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Fiscal Incentives and the Spatial Concentration of Battery Electric Vehicles in Portugal: A Network Approach

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Abstract

This paper investigates the spatial concentration of Battery Electric Vehicles (BEVs) across Portuguese municipalities and examines how fiscal incentives are associated with that concentration. Using municipality-level data on BEV registrations, population, density, charging infrastructure, and local parking incentives, this paper combines log-linear modelling, rank-size analysis, and network analysis. Municipalities are represented as nodes in a complete network constructed from geographical distances. A minimum spanning tree is used to identify the connectivity threshold required to keep all municipalities connected. Such a threshold is used to move from a complete network to a sparse one, to which centrality measures are computed. The analysis provides descriptive evidence on whether BEV adoption is concentrated in larger, denser, better connected, and better equipped municipalities. The results contribute to the understanding of spatial inequalities in electric mobility adoption in Portugal and highlight the importance of considering network analysis when evaluating fiscal incentives.

Keywords: Battery electric vehicles, fiscal incentives, network analysis, spatial concentration, road infrastructure, Portugal.

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 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, it is unlikely to occur uniformly in space. Instead, it may depend on local income, charging infrastructure, accessibility conditions, local policy incentives, and the structure of spatial networks. From a computational and evolutionary perspective, economic behaviour may emerge from local interactions, generating clustering and self-organised spatial patterns rather than homogeneous space distributions (Banish and Araújo, 2012).

Despite the growing adoption of BEVs, relatively little is known about how fiscal incentives interact with spatial structure 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). However, the interaction between fiscal policy, municipal heterogeneity, road infrastructure, and network position remains underexplored in the Portuguese case.

This paper addresses the following research question:

> *How are fiscal (local and global) incentives associated with the spatial concentration of BEVs across Portuguese municipalities?*

The paper contributes to the literature in three ways. First, it provides municipality-level evidence on the spatial concentration of BEVs in Portugal. Second, it applies a network-based framework in which municipalities are represented as nodes of a complete network, which is latter filtered with an endogeneous threshold. Third, it examines whether BEV

[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.

concentration differs according to local incentives, charging infrastructure, and municipal position within the network.

This paper is organized as follows, the next section presents the literature review on BEV adoption, fiscal incentives, and network analysis. Section three describes the data and the institutional framework of BEV incentives in Portugal. Section four presents the methodology, including the definition of the network measures often used. Results are presented in section five, the last section concludes and outlines future work.

2 Literature Review

This section reviews the main concepts related to BEV adoption, fiscal incentives, spatial diffusion, and network analysis.

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 Network Approach

A network approach is useful for analysing spatial systems in which aggregate outcomes emerge from local connections. In this framework, municipalities can be represented as nodes, while geographical proximity, road accessibility, or interaction flows can be represented as edges. This allows the analysis to move beyond isolated municipal characteristics and to examine how the position of each municipality within a broader spatial system may be associated with BEV adoption.

Networks can be analysed from structural, dynamic, and evolutionary perspectives (Araújo, 2011). A structural perspective focuses on the topology of the system, including connectivity, centrality, clustering, and shortest paths. A dynamic perspective examines how processes unfold over the network, such as the diffusion of behaviours. An evolutionary perspective considers how the network structure and the behaviour of agents may co-evolve over time.

In the context of BEV adoption, network structure may matter for several reasons. First, charging infrastructure is spatially distributed, and municipalities close to well-equipped areas may benefit from greater practical accessibility. Second, adoption may diffuse through neighbouring municipalities due to visibility, commuting patterns, and social learning. Third, local incentives may generate spillover effects if residents, firms, or commuters interact across municipal boundaries.

The network approach used in this paper therefore deals with BEV concentration as a spatially embedded process. Fiscal incentives, charging infrastructure, income, and urban density may affect local adoption, but their combined effects may also depend on the position of each municipality within the spatial network.

The following gaps remain in the literature:

- the spatial effects of fiscal incentives on BEV adoption in Portugal are underexplored;
- limited evidence exists on BEV concentration and urban–rural disparities;
- few studies integrate fiscal policy, spatial concentration, road structure, and topological metrics such as centrality, clustering, and spatial exposure in a unified framework.

This paper addresses these gaps by using network analysis to study how fiscal incentives interact with local structures to shape BEV distribution.

3 Data

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

- BEV registration or 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 allows for the representation of municipalities as nodes in a connected spatial system.

The dataset and the codes used in this dissertation are available online[1].

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 paper, 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.

[1]Please refer to https://github.com/bmaria7/WPNetwork

4 Methodology

This study combines descriptive modelling, rank-size analysis, and spatial network analysis to examine the concentration of BEVs across Portuguese municipalities. The methodology proceeds in five steps. First, a baseline log-linear model is estimated to assess the relationship between BEV adoption and municipal characteristics. Second, a rank-size specification is used to evaluate the degree of concentration in the municipal distribution of BEVs. Third, a spatial municipal network is constructed using a minimum spanning tree connectivity threshold. Fourth, network measures and spatial exposure to local incentives are computed. Fifth, rank-size patterns are compared between municipalities with and without local parking incentives.

4.1 Baseline Log-Linear Model

The first step estimates a log-linear relationship between BEV adoption and a set of municipal characteristics. The dependent variable is the number of BEVs in each municipality. The explanatory variables include population, population density, charging infrastructure, local parking incentives, spatial exposure to incentives, and network centrality.

Let BEV_i denote the number of BEVs in municipality i, pop_i the population, $density_i$ the population density, $charging_i$ the number of charging stations, $LocalIncentive_i$ the local parking incentive indicator, $SpatialIncentive_i$ the exposure to incentives in neighbouring municipalities, and $Centrality_i$ a network centrality measure.

The extended log-linear model is specified as:

$$\begin{aligned}\ln(BEV_i + 1) =& \beta_0 + \beta_1 \ln(pop_i) + \beta_2 \ln(density_i) + \beta_3 \ln(charging_i + 1) \\ &+ \beta_4 LocalIncentive_i + \beta_5 SpatialIncentive_i + \beta_6 Centrality_i + \varepsilon_i.\end{aligned} \tag{1}$$

This specification allows the analysis to evaluate whether BEV concentration is associated with municipal scale, density, charging infrastructure, local incentives, neighbouring incentives, and position within the spatial network [2].

A simpler benchmark specification is also estimated:

$$\ln(BEV_i + 1) = \beta_0 + \beta_1 \ln(pop_i) + \beta_2 \ln(density_i) + \beta_3 \ln(charging_i + 1) + \varepsilon_i. \tag{2}$$

[2] The dependent variable is specified as $\ln(BEV_i + 1)$ in order to retain municipalities with zero BEV registrations

This benchmark model provides a baseline against which the contribution of incentives and network variables can be compared.

4.2 Rank-Size Distribution of BEVs

The second step examines whether the distribution of BEVs across municipalities follows a rank-size or power-law pattern. Municipalities are ranked in descending order according to their total number of BEVs. Let $rank_i$ denote the rank of municipality i, where $rank_i = 1$ corresponds to the municipality with the highest BEV count.

The rank-size relationship is assumed to take the following form, following the literature on power-law and Zipf-type distributions in urban systems (Mansury and Gulyas, 2007; Clauset et al., 2009):

$$BEV_i = a \cdot rank_i^{-b}. \tag{3}$$

Since this relationship is non-linear in levels, it is estimated in log-log form:

$$\ln(BEV_i + 1) = \alpha + \beta \ln(rank_i) + \varepsilon_i. \tag{4}$$

with:

$$\alpha = \ln(a), \qquad \beta = -b. \tag{5}$$

This transformation allows the exponent of the power-law relationship to be estimated using ordinary least squares. However, the results are interpreted descriptively, since least-squares estimation in log-log space is a common but imperfect approach for identifying power-law behaviour (Clauset et al., 2009). A steeper slope implies stronger spatial concentration of BEVs across municipalities, whereas a flatter slope suggests a more even distribution.

Model fit is assessed through the coefficient of determination, R^2, computed in log-log space.

4.3 Spatial Network Construction Using a Minimum Spanning Tree

This study represents Portuguese municipalities as nodes in a spatial network. 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 geographical 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 i and j is denoted by d_{ij}.

The distance between municipalities is computed using the haversine formula, in order to consider for the spherical shape of the Earth, avoiding the distortion with the planar distance measures. In this case, acording to Sinnott (1984), the distance is:

$$d_{ij} = 2R \arctan\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right), \tag{6}$$

where R is the Earth's radius and:

$$a = \sin^2\left(\frac{\phi_j - \phi_i}{2}\right) + \cos(\phi_i)\cos(\phi_j)\sin^2\left(\frac{\lambda_j - \lambda_i}{2}\right). \tag{7}$$

Here, ϕ_i and ϕ_j are latitudes, while λ_i and λ_j are longitudes.

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

$$T^{MST} = \arg\min_{T \subset E} \sum_{(i,j)\in T} d_{ij}. \tag{8}$$

The maximum distance among the edges of the national minimum spanning tree is:

$$\delta = \max_{(i,j)\in T^{MST}} d_{ij}. \tag{9}$$

In a purely continuous territory, this value could be used directly as the connectivity threshold. However, Portugal includes mainland municipalities and island municipalities in Madeira and the Azores. A single national distance threshold may therefore become excessively large due to long maritime distances. Such a threshold would produce an overly dense mainland network.

To avoid this problem, the filtering procedure is applied within territorial components, while the edges of the global minimum spanning tree are retained to guarantee that all municipalities remain connected in the national network.

Let $c \in \{\text{Mainland}, \text{Madeira}, \text{Azores}\}$ denote each territorial component. For each component, a component-specific minimum spanning tree is computed and the corresponding territorial threshold is defined as:

$$\delta_c = \max_{(i,j)\in T_c^{MST}} d_{ij}. \tag{10}$$

The territorial filtered network is then defined as:

$$A_{ij}^{territorial} = \begin{cases} 1, & \text{if } d_{ij} \leq \delta_c \text{ and } i, j \in c, \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

The final network is defined as the union between the territorial filtered networks and the global MST backbone:

$$A = A^{territorial} \cup A^{MST}. \tag{12}$$

This procedure avoids an excessively dense network while preserving full national connectivity. It also replaces the use of an arbitrary fixed distance threshold, such as 50 kilometres, with a data-driven criterion based on the structure of the municipal distance matrix.

4.4 Network Measures

After constructing the filtered municipal network, several network measures are computed in order to characterise the position of each municipality within the spatial system.

Degree centrality is defined as the number of direct connections of municipality i:

$$Degree_i = \sum_{j=1}^{N} A_{ij}. \tag{13}$$

Weighted degree can also be computed by considering the inverse of geographical distance:

$$WeightedDegree_i = \sum_{j=1}^{N} \frac{A_{ij}}{d_{ij}}. \tag{14}$$

Betweenness centrality measures the extent to which municipality i lies on the shortest paths between other municipalities:

$$Betweenness_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}, \tag{15}$$

where σ_{st} is the total number of shortest paths between municipalities s and t, and $\sigma_{st}(i)$ is the number of those paths passing through municipality i.

Closeness centrality measures how close a municipality is to all other municipalities in the network:

$$Closeness_i = \frac{N-1}{\sum_{j \neq i} d_{ij}^{G}}, \tag{16}$$

where d_{ij}^G denotes the shortest-path distance between municipalities i and j in the filtered network.

These measures allow the analysis to identify whether BEV concentration is associated with more central, more accessible, or more connected municipalities.

4.5 Spatial Exposure to Local Incentives

To capture the spatial dimension of municipal incentives, the analysis constructs a network exposure variable. The adjacency matrix is row-normalized as:

$$W_{ij} = \frac{A_{ij}}{\sum_j A_{ij}}. \tag{17}$$

The spatial exposure to local incentives is then defined as:

$$SpatialIncentive_i = \sum_{j=1}^{N} W_{ij} LocalIncentive_j. \tag{18}$$

This variable measures whether a municipality is connected to other municipalities that provide local incentives for BEVs. It allows the analysis to distinguish between the municipality's own incentive policy and the incentive environment of its spatial neighbours.

4.6 Rank-Size Comparison by Local Incentives

The next step investigates whether the distribution of BEVs differs between municipalities with and without local parking incentives for electric vehicles. Municipalities are divided into two groups:

- municipalities with local incentives, defined as those with $LocalParkingIncentive_i > 0$;
- municipalities without local incentives, defined as those with $LocalParkingIncentive_i = 0$.

For each group separately, a rank-size equation is estimated:

$$\ln(BEV_i + 1) = \alpha_g + \beta_g \ln(rank_i) + \varepsilon_i, \tag{19}$$

where $g \in \{\text{local}, \text{no local}\}$ denotes the relevant group. The corresponding power-law exponent is:

$$b_g = -\beta_g. \tag{20}$$

The comparison by local incentives is motivated by the literature showing that EV and BEV diffusion depends on policy incentives, infrastructure, consumer heterogeneity, and spatial effects (Eppstein et al., 2011; Wolf et al., 2015; Kangur et al., 2017; Novizayanti et al., 2021; Zhu and Ma, 2025). This comparison is purely descriptive. It does not identify a causal effect of local incentives, since municipalities with and without incentives may differ systematically in size, composition, income, or infrastructure. Nevertheless, the exercise is informative in assessing whether the concentration pattern of BEVs differs across the two groups.

4.7 Key Variables

The main variables used in the analysis are defined as follows:

- **BEV adoption** (BEV_i): number of registered Battery Electric Vehicles in municipality i;
- **Population** (pop_i): total municipal population;
- **Population density** ($density_i$): inhabitants per square kilometre;
- **Charging infrastructure** ($charging_i$): number of charging stations in municipality i;
- **Local parking incentive** ($LocalIncentive_i$): municipality-level policy indicator capturing the existence of local parking benefits for BEVs;
- **Spatial incentive exposure** ($SpatialIncentive_i$): average exposure to local incentives in neighbouring municipalities;
- **Network centrality** ($Centrality_i$): degree, weighted degree, betweenness, or closeness centrality in the filtered municipal network;
- **Latitude and longitude**: geographical coordinates used to construct the municipal spatial network.

Charging infrastructure is included because previous EV diffusion and charging-behaviour models emphasise the role of charging availability and spatially distributed infrastructure in adoption dynamics (Helmus et al., 2019; Eppstein et al., 2011; Kangur et al., 2017).

4.8 Interpretation Strategy

The methodological framework is designed to address different aspects of BEV concentration.

First, the log-linear model identifies whether BEV adoption is associated with urban scale, density, charging infrastructure, local incentives, spatial incentive exposure, and network centrality. Second, the rank-size specification evaluates whether the municipal distribution of BEVs is highly concentrated. Third, the network analysis provides a spatial representation of municipal connectivity and centrality. Fourth, the comparison by local parking incentives explores whether policy heterogeneity is associated with different concentration patterns.

These exercises are primarily descriptive and structural. Their purpose is to characterise the distribution and correlates of BEV adoption across municipalities, rather than to estimate causal effects in a strict econometric sense.

5 Results

This section presents the preliminary results of the network-based analysis. The results should be interpreted as descriptive evidence on spatial concentration and network structure, rather than as causal estimates.

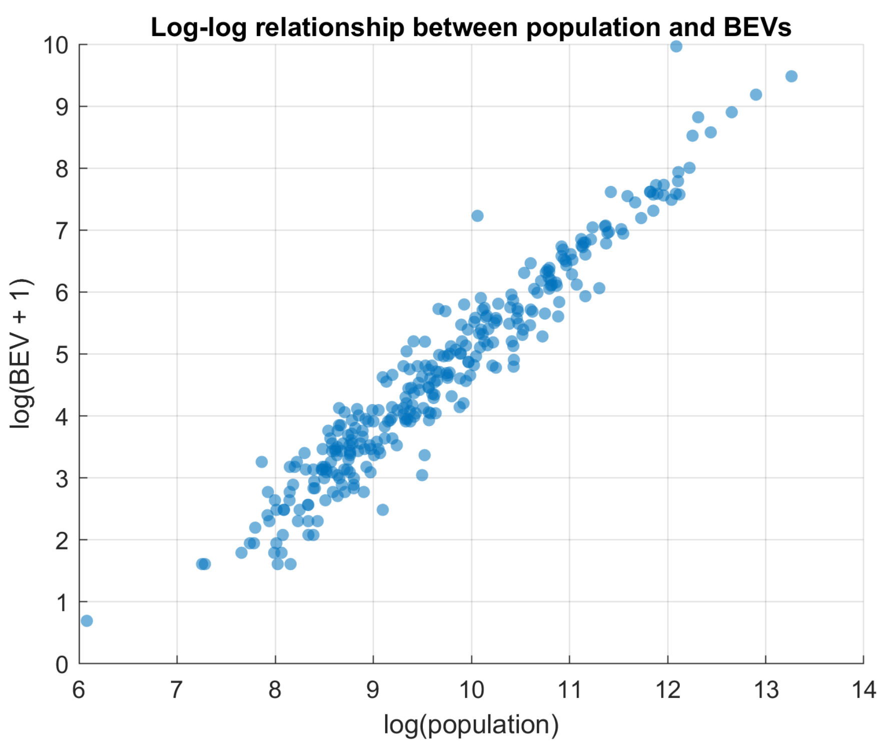

Figure 1: Log-log relationship between municipal population and BEV adoption

Figure 1 shows the log-log relationship between municipal population and BEV adoption.

The positive association indicates that larger municipalities tend to have more BEVs. This result is expected, since more populated municipalities have larger vehicle markets, more potential adopters, and often greater access to charging infrastructure.

However, municipalities with similar population levels may display different BEV counts, suggesting the relevance of additional factors such as income, density, charging infrastructure, local incentives, and network position. The relationship therefore supports the use of a broader network-based specification rather than a purely scale-based model.

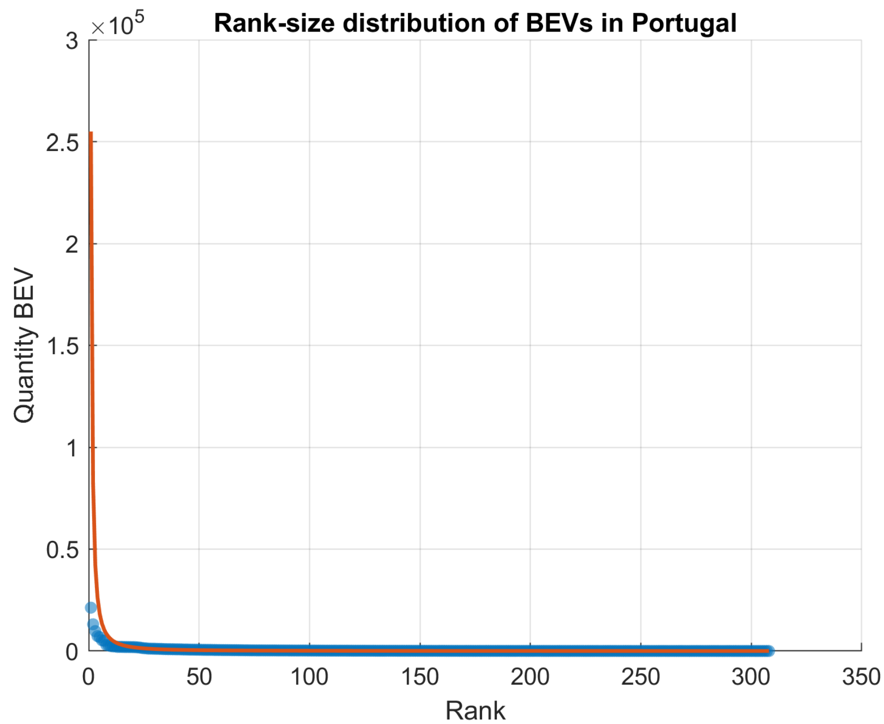

Figure 2: Rank-size distribution of BEVs across Portuguese municipalities

Figure 2 presents the rank-size distribution of BEVs across Portuguese municipalities. The distribution is highly skewed, with a small number of municipalities concentrating a large share of total BEVs, while many municipalities display much lower values. This pattern suggests that BEV adoption is spatially concentrated rather than evenly distributed across the national territory.

The steep decline at the top of the distribution indicates that the leading municipalities differ substantially from the rest of the municipal hierarchy. This is consistent with a cumulative advantage process, in which larger and better equipped municipalities are more likely to accumulate BEV adoption. Given the magnitude of the upper tail, the largest observations should be checked carefully to ensure that they correspond to municipality-level BEV counts for the selected year and not to accumulated values or duplicated totals.

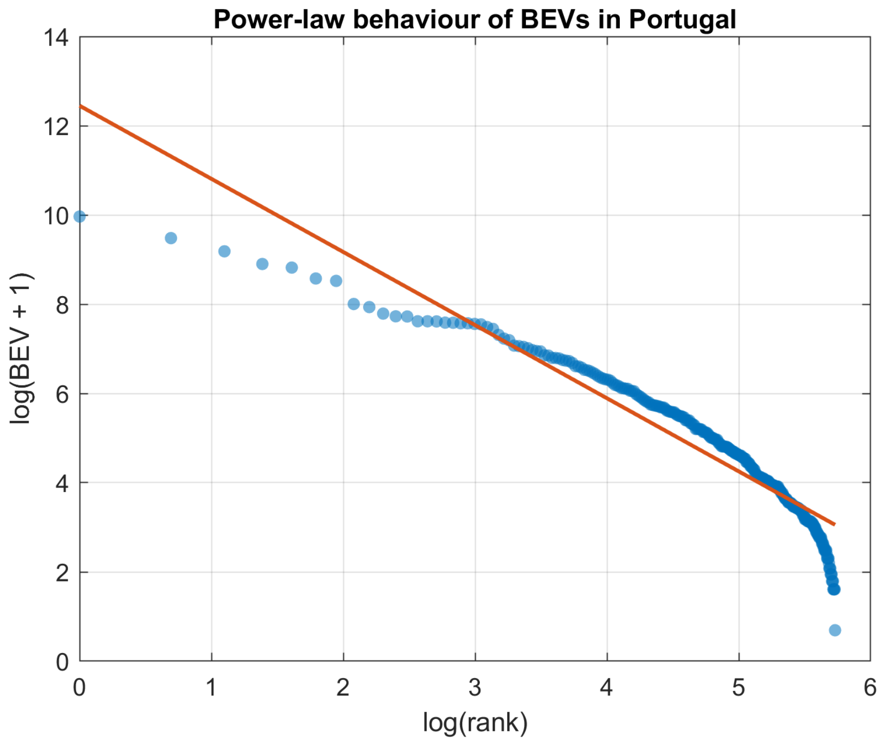

Figure 3: Power-law behaviour of BEV adoption across municipalities

Figure 3 displays the rank-size relationship in log-log scale. Part of the distribution follows an approximately linear pattern, suggesting that BEV concentration may display power-law-like behaviour over part of the municipal hierarchy. However, the deviations from the fitted line at both the upper and lower tails indicate that the power-law approximation should be interpreted cautiously.

The largest municipalities appear to behave differently from the middle of the distribution, while municipalities with very low BEV counts deviate from the fitted relationship at the lower tail. This suggests that BEV adoption is not governed by a single scaling mechanism across all municipalities. Instead, different mechanisms may operate across different parts of the distribution, including urban scale, infrastructure availability, income, local policy, and network accessibility.

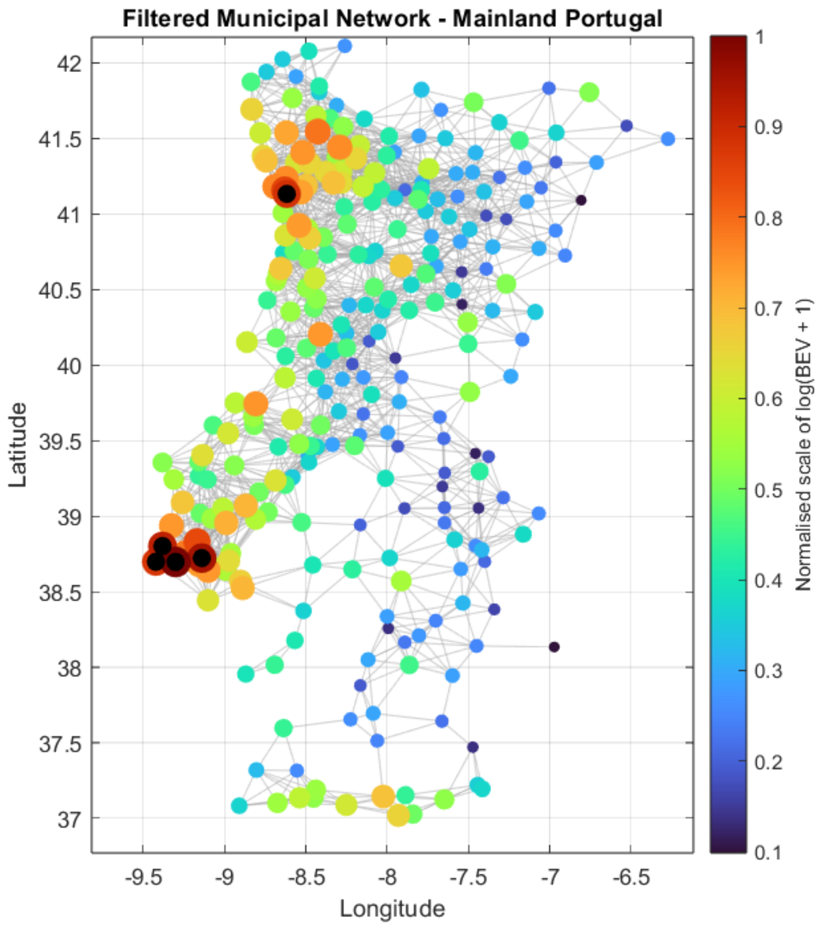

Figure 4: Filtered municipal network constructed - Only Mainland. Node colour represents the normalized value of $\log(BEV_i + 1)$.

Figure 4 presents the filtered municipal network for mainland Portugal. The network reveals a higher concentration of BEVs in municipalities located in coastal and metropolitan areas, particularly around Lisbon and Porto. By contrast, several inland municipalities display relatively lower levels of adoption, suggesting the existence of spatial inequalities in the diffusion of electric vehicles. The network structure also indicates that more connected municipalities tend to be associated with higher levels of BEV adoption.

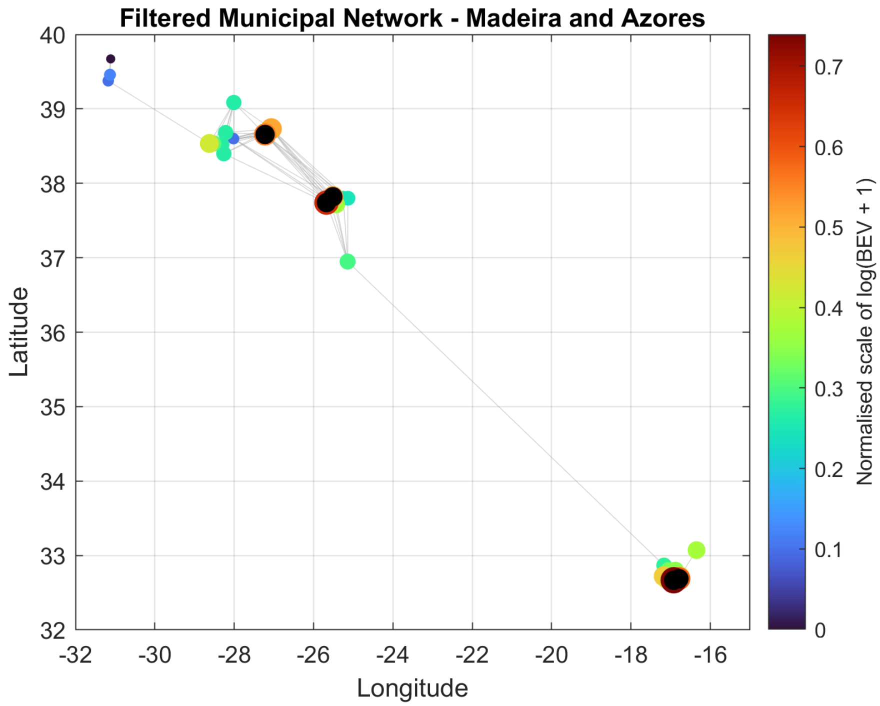

Figure 5: Filtered municipal network constructed - Only Islands. Node colour represents the normalized value of $\log(BEV_i + 1)$.

Figure 5 maps the filtered municipal network, with nodes coloured according to the normalized value of $\log(BEV_i + 1)$. The figure includes the filtered edges obtained from the filtered network procedure, allowing the visualisation of both the spatial distribution of BEVs and the underlying municipal network structure.

The figures 4 and 5 show that BEV concentration is stronger in specific parts of the network, particularly in more urbanised and coastal areas. Higher values are visible around the main metropolitan and coastal regions, while several inland and peripheral municipalities display lower levels of BEV adoption. The inclusion of Madeira and the Azores also illustrates why a purely national distance threshold can become problematic: long maritime distances may distort the filtering procedure. The territorial filtering strategy therefore provides a more appropriate representation of the municipal network.

The figures support the idea that BEV adoption is spatially driven. Adoption appears to be associated not only with municipal scale, but also with accessibility, territorial position, and proximity to more developed adoption clusters.

In order to move from a complete network to a sparse one, a minimum spanning tree (MST) is computed, following Spelta and Araújo (2012). The result, is presented in the figure 6.

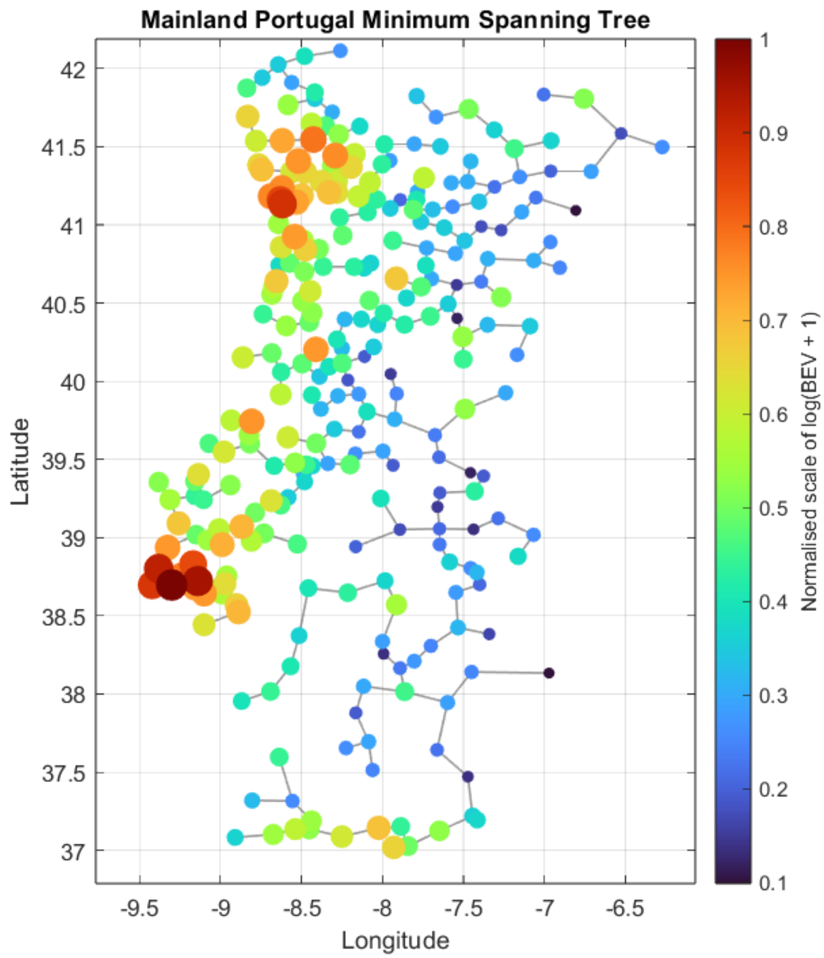

Figure 6: Minimum Spanning Tree of Portuguese Municipalities - Only Continent Area

Figure 6 illustrates the minimum spanning tree (MST) for mainland Portugal. The MST identifies the minimum set of links required to preserve municipal connectivity while minimising total geographical distance (Spelta and Araújo, 2012). Higher BEV concentration appears mainly in coastal and metropolitan areas, suggesting that BEV adoption is associated with more connected and urbanized regions.

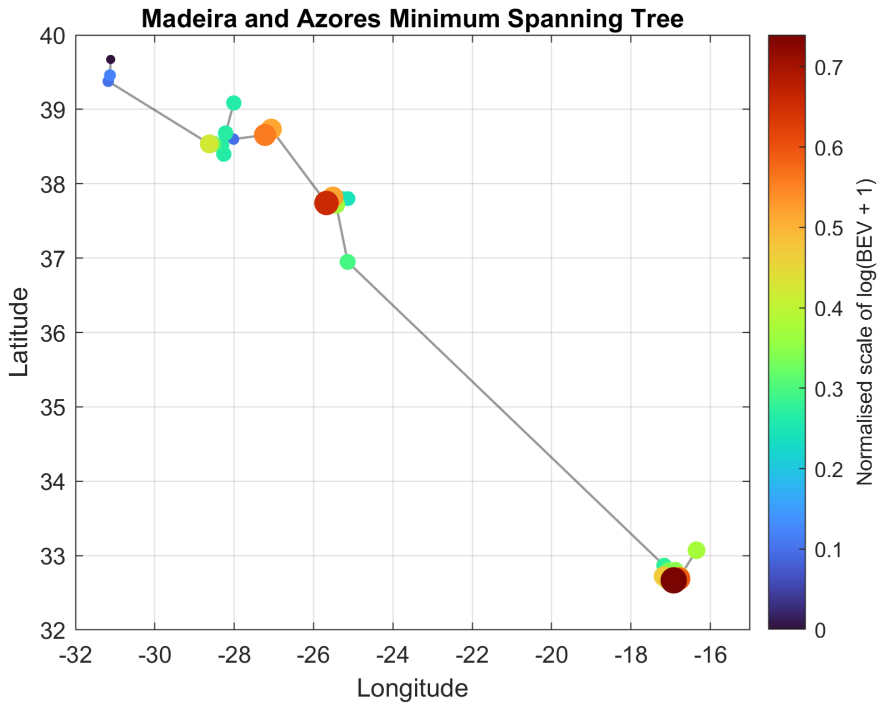

Figure 7: Global Minimum Spanning Tree of Portuguese Municipalities - Only Island Area

Figure 7 illustrates the minimum spanning tree obtained from the municipal distance matrix. following Spelta and Araújo (2012), the MST connects all municipalities through the minimum total geographical distance while avoiding cycles. In this sense, it provides a spatial backbone of the municipal system and identifies the set of links that are strictly necessary to preserve connectivity. The color and size of the nodes represent the normalized value of log(BEVi + 1), allowing the MST structure to be compared with the spatial distribution of BEV adoption.

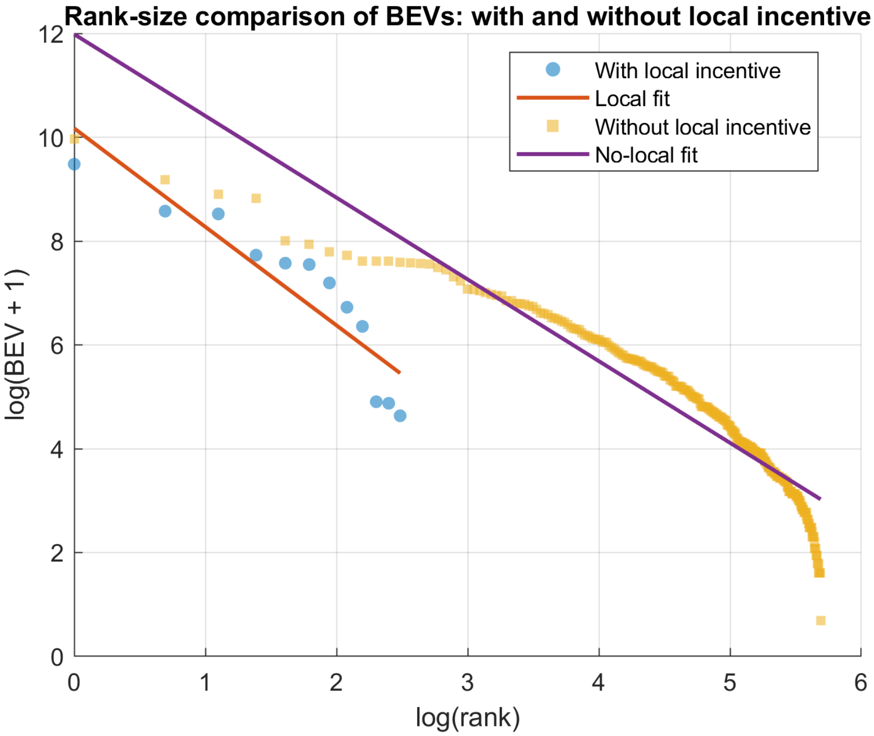

Figure 8: Rank-size comparison of BEV adoption between municipalities with and without local parking incentives

Figure 8 compares the rank-size distribution of municipalities with and without local parking incentives. The two groups display different rank-size profiles. Municipalities with local incentives form a smaller group and include some municipalities with relatively high BEV adoption, but the fitted line declines steeply. Municipalities without local incentives form a larger and more heterogeneous group, with a longer lower tail.

This comparison remains descriptive. Municipalities with local incentives may differ systematically from municipalities without local incentives in terms of population, income, density, charging infrastructure, metropolitan status, and political priorities. Therefore, the figure should not be interpreted as causal evidence that local incentives increase or decrease BEV adoption. Instead, it suggests that local incentives are associated with different municipal adoption profiles and should be analysed together with urban scale, infrastructure, and network position.

The results suggest that BEV adoption in Portugal is spatially concentrated and strongly associated with municipal scale. Larger municipalities tend to have more BEVs, which is consistent with the role of population size, market potential, income, and infrastructure availability. However, the observed dispersion around the population-BEV relationship indicates that urban scale alone is not sufficient to explain the geography of BEV adoption.

The rank-size analysis shows a highly unequal distribution of BEVs across municipalities.

A small number of municipalities account for a disproportionate share of BEV registrations, while many municipalities remain at relatively low levels of adoption. This pattern is consistent with a cumulative advantage mechanism, where municipalities with larger markets, stronger infrastructure, and greater visibility of electric mobility may attract further adoption.

The network analysis reinforces this interpretation by showing that the BEV concentration is not randomly distributed throughout space. Municipalities with stronger adoption tend to be located in more central or better connected parts of the spatial system. This suggests that the position of the network may matter for the diffusion of BEV, either directly through accessibility and infrastructure or indirectly through commuting, visibility, and spillover effects.

The use of a minimum spanning tree is important because it avoids arbitrary selection of a exogenous distance threshold. Instead of imposing a threshold such as 50 km, the analysis derives a connectivity criterion from the structure of the distance matrix itself. However, because Portugal includes mainland municipalities and island municipalities in Madeira and the Azores, a single national threshold can become excessively large. The territorial MST-based filtering procedure addresses this issue by applying the threshold within territorial components while preserving the global MST backbone required for national connectivity. The resulting network is less dense than the complete graph, remains connected, and provides a more meaningful basis for analysing centrality and spatial exposure.

The network map confirms the usefulness of this approach. The filtered network preserves the spatial separation between mainland Portugal, Madeira, and the Azores, while still allowing all municipalities to remain part of the same connected national system. This is particularly important in a country with discontinuous geography, where maritime distances can otherwise dominate the construction of a proximity-based network.

The comparison between municipalities with and without local incentives indicates that local policy may be associated with different adoption profiles. Nevertheless, this evidence should be interpreted cautiously. Municipalities that introduce local parking incentives may already be larger, denser, wealthier, or better equipped with charging infrastructure. Therefore, the observed differences cannot be interpreted as causal effects of local incentives. Instead, they suggest that local incentives are part of a broader urban and institutional environment associated with higher BEV adoption.

The spatial exposure measure extends this interpretation by considering not only whether a municipality has its own local incentive, but also whether it is connected to municipalities with incentives. This is relevant because BEV adoption may be influenced by neighbouring policy environments, commuting patterns, and cross-municipal visibility. A municipality surrounded by incentivized municipalities may experience different adoption conditions from an otherwise similar municipality located in a non-incentivized network environment.

Overall, the findings support the argument that fiscal incentives should not be analyzed independently from spatial structure. National incentives may reduce the general cost of BEV adoption, but their effects are likely to differ across municipalities depending on income, infrastructure, accessibility, and network position. Uniform national incentives may reinforce existing spatial inequalities if municipalities with better initial conditions are better able to convert incentives into actual adoption.

6 Conclusion

This paper focuses on the spatial concentration of Battery Electric Vehicles in Portugal using a network-based municipal framework. By representing municipalities as nodes in a spatial network, the analysis examined whether BEV adoption is associated with population, density, charging infrastructure, local incentives, spatial exposure to neighboring incentives, and network position.

The results indicate that the adoption of BEV is highly concentrated in Portuguese municipalities. Larger and more urban municipalities tend to show higher BEV counts, but population alone does not fully explain the observed variation. The rank-size analysis suggests a strongly skewed distribution, while the network analysis shows that adoption is spatially structured rather than randomly distributed.

The paper also shows that the construction of the municipal network is important. Instead of relying on an arbitrary distance threshold, the use of a minimum spanning tree provides a data-driven criterion for filtering the entire network. Because Portugal includes mainland and island territories, the analysis applies the MST-based filtering logic within territorial components while preserving the complete network backbone. This approach avoids a complete network, ensures that all municipalities remain connected, and offers a more consistent basis for analyzing spatial spillovers, centrality, and local policy exposure.

From a policy perspective, the results suggest that fiscal incentives can interact with existing spatial inequalities. National incentives reduce the general cost of BEV adoption, but municipalities differ in their ability to benefit from these incentives due to differences in income, infrastructure, density, and network accessibility. Local incentives, such as parking benefits, can contribute to adoption, but are also more likely to be present in municipalities that already have favorable conditions for the diffusion of BEV.

Future research could extend this network approach by incorporating panel data, road travel times, commuting flows, and agent-based behavioural mechanisms. This would allow a more dynamic analysis of how incentives, infrastructure, and spatial interactions jointly shape the diffusion of electric mobility in Portugal.

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Appendix: Network Construction Procedure

This appendix summarises the network construction procedure used in the paper.

Step 1: Municipal Coordinates

Each municipality is assigned latitude and longitude coordinates. These coordinates are used to compute pairwise geographical distances between municipalities.

Step 2: Complete Weighted Graph

A complete weighted graph is created. Each municipality is represented as a node, and each pair of municipalities is connected by an edge. The weight of each edge corresponds to the geographical distance between the two municipalities.

Step 3: Minimum Spanning Tree

A global minimum spanning tree is computed from the complete weighted graph. The minimum spanning tree connects all municipalities using the minimum total distance and without creating cycles. This global tree is used as the national connectivity backbone.

Step 4: Territorial Connectivity Thresholds

Because Portugal includes mainland municipalities and island municipalities in Madeira and the Azores, the maximum edge in the global minimum spanning tree may be very large. If this value were used as a single national threshold, the resulting mainland network would become excessively dense.

To avoid this problem, the municipalities are divided into territorial components: mainland Portugal, Madeira, and the Azores. A minimum spanning tree is computed within each territorial component, and the maximum edge distance within each component-specific minimum spanning tree is used as the corresponding territorial connectivity threshold.

Step 5: Filtered Network

The final filtered network is obtained in two stages. First, within each territorial component, all edges whose distance is lower than or equal to the corresponding territorial threshold are retained. Second, the edges of the global minimum spanning tree are also retained in order to guarantee that all municipalities remain connected in the national network.

This produces a network that is sparse graph, avoids a exogenous threshold driven by island-mainland distances, and remains connected.

Step 6: Network Measures

After constructing the filtered network, the analysis computes degree centrality, weighted degree, betweenness centrality, closeness centrality, and spatial exposure to local incentives.