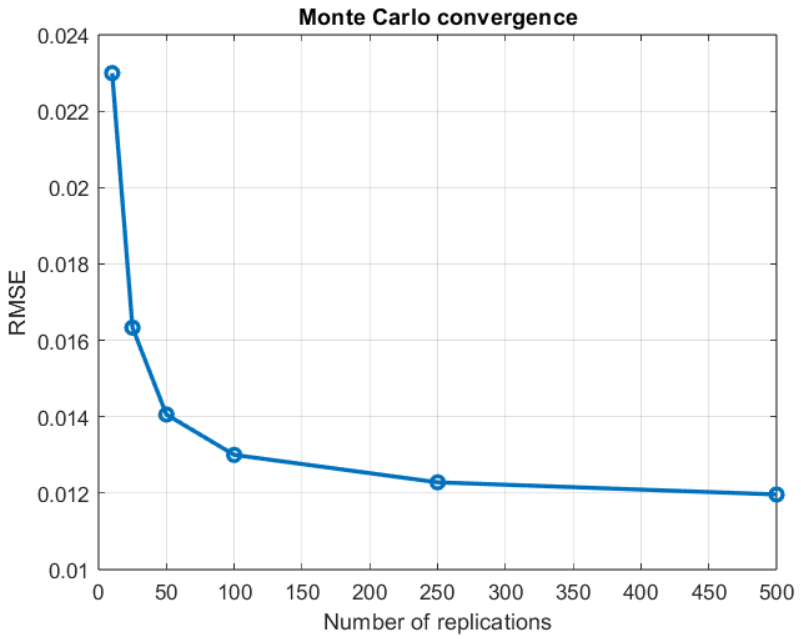


Figure 3: Monte Carlo Convergence

B Policy Scenarious

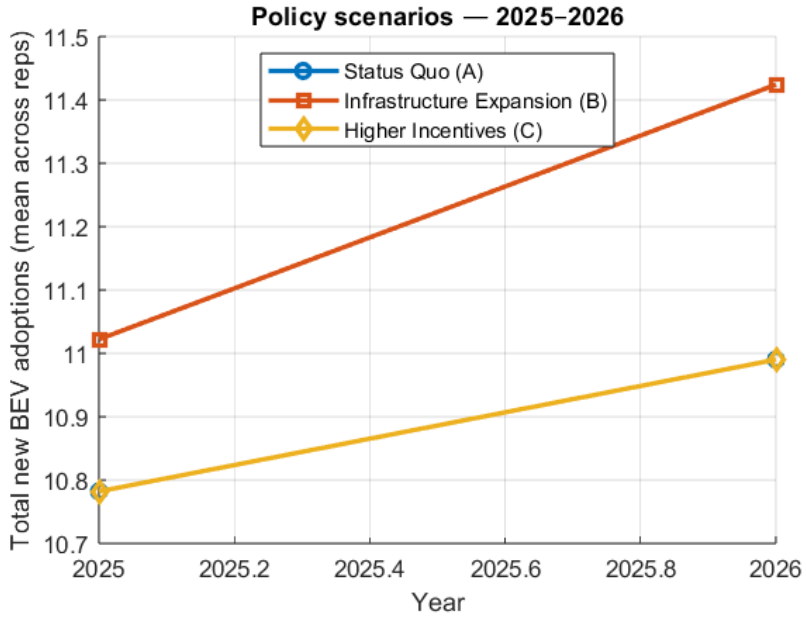


Figure 4: Policy Scenarious

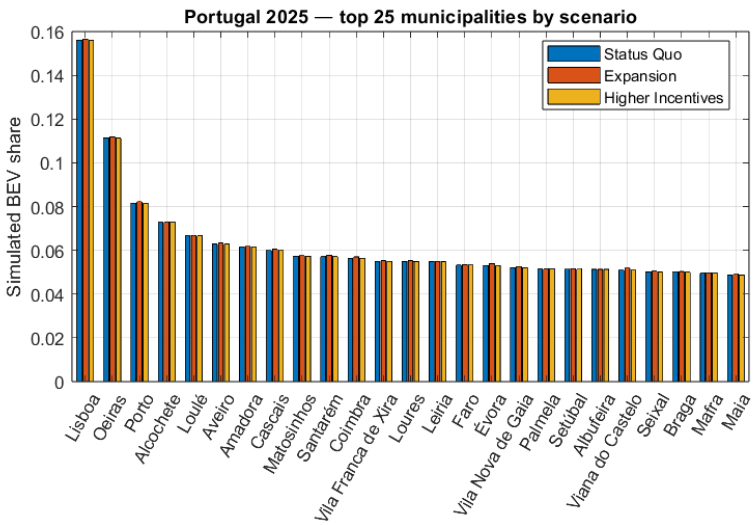


Figure 5: Top 25 Municipalities in 2025

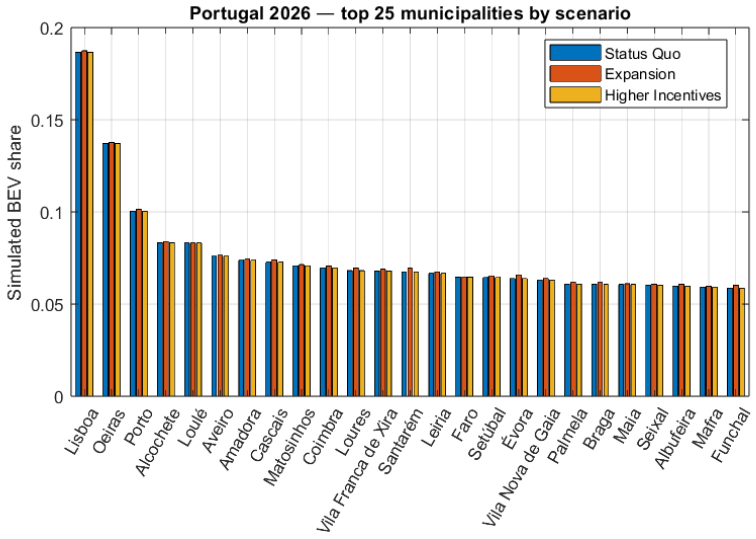


Figure 6: Top 25 Municipalities in 2026

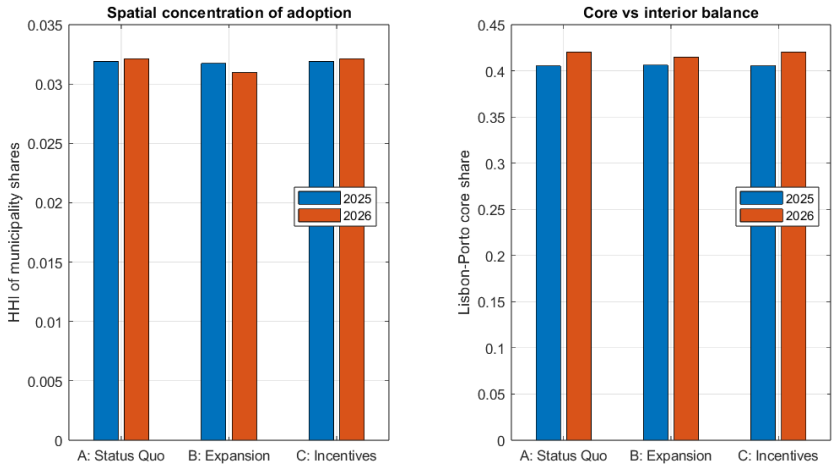


Figure 7: Policy Diagnostic

C ODD Protocol

This appendix provides a summary of the model using the ODD protocol: Overview, Design concepts, and Details.

Overview

Purpose

The purpose of the model is to simulate the adoption of Battery Electric Vehicles across Portuguese municipalities and to analyse how fiscal incentives, charging infrastructure, income, peer effects, network spillovers, and compensatory mechanisms shape spatial concentration patterns.

Entities, State Variables, and Scales

The model includes two main types of entities: agents and municipalities.

Agents represent synthetic potential adopters. Each agent is characterised by:

- home municipality;
- endowment;
- adoption status;
- adoption year;
- latent payoff;
- adoption probability.

Municipalities represent the spatial environment in which agents are located. Each municipality is characterised by:

- population;
- income;
- observed BEV share;
- charging density;
- number of charging stations;
- fiscal incentive;
- local parking incentive;
- metropolitan status;
- network connections to other municipalities.

The spatial scale is the Portuguese municipality. The temporal scale is annual.

Process Overview and Scheduling

The model proceeds in annual steps. In each year:

1. municipal state variables are updated;
2. local and network peer effects are computed;
3. a subset of non-adopting agents is selected to reconsider adoption;
4. each selected agent computes a latent adoption payoff;
5. adoption probability is calculated using a logistic function;
6. adoption status is updated probabilistically;
7. municipal simulated BEV shares are updated.

Design Concepts

Basic Principles

The model is based on the idea that BEV adoption is a decentralised behavioural process shaped by heterogeneous agents, local conditions, and spatial interactions. Adoption emerges from individual decisions rather than being imposed directly at the aggregate level.

Emergence

Spatial concentration of BEVs emerges from the interaction between individual endowment, incentives, infrastructure, peer effects, network spillovers, and redistributive mechanisms.

Adaptation

Agents adapt by reconsidering adoption when selected. Their probability of adoption depends on the latent payoff associated with BEV ownership.

Objectives

Agents do not maximise a fully specified lifetime utility function. Instead, they follow a probabilistic behavioural rule based on perceived adoption payoff.

Learning

Learning is represented indirectly through local and network peer effects. Higher adoption in the agent's own municipality or in neighbouring municipalities increases the perceived attractiveness of BEV adoption.

Interaction

Agents interact indirectly through municipal adoption shares. Adoption by one agent increases the simulated BEV share of the municipality, which affects future peer effects for other agents.

Stochasticity

The model includes stochasticity in agent endowment, idiosyncratic payoff shocks, selection of agents by timestep, and the adoption decision.

The model also includes a stochastic logistic diffusion process governing the evolution of charging infrastructure density.

Observation

The main observed outputs are simulated BEV shares, adoption probabilities, adopted agents per year, cumulative adopted agents, effective fiscal incentives, disadvantage indices, and prediction errors relative to observed BEV shares.

The model is evaluated across incremental behavioural specifications in order to compare the contribution of economic, social, spatial, and redistributive mechanisms.

Details

Initialisation

Agents are allocated to municipalities proportionally to base-year population. Initial endowment is assigned according to municipal income and an idiosyncratic stochastic component. Initial adoption status is set according to the simulation design.

Input Data

The model uses municipality-level data on population, income, BEV adoption, charging infrastructure, fiscal incentives, parking incentives, municipal area, and geographic location.

Submodels

The model includes the following submodels:

- spatial network construction using a minimum spanning tree threshold;
- synthetic agent allocation;
- endowment assignment;
- local peer effect calculation;
- network peer effect calculation;
- inverse Matthew effect calculation;
- redistributive incentive calculation;
- behavioural payoff calculation;
- probabilistic adoption decision;
- calibration and validation.