## Scaling Dynamics of the Electricity Utility Sector:

# Assessing the Role of Agglomeration Externalities and Sensitivity to Population Cutoffs in Spatial Dynamics Across European Regions

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Abstract. Urban scaling studies have gained popularity in the last two decades, summarising urban attributes' variation with population. Recent research, however, highlights scaling exponents' sensitivity to industry-specific dynamics, population cut-offs, and data distribution. Despite this, few studies systematically examine industry scaling using plant-level data while accounting for sector-specific externalities. This study addresses that gap by analysing longitudinal data on green electricity firms across 968 NUTS (Nomenclature of Territorial Units for Statistics)-3 regions in 14 European countries (1985-2023). We assess how scaling exponents for firm entry and concentration vary across population cutoffs, both with and without controls for agglomeration externalities. Our findings reveal predominantly sublinear scaling, suggesting that population size alone does not drive green energy growth. Concentration consistently scales more strongly than entry, indicating that large cities are more conducive to firm survival than to the creation of new firms. When agglomeration externalities are not controlled for, scaling exponents are systematically underestimated. While variability is observed in regions at population extremes, results remain robust across cutoffs, especially when using inverse thresholds. Comparative analysis with high-tech service and manufacturing sectors confirms sublinear scaling in entry across all sectors, with green electricity showing the lowest exponent, reinforcing its maturity and low innovation intensity. These findings align with the Smart Specialization framework, emphasizing the importance of targeted institutional support, supplier networks, and sector-specific strategies. They also highlight the potential for smaller or lagging regions to take a more active role in the green transition, particularly within cohesion policy efforts.

**Keywords:** Scaling Dynamics, Energy Sector, Agglomeration Externalities, Electricity Utilities, Population Cut-Offs.

## 1 Introduction

Originally developed to explain biological scaling, the concept of scaling has been increasingly applied in urban studies over the past two decades (Cottineau et al., 2017). Urban scaling theory offers a unified framework to describe how city attributes, such as GDP, wages, and innovation, scale with population, typically in a superlinear manner due to intensified socio-economic interactions (Bettencourt, 2013). However, recent work challenges the focus on aggregate measures, showing that specific industrial concentrations contribute significantly to observed scaling patterns (Sarkar et al., 2020). Despite this, most scaling studies have only indirectly addressed industry emergence and concentration, often using employment or patent data. Some evidence suggests that high-tech and complex economic activities scale superlinearly, while lower-tech sectors like manufacturing and utilities exhibit sublinear scaling (Arcaute et al., 2015; Balland et al., 2020; Cottineau et al., 2017). Traditionally, such questions have fallen within the domain of agglomeration literature, which attributes industry concentration to co-location benefits from similar, related, or diverse firms (Jacobs, 1970; Marshall, 1920). In contrast, the scaling literature treats these externalities as endogenous outcomes of increasing size, typically omitting industry-specific controls and overlooking policy relevance at the sectoral level. Importantly, scaling benefits are not static. Industry life cycles and innovation intensity influence spatial patterns, with young industries concentrating in large cities and mature sectors dispersing over time industries (Frenken et al., 2015; Pumain et al., 2006). Yet, most scaling analyses are cross-sectional and rarely incorporate temporal dynamics or granular plant-level data, which are essential for understanding medium- and low-tech sectors with limited patent activity (De Groot et al., 2016). Moreover, scaling estimates are highly sensitive to population cutoffs and underlying data distribution, raising further concerns when applying them for policy purposes (Cottineau et al., 2017; Leitao et al., 2016). This paper addresses these gaps by focusing on the green energy sector, whose spatial distribution has become a key interest for policymakers aiming to support sustainable transitions and regional job creation. Traditionally seen as a low-tech, regulated industry, the sector has been transformed by liberalisation (Bolton, 2021; Hancher & De Hauteclocque, 2010) and sustainability transitions such as decentralised production and demand-side management (de Gooyert et al., 2016; Tayal, 2016). Innovation has increasingly shifted downstream-from hardware to grid integration-giving the sector a hybrid character: technologically sophisticated but relatively mature in terms of firm entry (Huenteler et al., 2016). Both supply-side externalities and demand-side factors (Bednarz & Broekel, 2020; Geels & Schot, 2007) are critical to its evolution, making it a valuable case for assessing the interaction between population size, industrial dynamics, and agglomeration effects. This paper investigates three core questions: How do entry and concentration of green energy firms scale with population size over time? How sensitive are these scaling patterns to population cutoffs and industry-specific controls? How does the green energy sector compare to other sectors in terms of scaling behavior, innovation intensity, and maturity? The analysis covers electricity utilities involved in green energy production, transmission, distribution, and trading across 968 NUTS-3 regions in 14 European countries from 1985 to 2023. For comparison, we utilize one high-tech service sector and three manufacturing sectors with varying knowledge intensities. Our results show that green energy firm entry and concentration generally scale sublinearly,

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suggesting that population size alone does not drive the sector's growth. Concentration shows higher scaling exponents than entry, indicating that larger regions better support firm survival than foster new ones. Sensitivity to population extremes raises caution regarding the interpretation of edge cases, but results remain robust across a range of population thresholds, particularly when using inverse cutoffs. Moreover, without accounting for agglomeration effects, scaling exponents are systematically underestimated. Compared to benchmark sectors, green energy firms display the lowest scaling exponents for entry, reinforcing the sector's classification as mature and relatively low in innovation intensity. The remainder of the paper is structured as follows: Section 2 reviews the sensitivity of scaling estimates. Section 3 outlines data and methods. Section 4 presents the results. Section 5 discusses the implications, followed by conclusions in Section 6.

## 2 Scaling and its Sensitivity

Scaling laws offer a concise way to describe how system attributes change with size, typically expressed as a power-law:

$$Y = \alpha X^{\beta}, \tag{1}$$

where Y is the attribute of interest (e.g., GDP), X is population,  $\beta$  is the scaling exponent, and  $\alpha$  is a constant. In urban contexts, these laws help summarise how characteristics vary across cities. Depending on the value of  $\beta$ , scaling can be sublinear, linear, or superlinear (Bettencourt, 2013). Scaling laws can be seen as a generalisation of the Cobb-Douglas production function used in economics:

$$Y = \alpha L^{\beta} K^{1-\beta}, \tag{2}$$

where L and K denote labor and capital and the exponents are assumed to sum to 1, implying constant returns to scale. Unlike Cobb-Douglas, scaling laws relax the assumption of constant returns, replacing labour and capital with population (Lobo et al., 2013; Ribeiro et al., 2019). However, population alone may not fully capture productivity dynamics. Early work (Hyclak, 1986; Moomaw, 1981) showed its influence weakens when accounting for capital and labour inputs. More recent studies use disaggregated data: Sarkar et al. (2020) found superlinear scaling in knowledge-intensive sectors (localisation externalities) and linear returns across broader industry categories (urbanisation externalities) in Australian cities. Cottineau et al. (2017), examining French cities, reported that scaling exponents vary by industry type and population thresholds—high-tech sectors exhibit higher exponents in larger cities, while manufacturing and utilities often scale sublinearly. Crucially, the choice of model affects results (Shalizi, 2011), and high heteroskedasticity and fat-tailed distribution of city sizes can distort results (Leitao et al., 2016).

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### **3** Data and Methods

The analysis includes 962 NUTS-3 regions in 14 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, the Netherlands, Norway, Portugal, Spain, and Sweden, from 1985 to 2023. We use Orbis Bureau van Dijk (BVD) for firm entries and exits, and Eurostat for population, GDP, and employment. We use the North American Industry Classification System (NAICS) code 2211 to query electricity generation, transmission, and distribution utilities. The 6-digit NAICS codes identify firms active in solar (221114), wind (221115), geothermal (221116), and nuclear (221113) electric power generation. For comparison of emergence and concentration dynamics, we also query firms in four other sectors: one high-tech sector, Scientific Research and Development Services (5417), and three manufacturing sectors with varying knowledge complexity: Semiconductor and Other Electronic Component Manufacturing (3344), Plastics Product Manufacturing (3261), and Iron and Steel Mills and Ferroalloy Manufacturing (3311). We assess scaling patterns by estimating the following power-law relationship:

$$\log_{10} y = \log_{10} c + \beta \log_{10} x + \varepsilon$$
(3)

where y is either the number of entries of green energy companies in that region or the total number of active green energy companies in that region, x is the population of a NUTS 3 region, and  $\beta$  is the scaling exponent. To evaluate robustness, we estimate  $\beta$  across a series of population thresholds—both increasing and decreasing in increments of 10,000—by subsetting the data accordingly. This allows us to assess the sensitivity of scaling behavior due to potential distortions caused by extreme values in small or large regions. After calculating scaling exponents without controlling for industry-specific effects, we proceed to do so using a log-additive function similar to the one used by Shalizi (2011):

$$\log_{10} y = \log_{10} c + \beta \log_{10} x + \sum_{i=1}^{n} f_{i}(x_{i}) + u_{it},$$
(4)

where each  $f_j(x_j)$  denotes log-linear control terms and  $u_{it}$  captures the spatial (countrylevel) and temporal (annual) fixed effects, as scaling exponents vary over time (Figure 1). Controls include Marshallian and Jacobean externalities, related variety, GDP per capita, and employment rate—computed following the method of Kundu et al. (2025). Finally, we compare firm entry scaling across the green energy sector and the four benchmark sectors. Due to data limitations (no reliable firm exit information), comparisons are limited to firm entry dynamics and do not include active firm concentrations.

### 4 Results

#### 4.1 Without Controlling for Industry-Specific Factors

Figure 1a shows that firm concentration exhibits a gradual increase in scaling exponents, rising from ~0.4 (no cutoff) to ~1 at a 1.3 million population cutoff, eventually plateauing around 4.5 million. For firm entry (Figure 1b), the exponent increases from ~0.2 to ~1 by a 2 million cutoff, with a similar plateau. Notably, concentration rises

more steeply than entry, suggesting better survival prospects for firms in larger cities. Using inverse population cutoffs (i.e., excluding larger cities), scaling exponents are more stable. For concentration, the exponent hovers around 0.35, dropping slightly when cities over 1 million are excluded. Entry follows a similar trend, remaining around 0.2 and dipping to 0.1 after the same cutoff.



**Fig. 1.** Varying scaling exponents of firm concentration (orange) and firm entry (green) with a) positively incremental population cut-offs and b) inverse population cut-offs. Grey dashed lines indicate the upward trend in industry concentration scaling exponents over the past three decades. In panel (a), the trend line is truncated at a population threshold of 3 million due to instability in results caused by limited data beyond that point.

### 4.2 Controlling for Industry-Specific Factors

After adjusting for agglomeration externalities, GDP per capita, and employment rate, firm concentration (Figure 2a) starts superlinear (~1.1) and stabilizes near this level, dipping briefly between 2.5–3 million before sharply rising and becoming unstable due to limited data. Entry (Figure 2b) follows a similar shape but with lower exponents. Inverse cutoff results are again more stable—concentration stabilizes around 0.8, and entry near 0.2—remaining sublinear in all cases.



**Fig. 2.** Varying scaling exponents of firm concentration (orange) and firm entry (green) with a) positively incremental population cut-offs and b) inverse population cut-offs when controlling for agglomeration externalities, GDP per capita, and employment per capita.

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#### 4.3 Comparison with Other Sectors

Without controls (Figure 3a), all sectors show similar trends until diverging around a 3.5 million population cutoff. After adjusting for industry factors (Figure 3b), Scientific R&D consistently shows the highest scaling (0.75), followed by Plastics (0.55), Semiconductors (0.5), and Iron & Steel (0.35). All sectors exhibit a slight drop at higher inverse cutoffs before becoming unstable.



**Fig. 3.** Varying scaling exponents of firm entry with positively incremental population cut-offs, a) without controls, and b) with inverse population cut-offs when controlling for industry-specific factors for the four different sectors.

### 5 Discussion

This study examined the scaling of green electricity utilities, with and without industryspecific controls, across a range of population cutoffs. Using plant-level data, we found that both firm entry and concentration generally scale sublinearly, except in highly populous regions where scaling can appear superlinear. Electricity utility concentration consistently exhibits higher scaling exponents than entry, indicating population size supports firm survival more than new firm formation. Our results highlight the sensitivity of scaling estimates to both extremes of the regional size distribution. This pattern in terms of firm entry appears consistent across sectors, raising questions about the validity of scaling results in edge cases. Importantly, results suggest that without agglomeration externalities, size alone does not drive green sector growth, particularly for new entrants. While transition literature often emphasizes demand-side factors for green energy sector niche creation, our findings underscore the continued importance of supply-side dynamics like knowledge spillovers. Additionally, scaling exponents are often underestimated without industry-specific controls. Even with rising exponents over time, low-tech sectors continue to exhibit higher scaling than green electricity, suggesting that recent claims of increased sectoral complexity may be overstated. Despite recent criticisms of sensitivity issues, scaling literature remains a valuable framework for cross-sector comparisons. However, categorizing sectors as sublinear, linear, or superlinear based solely on firm entry may be unrealistic. While edge cases pose a challenge, claims of population cut-off sensitivity appear overstated, as robust results were observed with inverse population cut-offs.

### 6 Conclusion

This paper explored the scaling behavior of green electricity utilities, contrasting the assumptions of urban scaling and agglomeration literature. The scaling literature, based on a framework of interaction networks, treats externalities, including diversity and specialization, as endogenous outcomes of increasing size. The interest in scaling lies not at the sectoral level but rather in the aggregate behavior of cities. In contrast, agglomeration literature considers agglomeration externalities-such as Marshallian, Jacobean, and related externalities-distinct from size-derived benefits, which are categorized as urbanization externalities. Our findings show that accounting for industry-specific agglomeration externalities yields distinct scaling results, raising questions about the scaling approach. However, we suggest that concerns regarding the sensitivity of scaling exponents may be slightly overstated when excluding edge cases. Green electricity utilities largely scale sublinearly, with lower exponents than most other sectors, supporting their characterization as mature and relatively low in innovation intensity. The study focuses on green electricity utilities using the location of company headquarters rather than subsidiaries, as these are more likely to be knowledge centers driven by supply-side knowledge externalities and are less spatially constrained by energy production demands. These insights are especially relevant for regional transition and cohesion policies. Rather than relying solely on population size or general economic diversification, regions should focus on fostering targeted institutional support, supplier ecosystems, and industry-specific capabilities. This aligns well with the Smart Specialization approach and suggests the potential of smaller or lagging regions playing a more strategic role in the green transition. Future research could incorporate firm-level heterogeneity, such as differences in absorptive capacity and whether a firm is a typical spinoff or a new startup, to understand scaling dynamics better, as agglomeration externalities may affect these firms differently. Finally, due to limited data on employee numbers, we are constrained in assessing consolidation in large regions, which may underrepresent the sector's presence. Future studies could address this gap by combining granular occupation data with plant-level data.

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