Convergence of Corporate Growth and Gibrat's Law in European Electricity Generation Sectors

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Abstract: An important question in industrial development is about whether larger enterprises grow faster or slower than smaller ones. If smaller companies grow slower than larger ones, firms converge in company size. In comparison, Gibrat's law rejects a relationship between corporate growth and company size. Motivated by these diverging views, this study examines the effect of firm size on growth, using an unbalanced panel data set that covers firm-level information on European electricity generators from 2012 to 2020. European electricity generation sectors are particularly interesting due to the substantial liberalisations and market integration in the past decades and the capital-intensive production processes. Despite the interesting characteristics of network industries, this is one of the few studies investigating growth processes in electricity generation sectors. The study explores the nature of growth processes by investigating σ-convergence, and unconditional and conditional β-convergence. This study also adds to the literature by employing a variety of different measures of company size to compare the results. Besides, the study checks the endogeneity of initial company size and examines the variance of growth processes by employing quantile regression. The overall results highlight that European electricity generators converge in company size, clearly violating Gibrat's law. Additionally, the variance of growth processes is considerably driven by firm size. Last, Eastern European enterprises converge faster than Western European ones.

JEL: L25, L51, L94, O12

Keywords: Firm Growth and Size, Regulated Industries, Electricity Sector, Firms and Development

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1 Introduction

Economic growth is an interesting phenomenon that has not only fascinated economists and political philosophers but also other scientific fields. For instance, historians, natural scientists and public space planners are also interested in the way how societies organise production and economy develops due to the implications of economic growth to their fields of interest. Over centuries, the standard of living has considerably changed across countries and world regions, since they grew at different speeds, i.e.: some grew faster, while some others grew slower. [1] Trends in economic growth reverted in the 1980s and early 1990s. Starting from this point in time, developing countries such as China, India, Indonesia, and Thailand have grown faster than industrialised nations. Given the faster growth, relevant countries have caught up with the developed countries, i.e.: the gap in the standard of living declined. This development can still be observed today (Patel *et al.* , 2021; Rodrik, 2014; Arnold *et al.* , 2011; Adelman, 1995). Different speeds of economic development are not only limited to world regions. Also within world regions, some countries grow faster than others. After the collapse of the Soviet Union, Eastern European economies grew faster than Western European countries and caught up with them. Although the gap in GDP per capita has declined, it is still large (Fuchs-Schündeln & Schündeln, 2020) and catching-up processes have been slowing (Egri & Lengyel, 2024). Different speeds of economic development can even be observed within individual countries, i.e.: some regions grow faster than others. An especially interesting example is Germany. Before the collapse of the Soviet Union, Germany was divided in two parts: the capitalist West and the socialist East. Before the collapse of the Soviet Union and the following German reunification, the economy developed much slower in Eastern Germany than in its Western counterpart. The collapse of the Soviet Union and the following German reunification changed the game. Eastern and Western Germany switched roles. Given Eastern Germany's transition from a centrally-planned to a market economy, economic activity expanded faster in Eastern than in Western Germany (Becker *et al.* , 2020; Keller, 2000). Nevertheless, the catching-up by the post-soviet Eastern part slowed over time. 20 years after the German reunification, Eastern Germany's economy was relatively stagnant with Western Germany (Blum, 2013). Owing to these fascinating developments, a strand in Development Economics is particularly interested in the drivers of economic growth processes. Of special interest is the relationship between the initial level of economic activity and subsequent economic growth, i.e.: do developing countries grow faster than industrialised nations and catch up with them or not. The most important theoretical models analysing the drivers of economic growth are by Solow (1956) and Romer (1994) (Barro & Sala-i-Martin, 2003).

As different speeds of economic development can also be observed at the more granular firm-level, Industrial Organisation, escpecially the field of Industrial Development, also explores the dynamics of growth processes. Of particular interest is the relationship between corporate size and growth, i.e.: do smaller companies grow faster than larger firms and catch up with them or not (Daunfeldt & Elert, 2013). Answering this question is highly important, since the nature of growth processes influences future market structures and determines which type of companies industrial policies should specifically target, i.e.: should governments pass laws and use limited financial resources to support the growth of small enterprises, or should they encourage the growth of larger ones. An important theory that relates corporate growth and company size is Gibrat's law. In 1931, Gibrat (1931) concluded that the size of French manufacturing establishments is lognormally distributed. Based on this observation,

[1] For an overview of the estimates for how countries have evolved over the last 200 years, see `https://ourworldindata.org/grapher/gdp-per-capita-maddison?tab=chart`.

he suggested that firm growth does not depend on size, since it should be a purely random effect. [2] The theory by Gibrat (1931) has one important implication to the distribution of company size. If corporate growth is independent of size, growth rates will be similar across enterprises. Hence, larger corporations grow faster in levels than smaller ones. [3] As a result, the variance of firm size distributions grows over time. Thus, the gaps between enterprises rises over time. In other words, the corporations diverge in size (Pfaffermayr, 2007).

Since its development, many empirical studies have examined Gibrat's law. [4] Methodologically, some studies employ the macroeconomic concept of β-convergence (Distante *et al.* , 2018; Geroski & Gugler, 2004). In a nutshell, this model regresses the growth rate of a given variable on the initial value of the variable. Its coefficient is β. When assuming that all units (e.g., countries, regions) approach the same steady state, no additional regressors are added ('unconditional β-convergence'). If β is negative, smaller units grow faster than larger ones, implying that units converge in size. When assuming that each unit approaches its specific steady state, additional covariates are included in the model to control for the heterogeneity of steady states ('conditional β-convergence'). If β lies below zero, then units that are farer away from their steady state grow faster than units which lie closer to their steady state. Nonetheless, units may not converge in size, as smaller units' steady states might be smaller than larger units' steady states (Barro & Sala-i-Martin, 2003). Pfaffermayr (2007) applies the concept of σ-convergence to explore Gibrat's law. σ-convergence is observed, if differences in size across units, as measured by the standard deviation, shrink over time. If the standard deviation declines, units converge in size conditionally and unconditionally. If the standard deviation rises, units diverge in size (Barro & Sala-i-Martin, 2003). If σ-convergence is observed, Gibrat's law is supported given its implication to the company size distribution. In comparison, other studies employ autoregressive models that regress size on its lagged value (Daunfeldt & Elert, 2013; Lotti *et al.* , 2003). The vast majority of studies analyses the impacts of size on the average growth process by applying OLS. Given this issue, Córdoba (2008) generalises Gibrat's law. Particularly, size does not influence the average growth process as suggested by Gibrat (1931), but it influences the variance of the growth process. This generalised version model is usually explored by employing quantile regressions (Distante *et al.* , 2018). Most of the studies analyse manufacturing sectors, while only a few such as Daunfeldt *et al.* (2012) and Audretsch *et al.* (2004) investigate service sectors (Daunfeldt & Elert, 2013).

Overall, the empirical literature provides conflicting guidance. One strand (Axioglou & Christodoulakis, 2021; Arouri *et al.* , 2020; Daunfeldt *et al.* , 2012; Cefis *et al.* , 2007; Audretsch & Elston, 2006; Calvo, 2006; Dunne & Hughes, 1994; Dunne *et al.* , 1989; Evans, 1987a,b; Hall, 1987) concludes that smaller companies grow faster than larger enterprises, violating Gibrat's law. Related to this strand, Pfaffermayr (2007) investigates whether the variance of company size distributions grows over time as predicted by Gibrat's law, which is rejected. The second strand (Bentzen *et al.* , 2012; Singh & Whittington, 1975; Samuels, 1965) observes a faster growth by large firms, violating Gibrat's law as well. The third strand usually covering older studies (Distante *et al.* , 2018; Hymer & Pashigian, 1962; Simon & Bonini, 1958; Hart & Prais, 1956) often supports Gibrat's law. The last strand (Guerzoni *et al.* , 2024; Elston, 2023; Tang, 2014; Daunfeldt & Elert, 2013; Lotti *et al.* , 2009; Bottazzi & Secchi, 2005; Audretsch *et al.* , 2004; Geroski & Gugler, 2004; Lotti *et al.* , 2003; Becchetti & Trovato, 2002; Hardwick

[2] Similarly, macroeconomic growth models Solow (1956) and Romer (1994) also impose that growth becomes independent of size when reaching the long-run equilibrium.

[3] Suppose that two companies i and j grow by 5% each. Firm i's size is 100, while corporation j's size is 1,000. The level growth of firm i equals 5, whereas company j's level growth is 50.

[4] For an overview see Stam (2010), Santarelli *et al.* (2006), Caves (1998), Sutton (1997) or Geroski (1995).

& Adams, 2002; Cefis & Orsenigo, 2001; Hart & Oulton, 1996) finds mixed effects or support a weak form form of Gibrat's law. The few studies that investigate the generalised version of Gibrat's law by Córdoba (2008) either support or partially support it (Distante *et al.* , 2018; Lotti *et al.* , 2003). They find that company size can be both, an advantage and a disadvantage, depending on the point in the distribution. In other words, there is not only convergence or divergence but both, i.e.: at particular points in the growth distribtion, enterprises converge, while they diverage at other points. One reason why studies reject or partially reject Gibrat's law is the 'minimum efficient scale' (*MES*). Starting from this size threshold, corporations can produce and sell their products competitively (Daunfeldt & Elert, 2013; Strotmann, 2007). Some of these studies argue that Gibrat's law may hold but only for firms that are larger than the MES. According to Mansfield (1962), the farer away the firm from the minimum efficient scale, the larger the scale disadvantage. The larger the scale disadvantage, the stronger the incentive to invest and grow in size. Finally, they become more competitive, allowing them to stay in the market. If they would not grow and become more competitive, they would be forced to exit (Strotmann, 2007). One important determinant of the MES are high sunk costs (Cabral & Ross, 2008; Cabral, 1995). High sunk costs spur entrants to boost investment and, finally, their growth to become competitive. If they do not become sufficiently competitive, they need to exit and incur high losses due to the high sunk costs. According to Teruel-Carrizosa (2010), MES differ across industries. Particularly, MES should be smaller in service than in manufacturing sectors. Consequently, small service companies should grow slower than equally sized manufacturing corporation.

Motivated by the conflicting literature and the fact that no literature on energy sectors exists, this article sheds light on whether Gibrat's law applies to European energy sectors. Therefore, I employ micro-data on European electricity generators (D3511). The European electricity industry is of special interest for many reasons. First, governments have liberalised the sector and substantially support market entry. For instance, governments have subsidised renewables, eliminated market barriers, vertically disintegrated generation and grids, and privatised formerly state-owned companies and still do so. The liberalisation aimed to incentivise market entry by smaller companies and help them catch up to foster competition (Meletiou *et al.* , 2018). As a result, these policies reallocated resources from larger electricity generators to smaller ones. [5] From a policy perspective, these policies may have been necessary to support the growth of small enterprises and help them reach the MES. Without the support, they might have exited the market again. If they exited, resources would have been wasted due to the sunk costs. The liberalisation (e.g., vertical disintegration) may have reduced the MES, since entrants can access the grid more easily. Nevertheless, they might still be quite high given the high capital costs. This might also be a reason why electricity generation sectors are still highly concentrated despite the liberalisation. Given this aspects, the relationship between company size and corporate growth might be strongly negative, violating Gibrat's law. On the other hand, the European electricity directives promoted mergers and takeovers across the EU electricity and gas sectors, substantially boosting the growth of the large incumbents (e.g., Électricité de France, RWE, E.ON, Iberdrola, Enel, Vattenfall) (Pollitt, 2019). The accelerated growth of the big players may weaken the negative relationship between corporate growth and company size. If this negative relationship is sufficiently weakened, Gibrat's law could possibly be supported.
Second, the relationship between firm size and growth may considerably deviate from the literature. Unlike in manufacturing sectors, state ownership is still a widely used tool. State ownership serve as

[5] For example, particular policies such as renewable subsidies (e.g., feed-in tariffs) favour smaller generators in many European countries (Busch *et al.* , 2023).

one approach to tackle problems caused by lacking competition in network industries. Often, governments hold shares in some of the larger incumbent corporations' stock. State ownership, however, may result in performance losses (Steinbrunner, 2023). Hence, larger state-owned enterprises might grow slower. Given the slower growth, the negative relationship between corporate growth and company size is more pronounced, violating Gibrat's law. Additionally, Gibrat's law might possibly not hold even for the enterprises larger than the MES. Third, the industry produces capital-intensively. Due to its network industry characteristics, electricity generation may benefit from increasing returns to scale, which encourages firm growth. Fourth, Eastern European countries have transitioned from centrally planned to market economies after the collapse of the Soviet Union, and, therefore, have experienced major institutional changes and liberalisations. Yet, governments still pervasively influence the formerly state-owned companies in these countries. Especially in the post-communist countries, strong entry barriers aggravated the transition to well-functioning market economies. Furthermore, poorly implemented privatisations established legal monopolies and strengthened market barriers instead of creating open and contestable markets (Buccirossi & Ciari, 2018). Therefore, the relationship between firm size and growth might be even stronger in Eastern Europe.

To investigate the link between company size and corporate growth, I examine unconditional and conditional β-convergence of European electricity generators from 2012 to 2020. According to Barro & Sala-i-Martin (2003), β-convergence is achieved, when the partial correlation between the growth in corporate size over time and its initial level is negative. β-convergence is characterised by the phenomenon where small enterprises grow faster than large ones, which eventually narrows the economic gap between them. If all generators are presumed to converge toward the same steady state concerning company size and corporate growth, this form of β-convergence is termed 'unconditional'. If steady states differ, the form is termed 'conditional'. Following the literature (Distante *et al.* , 2018; Geroski & Gugler, 2004), I apply firm-level panel data to examine unconditional and conditional β-convergence. When analysing unconditional β-convergence, corporate growth is regressed only on company size in the previous year using OLS. Firm-level fixed effects and other controls are added to investigate conditional β-convergence. The endogeneity of the lagged company size is tested using 2SLS. I also examine whether growth processes differ between firms smaller and larger than the MES. Last, the version of Gibrat's law by Córdoba (2008) is also explored. Córdoba (2008) concludes that company growth primarily affects the variance of growth processes but not the mean. This hypothesis is examined using quantile regression. Given these theoretical considerations and empirical findings, I hypothesise that Gibrat's law will not be supported in electricity generation industries. Particularly, I expect unconditional and conditional β-convergence, i.e.: smaller enterprises grow faster than larger ones; companies farer away from their steady state grow faster than corporations closer to their steady state. When Gibrat's law is violated, the generalised version of the model by Córdoba (2008) is also violated. Although the generalised version may be violated, company size might still influence the variance of the growth process. Particularly, electricity generators could converge and diverge depending on the location in the growth distribution. Concerning the MES, it is difficult to formulate a hypothesis on whether enterprises smaller or larger than the MES converge faster. On the one hand, the remaining market barriers may still be high in spite of the liberalisation, implying high MES. This may imply that companies smaller than the MES grow fast, and that corporate growth depends on size. In comparison, enterprises larger than the MES may grow slower. Nevertheless, I still expect that corporate growth still depends on size, as the MES may still be quite high given the high capital costs (e.g., constructing power plants). In this case, all types of firms converge, while generators smaller

than the MES converge faster than the ones larger than the MES. On the other hand, liberalisations such as unbundling (vertical disintegration) might have eliminated many market barriers, i.e.: entrants can access grids more easily (Meletiou *et al.* , 2018). In this case, the MES could be lower. Thus, corporations larger and smaller than the MES converge at a similar speed. Last, I hypothesise that the negative relationship is more pronounced in Eastern Europe. This study combines the approaches taken by many other studies and, therefore, adds to the literature in several aspects. First, this is the first study examining electricity generation sectors and the second study analysing energy sectors next to Tang (2014). In comparison to Tang (2014), I only focus on electricity generation sectors given the differences across the industries within the energy sector. For instance, regulation systems differ considerably across electricity, gas, and steam and air conditioning industries (Meletiou *et al.* , 2018; European Commission, 2016; Growitsch & Stronzik, 2014). Owing to the reasons mentioned above, electricity generation sectors are unique industries that fundamentally differ from other ones. They do not only differ from other energy sectors but also from manufacturing industries. For instance, the industry generates electricity capital-intensively. Expanding capital, however, requires time given the long construction times of power plants, grids and related infrastructure. Therefore, electricity generators may converge slower than manufacturing and service enterprises. Besides, Tang (2014) only analyses Swedish firms. Including further countries is necessary given the integration of European energy markets. Particularly, the relationship in Sweden might not be representative for other countries (e.g., energy mix and geographic peculiarities, regulation and institutional setting, level of economic development). To overcome the lacking representativeness, my study includes electricity generators from other EU countries. European governments coordinate economic and energy policies (e.g., EU electricity directives). Although national policies and regulatory frameworks differ across countries (e.g., energy mix), they show some similarities. Besides, national electricity markets are integrated to a certain degree, as countries trade electricity with each other to meet peak demand. Next, European countries have different levels of economic development and historical backgrounds, but their histories are strongly related (Western vs. Soviet countries, European integration and EFTA). Therefore, covering additional European countries is important to provide a more comprehensive and representative picture of electricity market dynamics. These differences may substantially influence the speed of convergence that would be otherwise remain unexplored. Especially, Eastern European electricity generators may converge much faster than Western European ones because of the liberalisations and the considerable changes in the institutional settings. The difference in the convergence speed between Eastern and Western Europe is not only interesting to academics but also to regulators and the European Commission that aim to accelerate the catch-up by small companies through special support schemes. Second, I check the robustness of the results by employing a variety of different proxies for firm size. Although several different measures of firm size are used in the literature, every study usually relies on a specific measure without comparing results across concepts. As in the literature (Guerzoni *et al.* , 2024; Nakatani, 2023; Castelnovo *et al.* , 2019; Distante *et al.* , 2018; Hanousek *et al.* , 2015; Del Bo, 2013; Schiersch, 2013; Geroski & Gugler, 2004; Dewenter & Malatesta, 2001; Majumdar, 1997), I quantify company size using total assets, revenues and employment, but I also add variables that measure particular aspects of the capital structure such as tangible and intangible fixed assets, and equity. Employing a variety of measures allows for a more nuanced analysis and comparison of the results across measures. This approach avoids drawing wrong conclusions. For instance, if only one measure for company size is used, the result does not necessarily need to representative for other measures. If company size is only measured using revenues and Gibrat's law should hold only in revenues but not in

other variables, the conclusion that Gibrat's is supported is wrong because one overlooks that the other measures do not support it. Third, my dataset also includes some state-owned companies, which are primarily municipal utilities. As state ownership is still a widely employed tool to overcome problems caused by lacking competition in network industries, governments can provide additional capital to selected firms to accelerate their growth. Fourth, the literature (Distante *et al.* , 2018; Lotti *et al.* , 2003) employs quantile regressions to examine the generalised version of Gibrat's law by Córdoba (2008). Although other drivers of corporate growth are covered to avoid omitted variable biases, firm-level fixed effects are not included. Important country-specific determinants such as business cycles are also not considered. Omitting unobserved firm-specific time-invariant heterogeneity likely biases the results. Despite the potential bias, including firm-level fixed effects in quantile regressions was difficult before 2019. In 2019, Machado & Santos Silva (2019) suggested an algorithm that combines quantile regressions and fixed effects. Given the introduction of this new method, updating the estimations exploring Gibrat's law is highly required, since the nature of growth processes may considerable change when controlling for these omitted variables.
Overall, the results reject Gibrat's law. This conclusion is generally in line with the literature. Across the different proxies for company size, the regressions suggest that electricity generators converge unconditionally and conditionally. The inclusion of firm-level fixed effects and nested NUTS2 region-year dummies considerably influence the results, implying that studies excluding them may suffer substantially from omitted variable biases. The MES do not seem to influence the speed of convergence in most specifications. This conclusion may suggest that the MES have considerably decreased due to the liberalisation. As Gibrat's law is clearly rejected, the generalised version of the model by Córdoba (2008) is also rejected. Despite this issue, company size substantially drives the variance of the growth process. This supports Córdoba (2008) to some degree. Accounting for unobserved heterogeneity considerably influences the results. When excluding it like in the literature (Distante *et al.* , 2018; Lotti *et al.* , 2003), both, convergence and divergence, are observed. In other words, company size can be an advantage and a disadvantage. When controlling for unobserved heterogeneity, this behaviour almost completely disappears. Now, company size is almost always a disadvantage, i.e.: electricity generators converge in size along almost the entire growth distribution. Last, Eastern European electricity generators tend to converge faster than Western European ones.

The paper proceeds as follows. *Section 2* introduces the empirical framework and data, used to examine unconditional and conditional β-convergence of European electricity generators. *Section 3* provides the results, and discusses them and some robustness checks. Last, *Section 4* sums up and draws conclusions.

2 Empirical strategy and data

Following the literature (Distante *et al.* , 2018; Geroski & Gugler, 2004), I apply various conventional β-convergence models on panel data. Originating from macroeconomic theory, this model is described in Barro & Sala-i-Martin (2003) and is regularly employed and largely documented in the economic literature. Originally, the model examines how output growth of a given spatial zone (e.g., countries, regions etc.) depends on the initial level of output. It allows to investigate whether spatial zones farer away from their long-run equilibrium grow faster or slower. This framework can also be employed to investigate the relationship between company size and corporate growth at the firm-level. Particularly,

the growth rate of size is regressed on the initial value of size. In a panel setting, the initial value is the firm size lagged by one period (Distante *et al.* , 2018; Geroski & Gugler, 2004).

Two variants of β-convergence model exist. The first, known as 'unconditional' β-convergence, assumes that all units (e.g., countries, regions, companies) aim to converge to the same long-run equilibrium. In this model version, the growth rate is regressed only on the initial value. In contrast, the second variant, termed 'conditional' β-convergence, posits that each unit converges to its distinct long-run equilibrium. The heterogeneous steady states are accounted for by introducing additional covariates. This distinction allows for a nuanced analysis of convergence dynamics and sheds light on whether convergence is uniform across units or influenced by specific covariate factors (Barro & Sala-i-Martin, 2003).

Before laying out the estimation strategy, following subsection describes the data source. The data set used to run the regressions is a panel, varying across firms and years. Relevant firm-level data are sourced from the Orbis database. This database, published by Bureau van Dijk, provides accounting data, legal form, industry activity codes, and incorporation date for a large set of private and public firms worldwide. My dataset covers small, medium sized, large and very large [6]; active and inactive companies from industry D3511 ('electricity generation'), incorporated in Austria, Belgium, the Czech Republic, Estonia, France, Germany, Hungary, Italy, Latvia, Luxembourg, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, and the Switzerland. [7] The final sample is a nine-year unbalanced panel dataset, from 2012 to 2020. [8] It contains 10,844 firms with 64,206 observations. [9]

2.1 Unconditional β-convergence

First, I analyse unconditional β-convergence (Guerzoni *et al.* , 2024; Lotti *et al.* , 2009; Geroski & Gugler, 2004; Evans, 1987a,b). As shown in equation (1), the growth rate of firm size is regressed only on lagged firm size, as steady states are assumed to be identical. g denotes the annual growth rate of firm size. In the regression, it is the dependent variable. Firm size is denoted by s. Following Haltiwanger *et al.* (2013), the growth rate g is defined as the annual level-change in size $(s_t - s_{t-1})$ divided by the average of the current and previous size $\left(\frac{s_t + s_{t+1}}{2}\right)$. [10] This ratio is multiplied by 100 to obtain percentage points. This definition is frequently employed in the empirical literature on industry dynamics for two reasons. First, it includes entry and exit. Second, it has some useful properties of log-differences. i and t serve as the firm and year indexes, while α and ϵ represent the

[6] Orbis considers firms to be 'medium sized', when operating revenues $\geq$ 1 mio EUR or total assets $\geq$ 2 mio EUR or employees $\geq$ 15. Orbis defines firms to be 'large', when operating revenues $\geq$ 10 mio EUR or total assets $\geq$ 20 mio EUR or employees $\geq$ 150. Firms are 'very large', when operating revenues $\geq$ 100 mio EUR or total assets $\geq$ 200 mio EUR or employees $\geq$ 1,000 or the company is listed. Enterprises are defined as 'small', if they not cover by the other categories (Bureau van Dijk, 2007).

[7] Countries with too few observations, too many unavailable values, or unavailable deflators (e.g., Bulgaria, Finland, Croatia, Liechtenstein, Romania) are excluded from the analysis.

[8] The unbalanced panel helps to avoid selection biases because corporations that exit in the analysed time interval are included. If they would be excluded, coefficients would be estimated only from surviving firms that may behave systematically differently (Geroski & Gugler, 2004).

[9] Observations with implausible output and input values (e.g., negative values) or missing values are dropped. Firms with either unknown or unavailable activity status are eliminated.

[10] Given the definitions of the growth rates, every firm's first observation is dropped.

intercept and error term.

$$
\begin{aligned}
g_{i,t} &= \frac{s_t - s_{t-1}}{\left(\frac{s_t + s_{t+1}}{2}\right)} \cdot 100\% \\
&= \alpha + \beta \cdot log(s_{i,t-1}) + \epsilon_{i,t}
\end{aligned}
\tag{1}
$$

Although several different measures of firm size are used in the literature, every study usually relies on one single specific measure. Mostly, the literature measures company size using the number of employees (Guerzoni *et al.* , 2024; Schiersch, 2013; Geroski & Gugler, 2004), assets (Nakatani, 2023; Castelnovo *et al.* , 2019; Hanousek *et al.* , 2015; Del Bo, 2013; Dewenter & Malatesta, 2001) and revenue (Distante *et al.* , 2018; Majumdar, 1997). One of my study's contribution to the literature is the application of a variety of measures that allows to compare the results across concepts. For instance, convergence in size could be particular to specific proxies for company size. Hence, if only one measure is applied, wrong conclusions might be drawn, since the result do not necessarily need to extend to other measures. Therefore, a variety of measures provides valuable information on the robustness of the relationship. In total, I approximate company size using six different variables. s denotes the set of these different measures. The set includes the three measures that are popular in the literature: total assets, number of employees and revenues. It also covers three more exotic variables that are not involved in the literature. Therefore, it is interesting to see whether these variables show the same relationship as the variables popular in the literature. The real total assets are the first measure that I include. Total assets are the balance-sheet total, the sum of all different types of assets (e.g., machines, cash and bank accounts, inventory etc.) (Bureau van Dijk, 2007). Total assets are deflated by an uniform investment good price index, obtained from the OECD database. The investment good price indexes vary across countries and years but across industries. [11] In the context of electricity generation, assets may be the better proxy for firm size, since firm size will depend more strongly on the number of power plants and their capacities rather than on the number of workers or output.

Second, I quantify firm size using output. Following Distante *et al.* (2018), output is approximated by deflating the operating revenues by energy price indices obtained from the OECD database. [11] Operating revenues covering net sales, other operating revenues and stock variations excluding VAT (Bureau van Dijk, 2007).

The third measure involved is the number of employees included in the company's payroll.

The tangible fixed assets (e.g., machinery) serve as the fourth proxy for firm size. They are deflated by the same price index as the total assets. [11] This variable may be the best proxy of firm size. As compared with total assets, the tangible fixed assets only cover assets that are not frequently adjusted such as machines. Since, assets that fluctuate in the short-run such as inventory are excluded (Bureau van Dijk, 2007), the change in the tangible fixed assets may better reflect the real changes in company size.

I involve the intangible fixed assets as a fifth measure. Intangible fixed assets are deflated by the investment good price indexes. [11] Next to goodwill, this class of assets also covers technological capital (e.g., value of patents) (Bureau van Dijk, 2007). Some studies (Nakatani, 2023) calculate the first

[11] `https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI`

difference of this variable and apply it as a measure for innovation. Hence, the growth rate of this variable will also reflect the electricity generators' innovative activity.
The last proxy used is equity covering the part of the companies' funds that is provided by shareholders (Bureau van Dijk, 2007). Since most of the literature quantifies company size using assets, revenues and the number of employees, employing equity as a measure is a quite new approach. Assets reflect how capital is used. The investment required for growth can be financed internally (e.g., shareholders) or externally (e.g., debt). Therefore, employing equity to quantify corporate growth reflects by whom the necessary capital is provided. The capital composition can determines the firm's risk. For instance, the higher the leverage that is the ratio of long-term debt in equity, the higher risk (Nakatani, 2023; Hanousek *et al.* , 2015; Nickell & Nicolitsas, 1999; Lichtenberg & Siegel, 1990; Jensen, 1986). Thus, equity might also measure how sustainable and risky firm expansion is. If investment is financed internally to a larger degree, the growing equity will signal agents on the financial market that the given firm's expansion is less risky and, thus, a safer investment option.

The growth rates g of these different proxies for size are regressed on the logged firm size lagged by one year $log(s_{t-1})$ (Distante *et al.* , 2018; Geroski & Gugler, 2004). Its coefficient β allows to investigate whether the analysed firms unconditionally converge in company size or not. In equation (1), unconditional β-convergence is observed, if β is negative. In this case, initially smaller enterprises grow faster than initially larger ones. Thus, corporations converge in firm size. Conversely, if β is positive, then the initially smaller generators grow more strongly than initially larger ones, suggesting that firms diverge in size (Barro & Sala-i-Martin, 2003). Given the literature, I expect unconditional β-convergence.

The speed of convergence and the half-life period are calculated from the coefficient β as in Mankiw *et al.* (1992). The speed of convergence γ quantifies at which speed companies approach their long-run equilibria. After estimating the β coefficient, the identity $\beta = -(1 - e^{-\gamma})$ is solved for γ. The resulting formula for the speed of convergence is shown in equation (2) (Vu, 2013; Dobson *et al.* , 2006; Furceri, 2005). The β-coefficient is divided by 100, since the dependent variable is measured in percentage points. Half-life τ measures the number of years after which the distance between the initial firm size and the steady state is halved. It is calculated from the speed of convergence γ, as shown by equation (3) (Vu, 2013; Furceri, 2005; Mathur, 2005).

$$\gamma = -log\left(1 + \frac{\beta}{100}\right) \tag{2}$$

$$\tau = \frac{log(2)}{\gamma} \tag{3}$$

In adherence to the established literature, I estimate equation (1) and incorporate the lagged firm size as an exogenous variable, consistent with findings from various studies such as those by (Distante *et al.* , 2018; Daunfeldt & Elert, 2013; Geroski & Gugler, 2004; Lotti *et al.* , 2003). Nevertheless, the major problem might be omitted variables. Consequently, the lagged firm size will correlate with the error term. Hence, estimating equation (1) using OLS may generate inconsistent coefficients (Geroski

& Gugler, 2004). To solve this problem, I follow Geroski & Gugler (2004) and instrument the lagged firm size by the company size lagged by two years.

2.2 Conditional β-convergence

Since the long-run equilibria will likely differ across companies, I include a couple of control variables that account for the heterogeneity of steady states (Guerzoni *et al.* , 2024; Lotti *et al.* , 2009; Geroski & Gugler, 2004; Evans, 1987a,b). Owing to this additional covariate, conditional β-convergence of European electricity generators is investigated, as described in equation (4). This equation extends the structural equation by Mankiw *et al.* (1992). Like before, g, i, t, s, and ϵ denote the growth rate of company size, firm index, time index, firm size and the error term. $solv$ is the solvency ratio that is involved as a control variable to account for the heterogeneity of long-run equilibria. Its coefficient is denoted by δ. The equation also includes fixed effects for firms α_i. Furthermore, it involves nested NUTS2 region-year dummies $D_r \cdot D_t$. r is the region index, whereby R is the total number of NUTS-2 regions.

$$\begin{aligned} g_{i,t} &= \frac{s_t - s_{t-1}}{\left(\frac{s_t + s_{t+1}}{2}\right)} \cdot 100\% \\ &= \beta \cdot log(s_{i,t-1}) + \delta \cdot solv_{i,t-1} + \alpha_i + \sum_{r=1}^{R} \sum_{t=2009}^{2020} \rho_{r,t} \cdot D_r \cdot D_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

Conditional β-convergence is observed, if β is negative. In this case, firms located farer away from their steady state grow faster than companies closer to them. Nevertheless, conditional β-convergence does not necessarily imply unconditional β-convergence, i.e.: under conditional β-convergence, corporations do not necessarily converge in firm size. In other words, the differences in company size across firms could even increase. For instance, the large enterprise that lies closer to its steady state is approaching a steady state that is much higher than the steady of the small corporation that lies farer away from its long-term equilibrium. Conditional β-convergence only implies that smaller enterprises grow faster than larger companies, if steady states are identical across corporations (unconditional β-convergence). In comparison, if β is positive, then conditional β-divergence is observed, i.e.: companies closer to their steady state grow faster than firms farer away from them. Similarly, the model's conclusion does not necessarily imply that enterprises diverge. They would diverge, if long-term equilibria are uniform across corporations (Barro & Sala-i-Martin, 2003). Given the literature, I also expect conditional β-convergence.

Next to the lagged firm size, I introduce the solvency ratio denoted by $solv$. In comparison, Guerzoni *et al.* (2024) involves profitability and Becchetti & Trovato (2002) include various measures of financial health (e.g., leverage) and profitability when investigating convergence of companies. As profitability variables are likely endogenous, I introduce the solvency ratio as a proxy for financial health given the lower volatility. In Orbis, the solvency ratio is defined as the share of shareholder funds in total assets. It is multiplied b 100 and ranges between -200 and +200 (Bureau van Dijk, 2007). Like in Geroski & Gugler (2004), the variable is lagged by one year to avoid endogeneity concerns. Overall, I expect that

a higher solvency ratio boosts the growth rate of firm size. Larger investment projects such as power plants require more funds. A financially healthy corporation is more capable to bear such amounts.

Besides, the estimation introduces firm-level fixed effects α_i that control for unobserved time-invariant firm-level heterogeneity (e.g., ownership structure and management, location, etc.). As pointed out by Geroski & Gugler (2004), omitted variables that are correlated with lagged company size are the major problem. Unless not every relevant dimension of unobserved heterogeneity is considered, the OLS estimates will suffer from omitted variable biases (Islam, 1995). In the macroeconometric literature on convergence, fixed effects models serve as a viable option to consider unobserved heterogeneity (Scotti *et al.* , 2022; Esposti & Bussoletti, 2008). Despite their usefulness, firm-level fixed effects are barely involved in the literature analysing Gibrat's law that is discussed in *Section* 1. Hence, introducing firm-level fixed is a first attempt to tackle the problem which is usually ignored in the literature on Gibrat's law, making this study to one of few accouting for this issue. This study is also one of the few studies that control for a wide array of possible drivers of firm growth that are correlated with lagged company size. Particularly, the equation involves nested NUTS2 region-year dummies $D_r \cdot D_t$. They capture all the country-specific determinants that vary across years (e.g., types of regulation systems, European legislation, business cycles etc.) and are likely correlated with lagged firm size. Although they are relevant to avoid omitted variable biases, they are usually not included in the literature mentioned in *Section* 1. Together, firm-level fixed effects and nested country-year dummies capture age, which is found to be an important driver growth (Distante *et al.* , 2018; Evans, 1987a; Jovanovic, 1982) given learning processes.

I follow the other studies and estimate equation (4), treating the lagged firm size as an exogenous variable. One approach to counter omitted variables is to capture them by including firm-level fixed effects and nested dummies. Firm-level fixed effects, however, only control for firm-specific characteristics that are constant over time (e.g., location). Unobserved firm characteristics that vary over time are still not included and can turn the estimation inconsistent (Geroski & Gugler, 2004). To be on the save side, I follow Geroski & Gugler (2004) and estimate equation (4) using 2SLS. Like in this study, firm size lagged by two years is employed as the instrument. Endogeneity will be examined using endogeneity tests to see whether the conventional fixed effects estimation suffers from inconsistency or not.

2.3 Convergence clubs

Both concepts, unconditional and conditional β-convergence, are quite restrictive. Unconditional β-convergence assumes that all companies aim to reach the same steady state. Finally, smaller companies are growing faster than larger enterprises, implying that all enterprises will reach a similar size in the long-run. In comparison, conditional β-convergence does not suppose identical steady states. Nonetheless, conditional β-convergence assumes that disequilibrium responses are identical across firms, i.e.: they are heading towards their steady states at the same speed. Hence, corporations will exhibit similar growth rates in the long-run (Geroski & Gugler, 2004; Barro & Sala-i-Martin, 2003).
Convergence clubs alleviate these restrictive definitions. Convergence clubs are groups of companies that share a similar convergence speed. They can be modelled by examining common drivers of convergence speed (Barro & Sala-i-Martin, 2003; Bernard & Jones, 1996a,b; Dollar & Wolff, 1988; Abramovitz, 1986).

Given the different historic and institutional backgrounds of Eastern and Western European countries described in *Section* 1, convergence will likely differ between these two regions. In comparison to Western European nations, Eastern European countries are less economically developed. After the collapse of the Soviet Union, Eastern European states have transitioned from centrally planned to market economies after the collapse of the Soviet Union. Consequently, they have experienced major institutional changes and liberalisations. Despite the substantial changes in the institutional settings, governments still pervasively influence the formerly state-owned companies in these countries. Especially in the post-communist countries, strong entry barriers aggravated the transition to well-functioning market economies. Furthermore, poorly implemented privatisations established legal monopolies and strengthened market barriers instead of creating open and contestable markets (Buccirossi & Ciari, 2018). Owing to the considerable change in the business environment and the lower level of economic development, Eastern European electricity generators might converge faster than Western European countries, i.e.: the β-coefficient should more negative in Eastern European countries.

To investigate whether Eastern European countries converge faster than Western European countries, I follow the literature and interact the lagged log of firm size with a dummy for electricity generators operating in Eastern European countries. The test whether the effects separately differ from zero, the baseline effect is omitted. In other words, I involve the lag of the logged company size for the Eastern European companies and the log of the logged firm size for the Western European enterprises, as shown in equation (5). The equation is again regressed using conventional fixed effects estimation, treating the lagged logged company size as exogenous variable. Endogeneity will be examined re-estimating equation (3) employing 2SLS. The instruments will be the firm size lagged by two periods, once for the Eastern European countries and once for the Western European nations.

$$\begin{aligned} g_{i,t} &= \frac{s_t - s_{t-1}}{\left(\frac{s_t + s_{t+1}}{2}\right)} \cdot 100\% \\ &= \beta_{east} \cdot log(s_{i,t-1,east}) + \beta_{west} \cdot log(s_{i,t-1,west}) + \delta \cdot solv_{i,t-1} \\ &+ \alpha_i + \sum_{r=1}^{R} \sum_{t=2009}^{2020} \rho_{r,t} \cdot D_r \cdot D_t + \epsilon_{i,t} \end{aligned} \tag{5}$$

3 Results

The following section analyses the relationship between corporate growth and company size graphically and analytically. *Subsection* 3.1 starts by providing summary statistics and visualising the relationship. It is followed by *Subsection* 3.2 that shows the results of the regressions investigating unconditional β-convergence. *Subsection* 3.3 displays the results of the regressions exploring conditional β-convergence, while *Subsection* 3.4 examines the existence of Eastern and Western European growth clubs.

3.1 Descriptive analysis

Table 1 supplies some descriptive statistics of the variables employed in the empirical analysis. It also illustrates the high coverage of smaller firms (e.g., that only have few employees). In Orbis, companies are divided into four groups based on firm size ('small', 'medium sized', 'large' and 'very large'). Slightly more than half of the firms are classified as 'small' companies, while a third is defined as 'medium sized'. Like in manufacturing sectors, electricity generation are increasingly dominated by small and medium sized enterprises. Although electricity generation industries are still highly concentrated, only 15% of the firms are 'large' or 'very large' corporations.

Variable	Unit	Mean (SD)	Min - Med - Max	IQR
Growth rate of real total assets	Percentage points	-4.048 (48.711)	-200.000 < -7.033 < 200.000	12.802
Real total assets	Mill. Euro	26.918 (235.277)	0.000 < 0.617 < 10,392.280	8.741
Growth rate of real operating revenues	Percentage points	4.523 (59.176)	-200.000 < 1.552 < 200.000	33.773
Real operating revenues	Mill. Euro	31.123 (544.459)	0.000 < 0.307 < 41,542.640	1.567
Growth rate of employees	Percentage points	-0.047 (31.609)	-192.195 < 0.000 < 198.901	0.000
Number of employees	Integer	39.496 (285.801)	1.000 < 2.000 < 13,214.000	6.000
Growth rate of real tangible fixed assets	Percentage points	-4.048 (48.711)	-200.000 < -7.033 < 200.000	12.802
Real tangible fixed assets	Mill. Euro	26.918 (235.277)	0.000 < 0.617 < 10,392.280	3.200
Growth rate of real intangible fixed assets	Percentage points	-180.283 (84.484)	-200.000 < -199.635 < 200.000	0.126
Real intangible fixed assets	Mill. Euro	1.614 (29.969)	0.000 < 0.000 < 3,287.086	0.029
Growth rate of real equity	Percentage points	7.341 (46.130)	-200.000 < 2.285 < 200.000	23.124
Real equity	Mill. Euro	25.805 (340.376)	0.000 < 0.412 < 22,537.300	2.194
Solvency ratio	Percentage points	34.264 (35.267)	-100.000 < 28.031 < 100.000	52.437
Dummy Eastern Europe	Binary	0.217 (0.412)	0.000 < 0.000 < 1.000	0.000

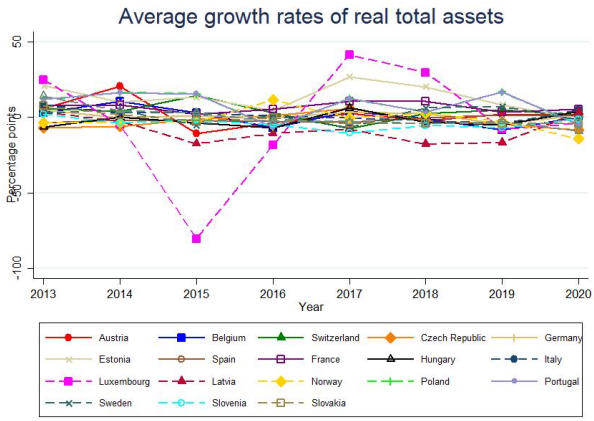
Note: 'Mean' denotes the average, 'SD' the standard deviation, 'Min' the minimum value, 'Med' the median, 'Max' the maximum value, and 'IQR' the interquartile range. Some values are shown to be zero given the rounding. Variance inflation factors (VIFs) are computed manually. In the regressions examining unconditional β-convergence, the single explanatory variable is the logged company size lagged by one year. As it is the single explanatory variable, the VIF always equals one. In the regressions investigating conditional β-convergence, the VIFs are calculated from the within-R2s of fixed effects regressions of each covariate on the other covariate including the nested NUTS2 region-year dummies, and firm-level fixed effects. In relevant regressions, the VIFs vary between 1.086 and 1.269 and, thus, do not suggest multicollinearity.

Table 1: *Descriptive statistics*

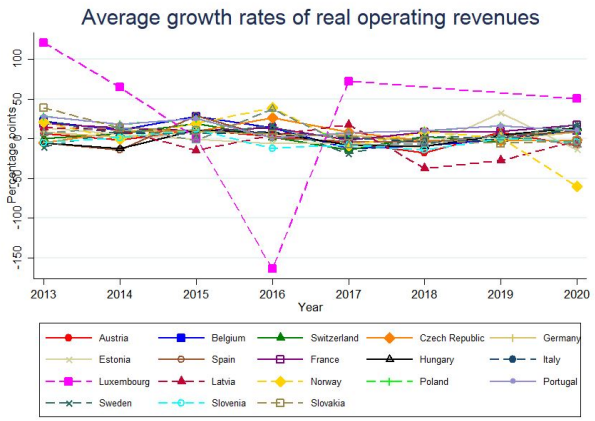
Figure 1 displays the average corporate growth rates by variables across countries and years. In a given year and country, the average corporate growth is the average of the firm-specific growth rates across enterprises. (a) shows the average growth rate of the real total assets, (b) the average growth rate of the real operating revenues, (c) the average growth rate of the number of employees, (d) the average growth rate of the real tangible fixed assets, (e) the average growth rate of the real intangible fixed assets, and (f) the average growth rate of real equity. For most of the proxies for company size, the average growth rates fluctuate between -50 and +50. Only in Luxembourg, average growth rates spot out stronger. In comparison to the other measures of company size, real intangible fixed assets declines on average over time. The reason might be potential losses in goodwill or reductions in R&D.

Figure 2 visualises the average company size by variables across countries and years. Interestingly, Central European companies (Austria, Germany, the Switzerland) and Belgian electricity generators are on average the largest. Except for Germany, relevant countries are small and open economies. This observations is partially in line with Geroski & Gugler (2004). In their study, Swiss and German enterprises are one of the largest. Besides, Austria and Switzerland also cannot access the sea and are located in the Alps. Hence, they cannot use offshore wind power to generate electricity, while the potential of onshore wind power is limited.

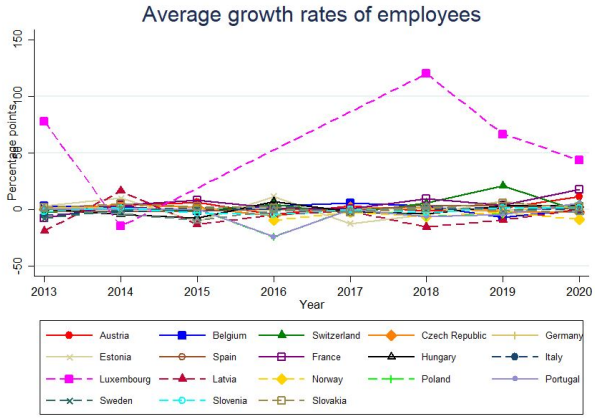
Figure 3 provides histograms illustrating the densities of corporate growth by variables. Like in Geroski & Gugler (2004), the density of corporate growth deviate from the density of the Normal distribution.



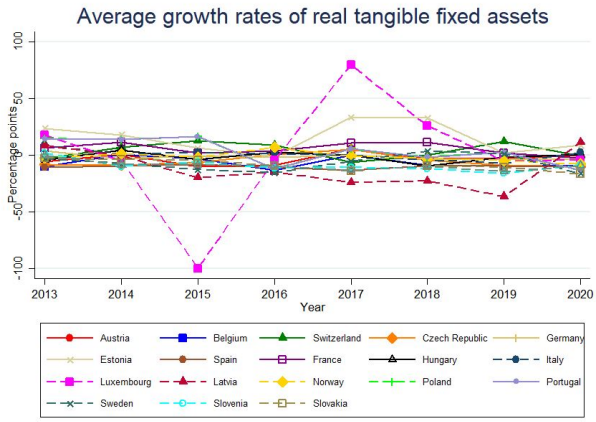
(a) *Real total assets*



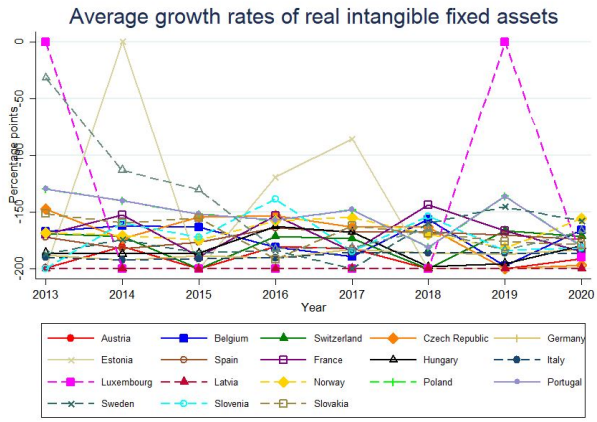
(b) *Real operating revenues*



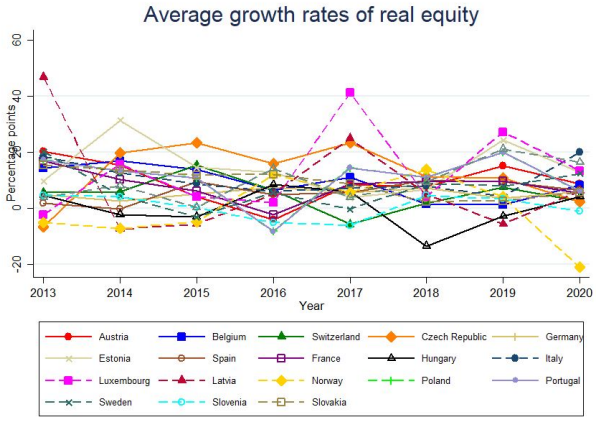
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*

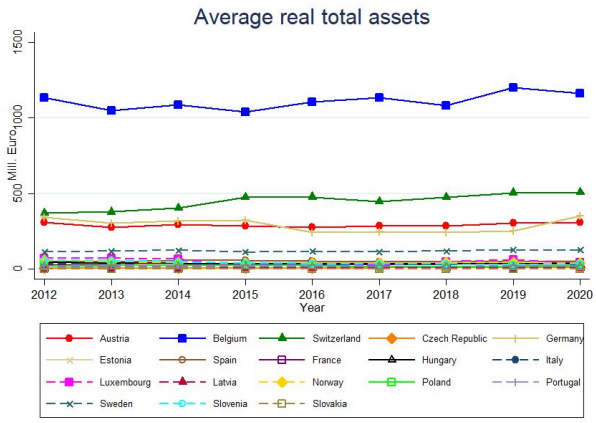


(f) *Real equity*

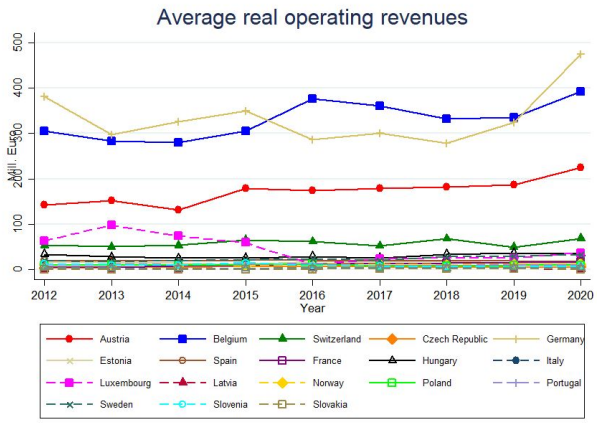
Figure 1: *Corporate growth by variables, countries and years*

Note: The figure shows the average corporate growth rates by variables across countries and years. The mean growth rate in a given country and year is calculated by averaging firm-level growth rates. The figure consists of six subfigures. (a) shows the average growth rate of the real total assets, (b) the average growth rate of the real operating revenues, (c) the average growth rate of the number of employees, (d) the average growth rate of the real tangible fixed assets, (e) the average growth rate of the real intangible fixed assets, and (f) the average growth rate of real equity.

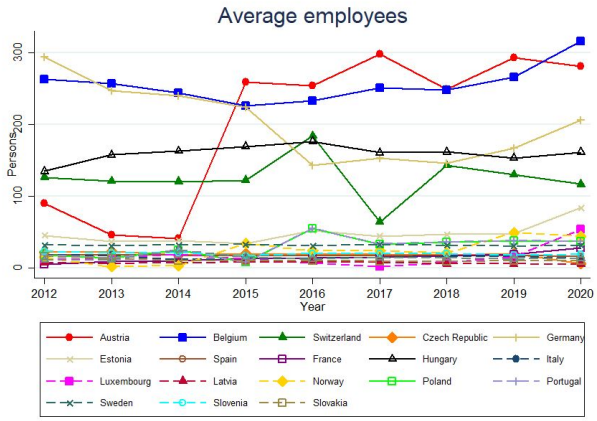
Although observations usually cluster around the mean (red line) and median (blue line), some further



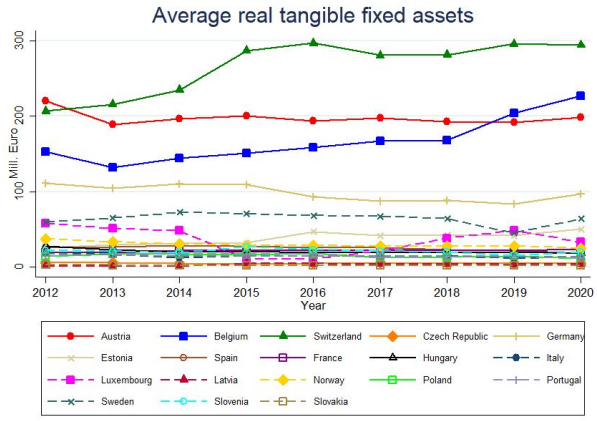
(a) *Real total assets*



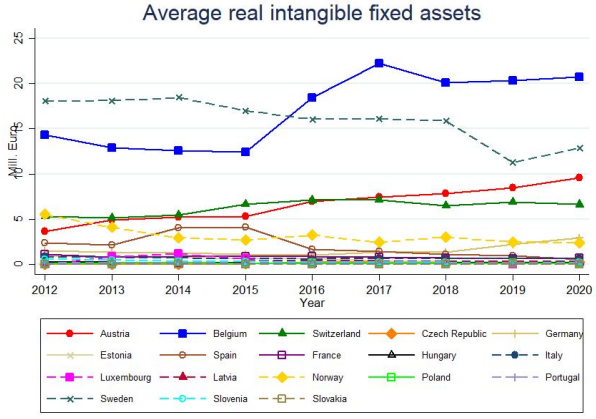
(b) *Real operating revenues*



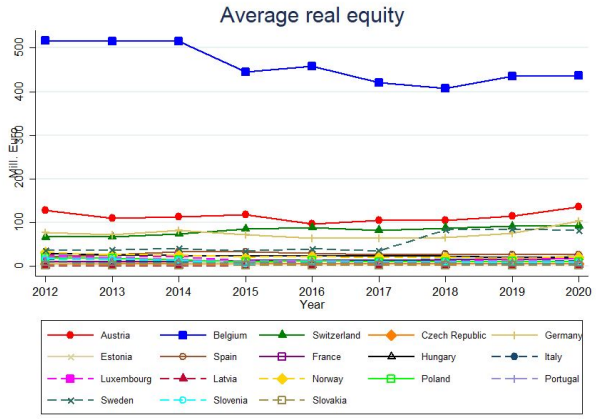
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*



(f) *Real equity*

Figure 2: *Company size by variables, countries and years*

Note: The figure visualises the average company size by variables across countries and years. The mean size in a given country and year is calculated by averaging firm-level company sizes. Again, the figure consists of six subfigures, one for each proxy of company size. (a) shows the average real total assets, (b) the average real operating revenues, (c) the average number of employees, (d) the average real tangible fixed assets, (e) the average real intangible fixed assets, and (f) the average real equity.

observations cluster at the extremes. These blown up tails have more mass than the tails of the Normal distribution's density. Concerning the real intangible fixed asets, *Figure* 3 again reflects what

has already been shown in *Figure* 1, i.e.: the growth rates of real intangible fixed assets are mostly negative and cluster at the negative extreme. Later, in the empirical analysis, the variance of growth processes is analysed by employing quantile regressions. Unlike OLS, quantile regressions do not estimate the conditional mean but quantiles, allowing to evaluate the relationship between corporate growth and company size at different points of the growth distributions. Quantile regression is a valuable tool when analysing data that are not identically distributed (Machado & Mata, 2000). In the case of non-identically distributed data, the impacts of company size on corporate growth likely differ across the different points of the growth distribution. The variation of coefficients is not only due to shifting location along the distribution but also due to scale shifts and asymmetry reversal (Distante *et al.* , 2018). [12]

Some quantiles of corporate growth and how they evolve over time are shown in *Figure* 4. For all the different variables used to quantify corporate growth, the first and third quartile lie close to the mean and median, while the first and ninth decile are farer away. This highlights the quite broad densities provided in *Figure* 3. Since revenues also capture business cycles, the growth rates fluctuate more strongly over time than the other proxies for company size.

One first approach to explore whether electricity generators converge in size is to evaluate σ-convergence. The intuition is that enterprises converge in company size, if the differences in size decline over time. If they do, the standard deviation decreases. In other words, firms become more and more similar in company size. *Table* 2 provides the standard deviations of each proxy for company size over years. The standard deviation of all variables that are more strongly related to the capital side such as the real total assets or equity shrinks over time. In other words, the differences in these variables across European electricity generators become smaller and smaller. This result suggests σ-convergence in these variables. Conversely, the standard deviation of the number of employees and real revenues declines and grows again. As the differences decline and grow over time, there is no σ-convergence in these variables. One reason might be the volatility of relevant variables. Revenues are usually volatile and respond to business cycles. Besides, labour is a more flexible input than capital (Geroski & Gugler, 2004). Therefore, employment can be adjusted more quickly to respond to demand shocks (Carlsson *et al.* , 2021).

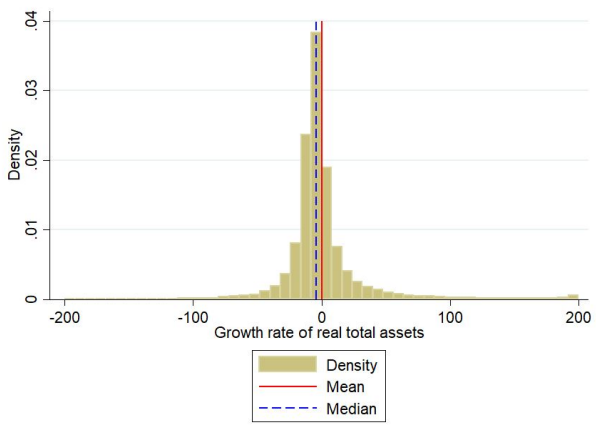
The table displays σ-convergence, which is a first evidence against Gibrat's law, since Gibrat's law requires standard deviations of corporate size to rise over time (Pfaffermayr, 2007).

3.2 Unconditional β-convergence

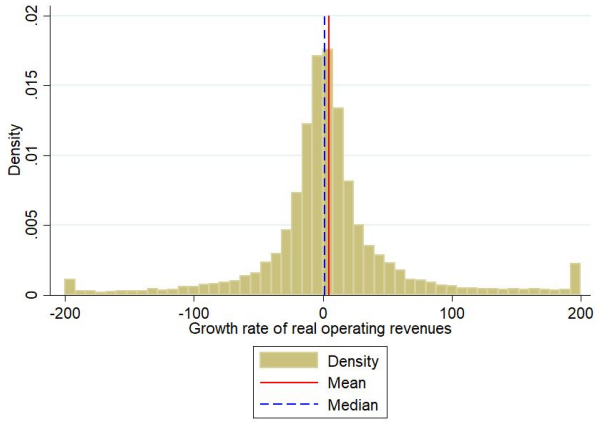
3.2.1 OLS estimation

The analysis is performed as outlined in *Section* 2.1. To investigate unconditional β-convergence, the growth rate of firm size is regressed only on the logged company size lagged by one year using OLS, as shown in equation (1). *Table* 3 displays the result. In column (1), the real total assets approximate for firm size, i.e.: in this regression, the growth rate of the real total assets is regressed on the logged real total assets lagged by one year. In columns (2)-(6), the real operating revenues, number of employees,

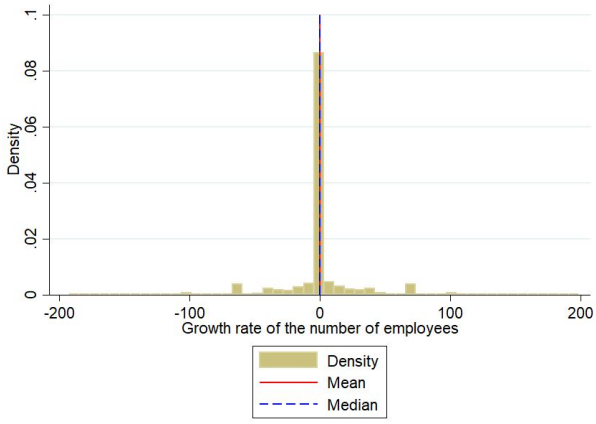
[12] 'Scale shifts' mean that the degree of dispersion changes, while 'asymmetry reversal' means the change in the sign of the skewness of the density (Distante *et al.* , 2018).



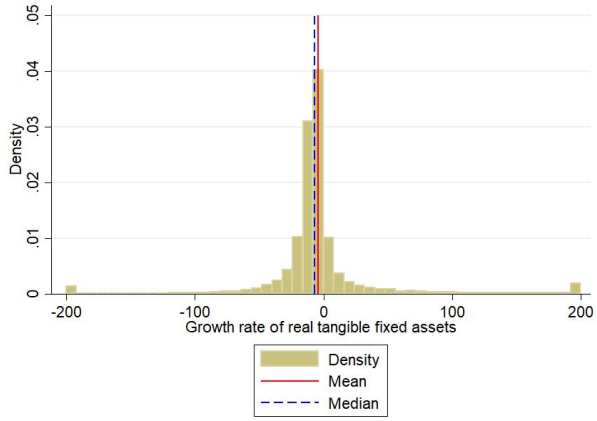
(a) *Real total assets*



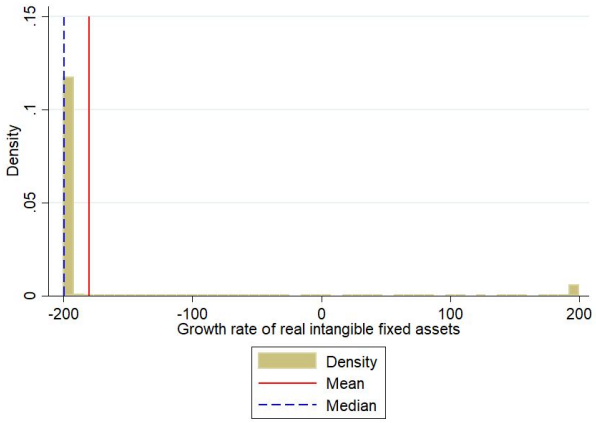
(b) *Real operating revenues*



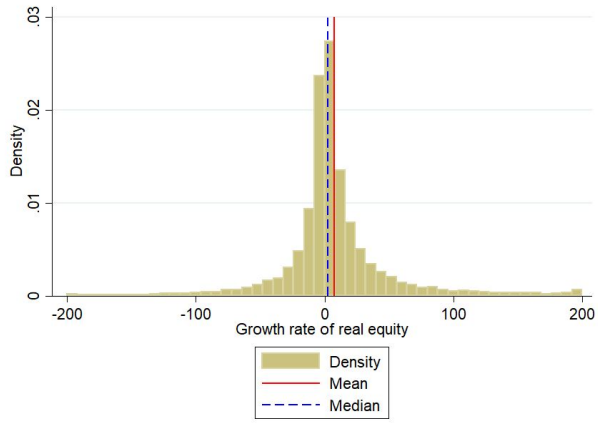
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*



(f) *Real equity*

Figure 3: *Densities of corporate growth by variables*

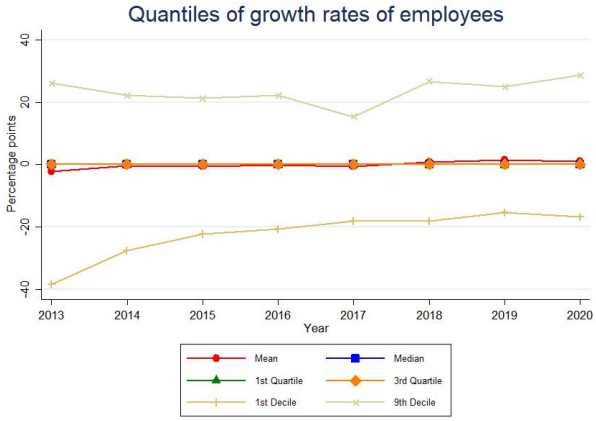
Note: The figure provides histograms showing the density of each proxy for company size. Again, the figure consists of six subfigures, one for each proxy of company size. (a) shows the density of real total assets, (b) the density of real operating revenues, (c) the density of number of employees, (d) the density of real tangible fixed assets, (e) the density of real intangible fixed assets, and (f) the density of real equity. The mean of the variable is shown by the solid red line. The median is represented by the dashed blue line. All the densities deviate from the Normal distribution's density, since the tails have a higher mass.



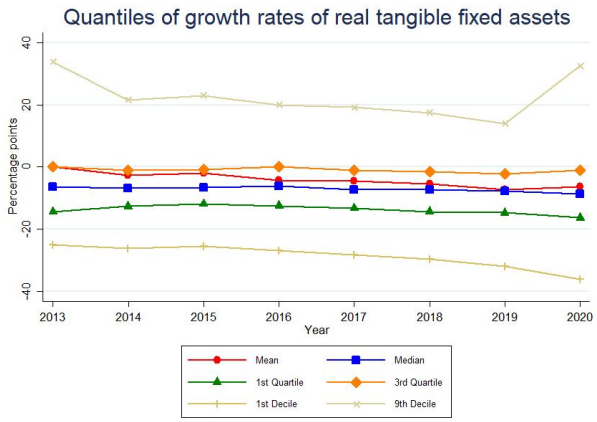
(a) *Real total assets*



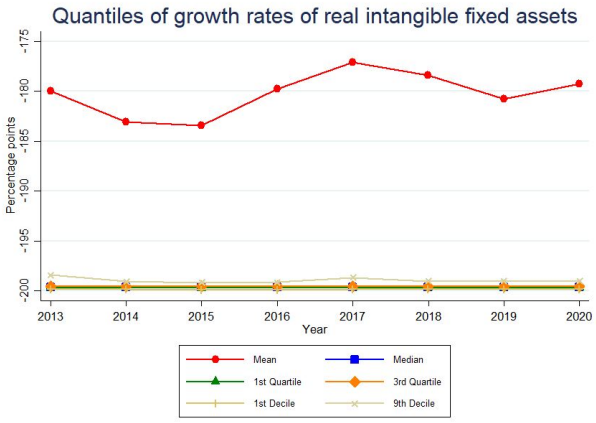
(b) *Real operating revenues*



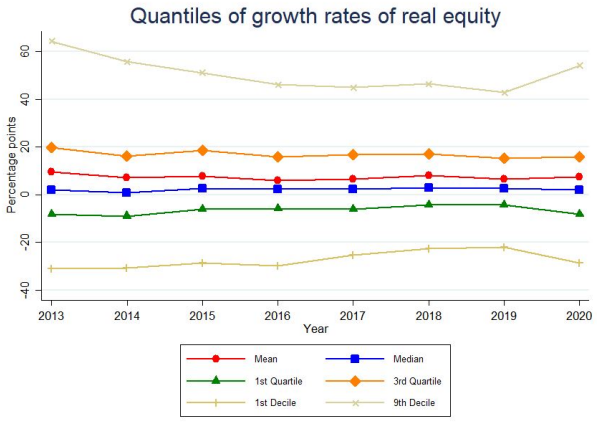
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*



(f) *Real equity*

Figure 4: *Quantiles of corporate growth by size variables and years*
Note: The figure displays the mean, median, first and third quartile, and first and ninth decile of corporate growth rates over time. The statistics are displayed for each proxy for company size. (a) shows the statistics of the real total assets, (b) the statistics of the real operating revenues, (c) the statistics of the number of employees, (d) the statistics of the real tangible fixed assets, (e) the statistics of the real intangible fixed assets, and (f) the statistics of the real equity.

real tangible and intangible fixed assets, and real equity quantify corporate size. The rows in the first part of the table provide the estimates for the β-coefficient and the intercept, while the middle part

	Real total assets	Real operating revenues	Employees	Real tangible fixed assets	Real intangible fixed assets	Real equity
2012	928.828	576.978	358.088	274.840	27.023	369.852
2013	859.790	495.885	317.013	265.499	24.575	372.708
2014	855.891	508.737	299.641	245.258	46.199	384.515
2015	851.400	581.674	277.490	249.866	48.396	369.918
2016	828.100	529.658	218.452	241.700	25.606	345.416
2017	810.536	504.219	266.735	231.717	23.566	310.034
2018	744.856	533.942	264.129	217.099	21.249	305.891
2019	776.444	597.004	285.268	191.163	17.289	310.774
2020	701.261	565.872	278.082	180.611	16.090	279.323

Note: The table shows the annual standard deviations of each variable used as a proxy for company size. In each year, the standard deviation of a given variable across enterprises is calculated. All variables are measured in million Euro and so is the standard deviation. Only, the number of employees is an integer. Its standard deviations have to be interpreted accordingly.

Table 2: *σ-convergence*

shows the estimates for the speed of convergence and half-life. The last part of the table supplies the numbers of observations and companies, and adjusted R^2. In all columns, standard errors are clustered at the firm-level.

Overall, the results suggesting unconditional β-convergence. In almost all columns, the lagged logged corporate size significantly reduces company size. Hence, smaller enterprises grow faster than larger ones. Thus, Gibrat's law is clearly rejected, as corporate growth is not independent of company size. Overall, this conclusion supports the vast majority of studies that rejects Gibrat's law (Axioglou & Christodoulakis, 2021; Arouri *et al.* , 2020; Daunfeldt *et al.* , 2012; Cefis *et al.* , 2007; Audretsch & Elston, 2006; Calvo, 2006; Dunne & Hughes, 1994; Dunne *et al.* , 1989; Evans, 1987a,b; Hall, 1987). This conclusion is also plausible due to the continuing integration of electricity markets. The β-coefficient is only insignificant in column (4). Only in this column, Gibrat's law is supported. Given the linear-log specification, the β-coefficients are interpreted as semi-elasticities. If the company is by 1% larger, firm growth significantly declines by 0.005-0.036% depending on the measure of corporate size. The growth rate of the real tangible fixed assets does not respond. Besides, the magnitudes are perfectly in line with Geroski & Gugler (2004). The number of years until the distance to the steady state is halved varies between 19 and 127 years. Plausibly, the estimated half-life of the real intangible fixed assets is higher, since developing new technologies requires time. The estimtes are also consistent with macroeconomic studies, especially with the lower half of the estimates by the analysed studies examined in the meta-analysis by Abreu *et al.* (2005). [13]

3.2.2 Endogeneity of lagged company size

To preserve space, I only present the results of the OLS regression. Nevertheless, I check whether the logged firm size lagged by one year is endogenous by applying 2SLS. As in Geroski & Gugler (2004), I instrument the this variable by the logged company size lagged by two years. In the first stages, the instrument has a highly significant positive effect. Particularly, the t statistic of the instrument exceed

[13] For a brief overview, see *Table* 1 in Abreu *et al.* (2005)

	Real total assets	Real operating revenues	Employees	Real tangible fixed assets	Real intangible fixed assets	Real equity
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{firm size}_{t-1}$	$-2.317***$	$-3.553***$	$-2.033***$	0.232	$-0.542***$	$-3.391***$
	(0.120)	(0.153)	(0.140)	(0.144)	(0.078)	(0.117)
Intercept	$1.465***$	$-0.653**$	$2.001***$	$-6.346***$	$-196.550***$	$4.796***$
	(0.253)	(0.273)	(0.270)	(0.238)	(0.376)	(0.241)
Speed	0.023	0.036	0.021	-0.002	0.005	0.034
Half-life	23.569	19.158	33.742	-298.919	127.453	20.095
Observations	44785	41961	22113	41338	19720	38343
Units	6925	6806	5166	6641	3736	6356
Adjusted R-squared	0.023	0.028	0.010	0.000	0.014	0.036

Note: In each regression, corporate growth is regressed on company size only, including the intercept. In column (1), company size is measured using the real total assets. In column (2), company size is quantified employing the real operating revenue. The number of employees serves as the measure in column (3). The real tangible fixed assets are used in column (4), the real intangible fixed assets in column (4), and real equity in column (6). All standard errors, in parenthesis, are clustered at the firm-level to overcome residual serial correlation. The top part of the table displays the coefficients, the middle part provides the estimates for the speed of convergence and half-life. The number of observations and firms, and the adjusted R^2 are supplied at the bottom of the table.

*p<0.1; **p<0.05; ***p<0.01

Table 3: *OLS regressions of corporate growth on firm size examining unconditional β-convergence*

three, suggesting that the instruments are sufficiently strong (Stock *et al.* , 2002; Staiger & Stock, 1997). [14] In general, the second-stage coefficients grow. While the effect of lagged firm size on company growth is still significantly negative in the regressions quantifying size using the real total assets, intangible fixed assets and equity, the impacts in the regressions employing real operating revenues, real tangible fixed assets, and the number of employees as proxies for company size turn insignificant. Thus, half of the measures of company size support Gibrat's law, while the other half rejects it. Almost all studies involve the lagged corporate size as an exogenous variable. To investigate whether this assumption should be too restrictive, endogeneity tests are performed. Since the p-values of all tests, except for the regression in which company size is measured using the number of employees, exceed 0.05, endogeneity can be rejected (Wooldridge, 2010). Hence, the conclusion supports this assumption imposed in the literature, implying that the lagged corporate size can be treated exogenously.

3.2.3 Role of MES

One reason why studies reject Gibrat's law or find mixed results might be the MES. Gibrat's might only hold for companies that are larger than the MES, as smaller corporations are forced to grow faster to become more competitive (Strotmann, 2007; Mansfield, 1962). The literature proposes various ways to approximate for the MES. The most prominent proxies are the size of the industries' median plant and the share of this plant's output in industry output (Sutton, 1991). To investigate whether Gibrat's law holds for companies larger than the MES, I split the sample into two partitions: firms larger than the MES, and companies smaller than the MES (Tang, 2014; Mansfield, 1962). Like Tang (2014), a dummy for firms larger than the MES is constructed. In a given year t, this dummy equals one, if firm

[14] According to Staiger & Stock (1997), the instruments are sufficiently strong in case of one endogenous variable and one instrument, if the t statistic exceeds three.

i's size is larger than the country median in this year $\mu_{c,t}$, and is zero otherwise.

$$AboMES_{i,t} = \begin{cases} 1 & \text{if } s_{i,t} \geq \mu_{c,t} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

The country median in a given year t is the median of firm-level corporate size in a given country c in this year.

$$\mu_{c,t} = Med_{c,t}[s_{i,t}] \tag{7}$$

Then, I follow Mansfield (1962) and rerun the OLS regression of equation (1) separately for each partition: one regression for the firms that were larger than the MES in the previous year, and one regression for the companies smaller than the MES in the previous year. [15] β-coefficients are compared across partitions to explore whether larger or smaller enterprises converge faster. The results support the argument by Mansfield (1962) to some degree. Particularly, both groups show significantly negative β-coefficients. Besides, the coefficients of enterprises smaller than the MES are more negative than those the of corporations larger than the MES. [16] Hence, companies smaller than the MES converge faster than firms larger than the MES. As expected, corporate growth depends on company size in every partition. Summing up, there is a relationship between corporate growth and company size among electricity generators smaller and larger than the MES, while the relationship is stronger among the enterprises smaller than the MES, supporting my hypothesis. Although some studies such as Guerzoni *et al.* (2024) conclude that Gibrat's law might hold for large enterprises, I find evidence that this claim does not apply to the European electricity generation sector. Next to the possibly still high MES, another reason may be the concave relationship between productivity and corporate size. Although the impact of firm size on technical efficiency diminishes over corporate size, it is still positive for larger enterprises (Steinbrunner, 2024). Thus, larger companies can improve their productivity when growing larger. The resulting productivity growth might provide additional funds that can be invested, increasing size. Consequently, there will also be a relationship between corporate size and growth among the larger companies. Another reason might be fiercer competition. Competition intensified due to the liberalisation (Meletiou *et al.* , 2018), spurring the entry by smaller companies. Given the fiercer competition, larger companies are forced to grow faster, which also establishes a relationship between corporate growth and size. The results are robust when approximating for the MES using the annual country-specific averages of firm size.

3.2.4 Variance of growth processes

An interesting generalisation of Gibrat's law is the model by Córdoba (2008). As Gibrat (1931) suggests, the average growth process is independent of company size. Company size, however, influences the variance of the growth process. In other words, the effect of corporate size on growth depends

[15] Note that the dummy for being larger than the MES is lagged by one period to avoid endogeneity.
[16] The only exceptions are the regressions that employ tangible and intangible fixed assets as measures for corporate size. In relevant regressions, the coefficients are insignificant.

on the value of the growth rate, i.e.: the impact may be more pronounced for fast or slowly growing companies. Nevertheless, the impact is zero at the mean. Testing this theory has gained importance due to the growing macroeconomic literature investigating the influence of firm-specific shocks on aggregate fluctuations. It shows that firm-specific idiosyncratic shocks may not wash out in the aggregate, driving aggregate fluctuation (Carvalho & Grassi, 2019; Gabaix, 2011; Luttmer, 2010). To explore whether the generalised version of Gibrat's law by Córdoba (2008) is supported, equation (1) is regressed using quantile regression (Distante *et al.* , 2018; Lotti *et al.* , 2003). The regressions model all percentiles from 1 to 99.

Figure 5 displays the estimated β-coefficients across quantiles and measures for company size. (a) illustrates the impacts of size on growth predicted by the regression that quantifies firm size using the real total assets. (b) visualises the estimated β-coefficients of the regression that defines company size using the real operating revenues etc. The estimated coefficients are again interpreted as semi-elasticities. In four out of six plots, the impacts of firm size on growth start at positive values, declining over percentiles, and finally turn negative. When β-coefficients are positive, size is an advantage. As a result, firms diverge in size at relevant points in the growth distribution. [17] When the β-coefficients are negative, size is a disadvantage, since it slows corporate growth. Consequently, electricity generators converge at relevant points in the growth distribution. This result is perfectly in line with the literature (Distante *et al.* , 2018; Lotti *et al.* , 2003). This behaviour is in line with the observation by Fama & French (2000) who find a similar pattern of competitive convergence when analysing corporate profitability. According to Fama & French (2000), this property is a necessary condition for long-run convergence of firms within and between competitive sectors. Given competition, companies develop new products, mimic successful products and reallocate resources to grow, avoid bankruptcy and takeover. Finally, this competitive behaviour by smaller companies deteriorates the larger firm's profitability (Distante *et al.* , 2018; Fama & French, 2000).

As shown in (c) and (e), the number of employees and real intangible fixed assets do not show declining β-coefficients. In (c), β-coefficients are negative at the tails of the growth distribution, while effects are close to zero in the middle. One reason might simply be the fact that unconditional β-convergence is examined by regressing growth only on size omitting other variables. In contrast to capital, labour is a more flexible input (Geroski & Gugler, 2004). Indeed, firm-level employment strongly responds to demand shocks (Carlsson *et al.* , 2021). Therefore, employment as a measure for corporate size will capture short-run business cycle shocks. When not including them, estimated coefficients will be biased. In (e), the estimated impacts of the real intangible fixed assets fluctuate around zero before starting to decline sharply after the 8^{th} decile. The reason may be that larger companies may be more capable to invest in R&D than smaller ones that might lack funds.

Summing up, company size influences the variance of the growth process as in the generalised version of Gibrat's law by Córdoba (2008). Nevertheless, the generalised version of Gibrat's law is still rejected, since company size significantly influences the average growth process, as shown in *Table* 3. At particular points in the growth distribution, size can be advantage, as it boosts corporate growth. Hence,

[17] Concerning the real total assets, the effect switches sign around the median as in Distante *et al.* (2018). In the regressions quantifying company size using the real operating revenues and real equity, the coefficients become negative around the 30^{th} percentile. As revealed in (d), the impact of the lagged logged real tangible fixed assets switches sign at the seventh decile. The coefficient is positive over a wide range of the growth distribution, which is the reason why its effect is insignificantly positive when investigating unconditional β-convergence using OLS in *Table* 3, when examining endogeneity and when analysing the role of MES. Hence, this variable supports Gibrat's law in all specifications.

enterprises diverge at relevant points in the growth distribution. At other points, size slows corporate, implying that corporations converge in size at relevant points. This result is especially interesting to policy makers. Particularly, it suggests policy makers to support larger companies that are growing slower. This can spark their growth, possibly boosting industry growth. For instance, policy makers could facilitate getting building permits. Note that larger players could be among these companies. If this is the case, then limited resources would be reallocated from smaller to larger electricity generators, possibly fostering market concentration.

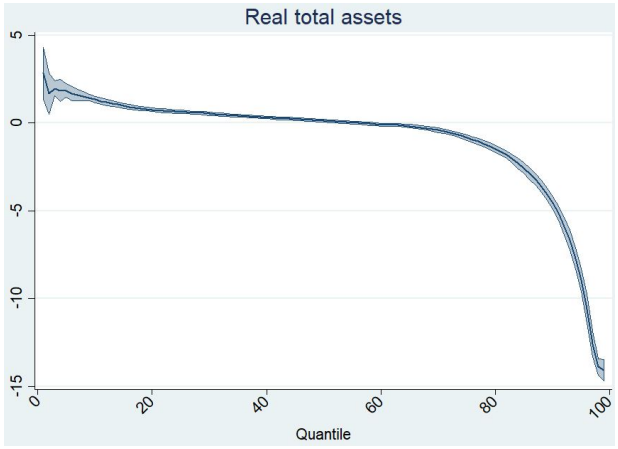
3.3 Conditional β-convergence

3.3.1 Fixed effects estimation

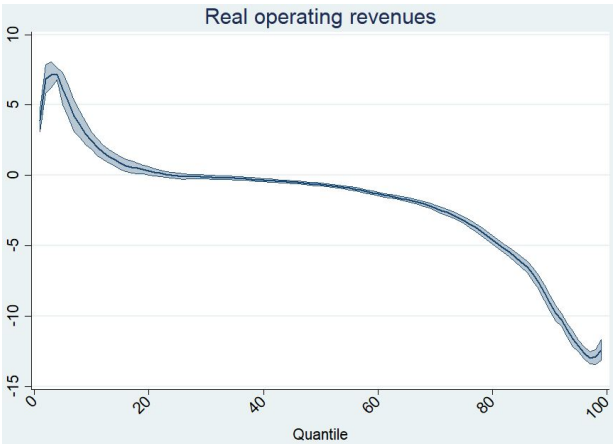
Table 4 supplies the results of the estimation of equation (4). Relevant regressions delve into conditional β-convergence, where companies strive for their individual steady state. The heterogeneity of long-run equilibria is accounted for by including firm-level solvency ratios, firm-level fixed effects and nested country-year dummies. The equation is regressed using fixed effects estimation treating the logged corporate lagged by one year as an exogenous variable.

In comparison to *Table* 3, the β-coefficients' magnitudes increase considerably. Overall, they are still in line with Geroski & Gugler (2004). Besides, all of them including the one of the lagged logged real tangible fixed assets are significantly negative. Thus, conditional β-convergence can be observed for every measure of corporate size. In other words, companies that lie farer away from their steady states grow relatively faster than enterprises that are closer to their long-run equilibria. The β-coefficients are again interpreted as semi-elasticities, i.e.: if the company has been by 1% larger in the previous year, the corporate growth significantly declines by 0.039-0.429%. These observations highlight the importance of involving firm-level fixed effects. By allowing the steady states to differ across firms, they help capture omitted variables that bias the β-coefficients in regressions exploring unconditional β-convergence.

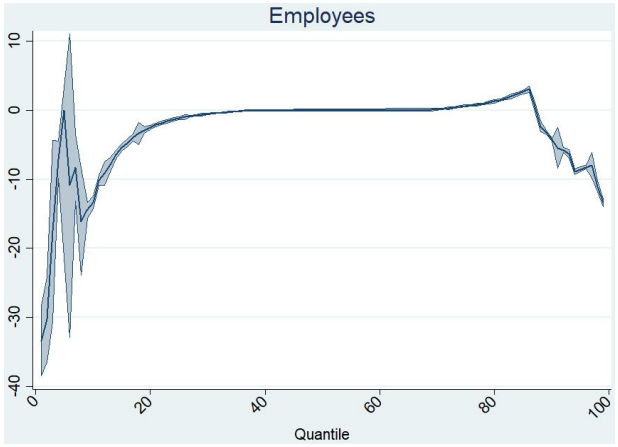
Financial soundness as quantified by the solvency ratio shows ambiguous effects. On the one hand, financial soundness significantly accelerates the growth of real total and tangible fixed assets because it improves the capability to finance investment. On the other hand, the growth rate of the real operating revenues and real equity respond significantly negative. Given the linear-linear specification, the coefficients are interpreted as usual. If the lagged solvency ratio rises by one percentage point, firm growth changes by -0.299-+0.085 percentage points. The negative impact on the growth rate of the real operating revenues might be due to risk. The solvency ratio is related to the leverage. If the solvency ratio, the share of shareholder funds in total assets, improves, there will be more equity relatively to borrowed capital. Hence, the leverage, which is ratio of long-term debt in equity and serves as a measure for financial pressure, will decline (Nakatani, 2023; Hanousek *et al.* , 2015; Nickell & Nicolitsas, 1999; Lichtenberg & Siegel, 1990). According to the free cashflow theory by Jensen (1986), corporate debt spurs enterprises to produce more efficiently. The implied interest payments on the borrowed capital force the management to improve corporate efficiency. As managers focus more strongly on profit maximisation and, therefore, act in the interest of the owners, principal-agent problems are weakened. Hence, shareholders prefer issuing debt over shares. This might also explain why the growth rate of real equity significantly declines. If a larger part of the company's capital is



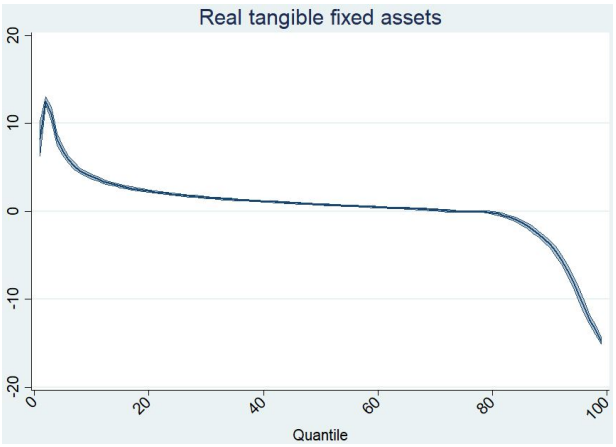
(a) *Real total assets*



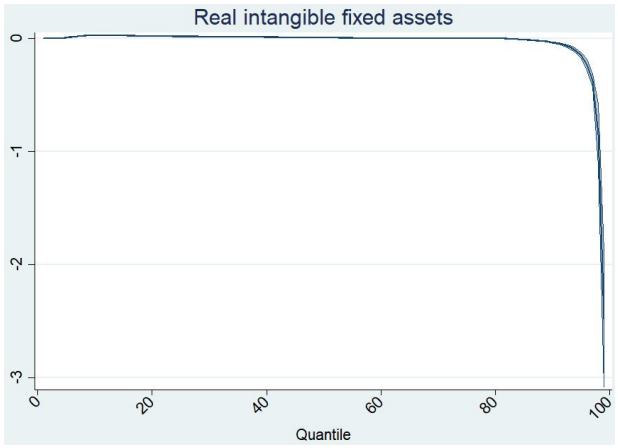
(b) *Real operating revenues*



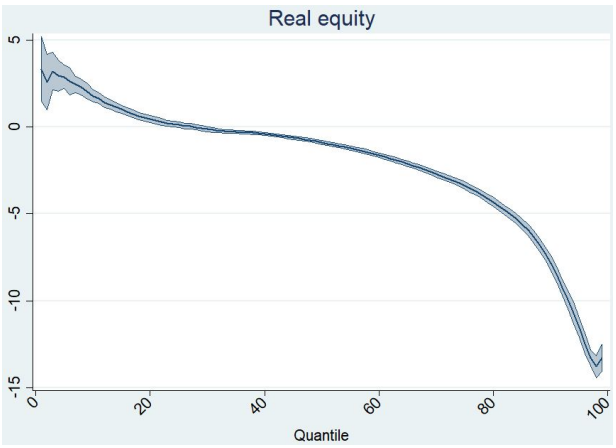
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*



(f) *Real equity*

Figure 5: *β coefficients in model examining unconditional β-convergence estimated using quantile regression*

supplied by shareholders, the shareholders may require managers to issue debt instead of additional equity, slowing the growth of equity.

	Real total assets	Real operating revenues	Employees	Real tangible fixed assets	Real intangible fixed assets	Real equity
	(1)	(2)	(3)	(4)	(5)	(6)
log(firm size$_{t-1}$	−24.899***	−26.426***	−42.871***	−18.066***	−3.893***	−28.508***
	(0.772)	(0.885)	(1.396)	(0.815)	(0.474)	(0.772)
solvency ratio$_{t-1}$	0.062***	−0.299***	0.021	0.085***	0.002	−0.268***
	(0.018)	(0.030)	(0.024)	(0.024)	(0.011)	(0.030)
Speed	0.286	0.307	0.560	0.199	0.040	0.336
Half-life	2.421	2.259	1.238	3.479	17.456	2.065
Firm-level fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Nested NUTS2 region-year dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	43988	41303	21554	40796	19549	38327
Units	6925	6756	5081	6596	3715	6355
Within R squared	0.302	0.312	0.317	0.174	0.157	0.300

Note: In each regression, corporate growth is regressed on company size, the solvency ratio, firm-level fixed effects, and nested NUTS2 region-year dummies. In column (1), company size is measured using the real total assets. In column (2), company size is quantified employing the real operating revenue. The number of employees serves as the measure in column (3). The real tangible fixed assets are used in column (4), the real intangible fixed assets in column (4), and real equity in column (6). All standard errors, in parenthesis, are clustered at the firm-level to overcome residual serial correlation. The top part of the table displays the coefficients, the middle part provides the estimates for the speed of convergence and half-life. The number of observations and firms, and the within R^2 are supplied at the bottom of the table. As can be seen from the table, the introduction of firm-level fixed effects and nested NUTS2 region-year dummies considerably influences the magnitude of the coefficients. Particularly, estimated β-coefficients become more negative. This highlights their importance to avoid omitted variable biases.

*p<0.1; **p<0.05; ***p<0.01

Table 4: *Fixed effects regressions of corporate growth on firm size examining conditional β-convergence*

3.3.2 Endogeneity of lagged company size

When re-estimating the equation with 2SLS instrumenting the lagged logged corporate size with its value lagged by two years, the results barely change. In all regressions, company size significantly decreases corporate growth. Additionally, the instrument passes both, the underidentification test and weak identification test, in all regressions. [18] Moreover, the endogeneity tests generally suggest the potentially endogenous lagged logged corporate size to be exogenous. Only in the regressions in which corporate size is quantified using real operating revenues and employment, lagged firm size is endogenous. Hence, this conclusion generally supports the empirical literature that involves the lagged company size as an exogenous variable.

3.3.3 Role of MES

Like in the model examining unconditional β-convergence, corporate growth of both types of firms, enterprises larger and smaller than the MES, depends on company size. As size also influences the growth of firms larger than the MES, the hypothesis that Gibrat's law holds for large enterprises is again violated.

Concerning the definition of the MES using the average firm size, the impacts on the companies larger and smaller than the MES do not significantly differ mostly. Only in the regressions that quantify company size using the number of employees and the real intangible fixed assets, larger enterprises converge significantly slower than small companies. In comparison, the regression in which the MES are approximated using the median company size show more significant differences. In the regressions that quantify company size using the number of employees and real equity, larger enterprises converge

[18] The critical values by Stock-Yogo have to be interpreted with caution, as they actually refer to Cragg-Donald Wald F statistic that assumes i.i.d. errors and can only be tabulated for up to three endogenous variables (Baum *et al.* , 2007).

significantly faster than smaller corporations. In contrast, in the regression that quantify company size using the real operating revenues and real tangible fixed assets, larger electricity generators converge significantly faster than smaller ones.

3.3.4 Variance of growth processes

So far, an important conclusion is that involving firm-level fixed effects considerably helps avoid omitted variable biases. When accounting for unobserved firm-specific heterogeneity, corporate growth is found to respond more strongly to lagged company size. Another important conclusion is that firm size influences the variance of growth processes as suggested by Córdoba (2008). At particular points in the growth distribution, size is advantageous, as it accelartes corporate growth. Thus, electricity generators diverge in size at these points in the distribution. At other points, size is a disadvantage, since it slows corporate growth. At relevant points in the distribution, enterprises converge in size. In other words, both, convergence and divergence, can be observed along the growth distribution (Distante *et al.* , 2018; Lotti *et al.* , 2003). Despite the influence of size on the variance of the growth process, the generalised version of Gibrat's law by Córdoba (2008) is rejected. The reason is that the average growth process significantly depends on the company size. This conclusion opposes the results of the studies examining the generalised version of Gibrat's law (Distante *et al.* , 2018; Lotti *et al.* , 2003), since this studies either support or partially support it.

Owing to these important lessons, I re-perform the quantile regressions. In comparison to the conventional quantile regression conducted in *Section* 3.2.4, I introduce firm-level fixed effects. To cover firm-level fixed effects in the quantile regressions, I apply the algorithm by Machado & Santos Silva (2019). Since this method has been recently developed, no study investigating the generalised version of Gibrat's law by Córdoba (2008) controls for unobserved heterogeneity across companies. In other words, this is the first study that applies this newly developed method to analyse the generalised version Gibrat's law. Next to including firm-level fixed effects, I also introduce the nested NUTS2 region-year dummies as fixed effects.

As company size is observed to reduce firm growth more strongly when accounting for firm-specific unobserved heterogeneity, the variance of the growth process may considerably change because of accounting for omitted variables. As the estimated β-coefficients tend to shrink when involving unobserved heterogeneity and other drivers of corporate growth, the estimated β-coefficients in the quantile regressions may also shrink when controlling for these drivers. Finally, all coefficients could turn negative. In this case, company size would never be an advantage, as it always slows corporate growth. Thus, electricity generators would converge along the entire growth distribution. Policy makers should target smaller companies given their faster growth. Supporting them helps them catch up with the big players, which could also reduce market concentration. Hence, limited resources should primarily target smaller electricity generators (e.g., feed-in tariffs and investment subsidies that favour smaller firms). Nevertheless, policy makers should not completely forget about the larger companies. Since results and policy recommendations could substantially change, updating the estimated β-coefficients is highly needed.

Note that involving fixed effects in quantile regressions does not provide consistent estimates. The reason is that means only go through linear functions but not through non-linear functions. Given

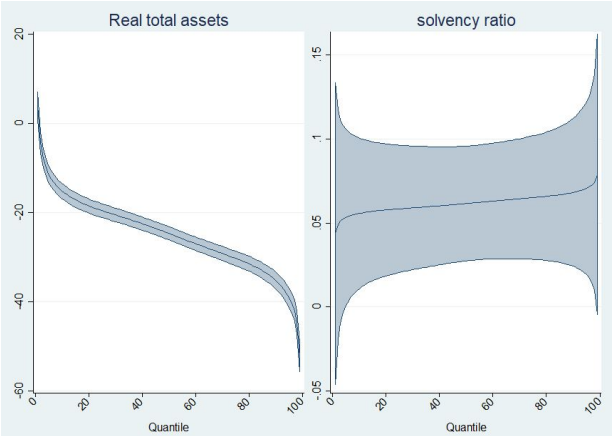
the non-linearity of the equations estimated using quantile regressions, the demeaning does not perfectly eliminate the unobserved heterogeneity, resulting in inconsistent estimates (Machado & Santos Silva, 2019; Wooldridge, 2010). Despite this issue, updating the estimates for the β-coefficients is highly needed, since the variance of the growth process could change considerably due to the omitted variables.

The results are provided in *Figure* 6. The figure consists of six subfigures numbered from (a) to (f). Like in *Figure* 5, (a) illustrates the impacts of size on growth predicted by the regression that quantifies firm size using the real total assets. (b) visualises the estimated β-coefficients of the regression that defines company size using the real operating revenues etc. Each subfigure shows two plots. The left one displays the estimated β-coefficients across percentiles, while the right one supplies the coefficients of the solvency ratio across percentiles. The estimated β-coefficients are again interpreted as semi-elasticities. Like in *Section* 3.2.4, the variance of the growth process responds to company size (Distante *et al.* , 2018; Lotti *et al.* , 2003). Nevertheless, the generalised version of Gibrat's law is still rejected, as the average growth process significantly responds to company size, as shown in *Table* 4. As expected, the β-coefficients shrunk considerably given the consideration of unobserved heterogeneity and other drivers of corporate growth. This suggests that the literature's estimates are biased upwards. Although the impact of company size on corporate growth declines across percentiles like before, the estimated β-coefficients are negative along almost the entire growth distribution. Hence, companies converge in size at almost every point of the growth distribution, implying that company size is almost always disadvantageous. These results completely oppose the literature that does not account for omitted variables (Distante *et al.* , 2018; Lotti *et al.* , 2003). These studies observe both, divergence and converge. Overall, I observe convergence along almost the entire distribution. Along almost the entire growth distribution, smaller electricity generators catch up with the larger ones. Hence, policy makers should especially target small firms to boost their growth and help them catch up. For instance, regulations could favour small generators (e.g., feed-in tariffs, investment and R&D subsidies) and encourage entry by fostering liberalisation and vertical disintegration. This results in a stronger reallocation of resources to smaller companies.

Concerning the solvency ratio, the results support the conclusions drawn from the conventional fixed effects regressions. The solvency ratio significantly accelerates the growth rates of the real total assets and real tangible fixed assets, while the growth rates of real operating revenues and real equity significantly decline. In comparison, the number of employees and real intangible fixed assets do not respond significantly.

3.4 Convergence clubs

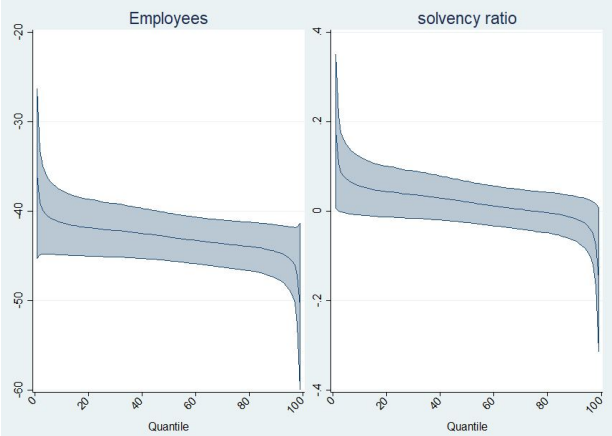
One interesting aspect is whether the speed of convergence differs across particular groups of enterprises. Given the different historic and institutional backgrounds and changes (Buccirossi & Ciari, 2018), and the resulting different levels of economic development, the speed of convergence may differ across Eastern and Western European countries. *Table* 5 supplies the results of the regressions of equation (5) that investigate this issue. In all equations, the β-coefficients are more negative in Eastern European countries. In other words, Eastern European electricity generators converge faster than Western European ones, which is plausibly due to lower level of economic development and the considerable institutional changes. The β-coefficients are again interpreted as semi-elasticities. If an



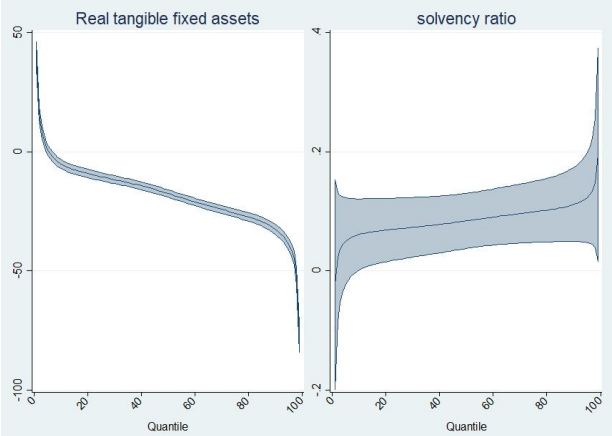
(a) *Real total assets*



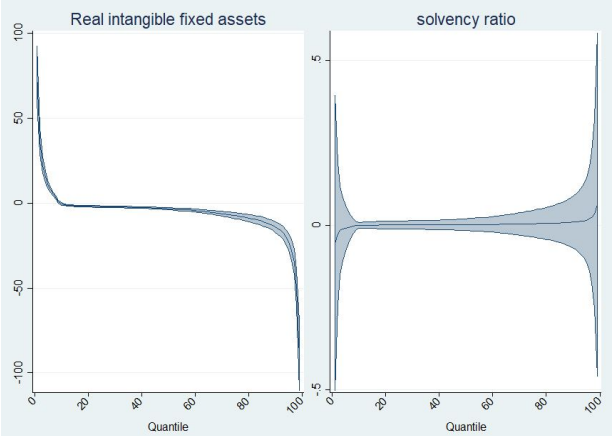
(b) *Real operating revenues*



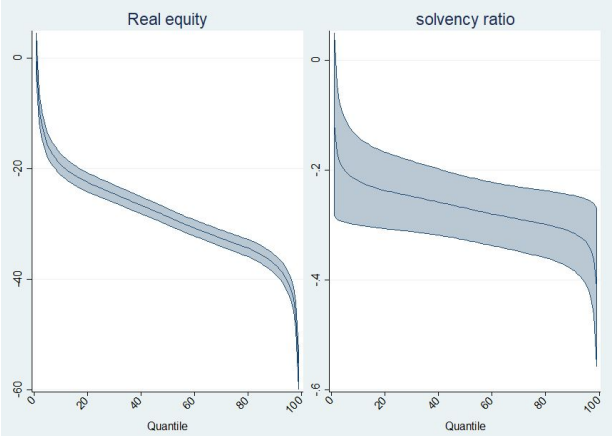
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*



(f) *Real equity*

Figure 6: *β coefficients in model examining conditional β-convergence estimated using quantile regression*

Eastern European electricity generator is by 1% larger, its corporate growth rate significantly declines by 0.057-0.452%. In comparison, the growth rate of an Western European firm significantly declines by 0.038-0.426%, if the company is by 1% larger. To check whether the coefficients significantly differ across regions, I perform F tests that test the hypothesis that Eastern and Western European companies converge equally fast: $\beta_{east} = \beta_{west}$. The differences in the coefficients, however, are only significant in columns (1) and (2). Hence, Eastern European electricity generators only converge significantly faster than Western European ones in revenues and total assets.

Hence, growth processes are mostly quite similar across Eastern and Western European countries. This results suggests that Eastern and Western European electricity generators form one single club in whose members conditionally converge in company size. At the first glance, this observation is not surprising. Eastern European countries are catching up with Western European countries but slowly (Egri & Lengyel, 2024). Electricity markets have been integrated like other product and input markets. Countries coordinate their energy policies etc. (Meletiou *et al.* , 2018). The reason why output and total assets exhibit different conclusions might be that output is more volatile and can be adjusted more quickly. Total assets also cover cash, bank accounts, and inventory that are more liquid assets. In comparison, it takes more time to adjust the other capital types (e.g., tangible fixed assets such as power plants, intangible fixed assets such as patents).

	Real total assets	Real operating revenues	Employees	Real tangible fixed assets	Real intangible fixed assets	Real equity
	(1)	(2)	(3)	(4)	(5)	(6)
log(firm size$_{t-1,east}$	−26.924***	−32.640***	−45.159***	−20.578***	−5.741**	−29.114***
	(1.199)	(1.323)	(3.518)	(1.936)	(2.438)	(1.281)
log(firm size$_{t-1,west}$	−24.250***	−24.948***	−42.602***	−17.512***	−3.758***	−28.350***
	(0.917)	(1.007)	(1.502)	(0.895)	(0.474)	(0.875)
solvency ratio$_{t-1}$	0.061***	−0.297***	0.021	0.084***	0.002	−0.268***
	(0.018)	(0.030)	(0.024)	(0.024)	(0.011)	(0.030)
Speed$_{east}$	0.313	0.395	0.601	0.230	0.059	0.344
Half-life$_{east}$	2.210	1.754	1.154	3.009	11.723	2.014
Speed$_{west}$	0.278	0.287	0.555	0.193	0.038	0.333
Half-life$_{west}$	2.496	2.415	1.249	3.600	18.096	2.079
Firm-level fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Nested NUTS2 region-year dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	43988	41303	21554	40796	19549	38327
Units	6925	6756	5081	6596	3715	6355
Within R squared	0.302	0.315	0.317	0.175	0.158	0.300

Note: In each regression, corporate growth is regressed on company size, the solvency ratio, firm-level fixed effects, and nested NUTS2 region-year dummies. In column (1), company size is measured using the real total assets. In column (2), company size is quantified employing the real operating revenue. The number of employees serves as the measure in column (3). The real tangible fixed assets are used in column (4), the real intangible fixed assets in column (4), and real equity in column (6). All standard errors, in parenthesis, are clustered at the firm-level to overcome residual serial correlation. Each regression covers two company-size variables. The first one is the one for Eastern European enterprises. This variable is the size, if the company operates in an Eastern European country, and is zero otherwise. The second one is the one for Western European countries, i.e.: it equals the size, if the company is operating in Western Europe, and is zero otherwise. The top part of the table displays the coefficients, the middle part provides the estimates for the speed of convergence and half-life. The number of observations and firms, and the within R^2 are supplied at the bottom of the table. As can be seen from the table, the introduction of firm-level fixed effects and nested NUTS2 region-year dummies considerably influences the magnitude of the coefficients. Particularly, estimated β-coefficients become more negative. This highlights their importance to avoid omitted variable biases.

*p<0.1; **p<0.05; ***p<0.01

Table 5: *Fixed effects regressions of corporate growth on firm size examining conditional β-convergence*

To explore whether company size influences the variance of growth processes differently across Eastern and Western Europe, I regress equation (5) applying the algorithm by Machado & Santos Silva (2019) that combines quantile regression with fixed effects. Next to the firm-level fixed effects, the equation involves nested NUTS2 region-year fixed effects that help avoid likely omitted variable biases. Nonetheless, keep in mind that the method does not produce consistent estimates, since demeaning a non-linear function does not kill the unobserved heterogeneity (Machado & Santos Silva, 2019; Wooldridge, 2010).

Figure 7 displays the results. Again, the figure consists of six subfigures numbered from (a) to (f). (a) visualises the impacts of size on growth predicted by the regression that quantifies firm size using the real total assets, while (b) supplies the estimated β-coefficients of the regression that defines company size using the real operating revenues etc. Each subfigure shows two plots. The left one

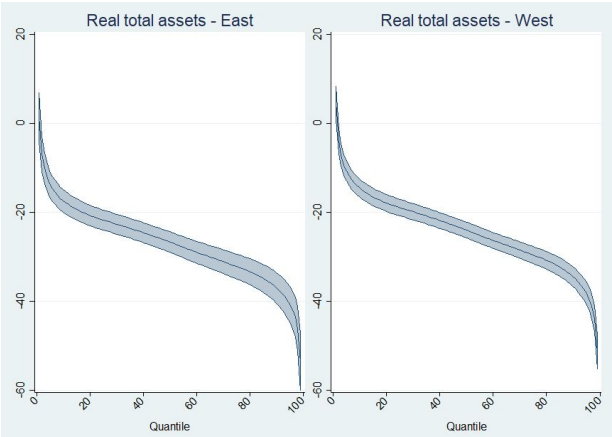
displays the estimated β-coefficients across percentiles in Eastern Europe. The right one shows the β-coefficients across percentiles in Western European countries. [19] Like before, the estimated β-coefficients are interpreted as semi-elasticities. In each subfigure, company size influences the variance of growth processes as suggested by Córdoba (2008). The generalised version of Gibrat's law by Córdoba (2008), however, is not supported, since company size influences the average growth processes in both regions, as shown in *Table* 5. Similar to *Figure* 6, companies converge in size almost along the entire growth distribution. Thus, growth is almost never advantageous in both regions. Besides, the β-coefficients in Eastern Europe usually lie below the ones in Western Europe. Thus, Eastern and Western European electricity show a different convergence behaviour. Particularly, Eastern and Western European countries do not appear to form a common convergence club. Although the analysis of the average growth process in *Table* 5 suggests that Eastern and Western Europe converge at the same speed and form a common growth club together, the results look different at other points in the growth distribution. In fact, Eastern European corporations appear to converge faster than Western European firms at many points in the distribution. As the variance of growth processes differ across countries, Eastern and Western European countries likely do not conditionally converge in size. In fact, there are many differences between Eastern and Western European countries that likely result in separate growth clubs such as the historical background and institutional setting, the still strong influence of the government on the economy, the incomplete liberalisation (Buccirossi & Ciari, 2018), the energy mix favouring fossil sources, etc. The result suggests that European policies need to account for the differences between Eastern and Western Europe. Policies need to be targeted to the different regions. Besides, as Eastern and Western European electricity generations do not appear to conditionally converge, European policies need to take care of that the regions do not diverge.

3.5 Discussion

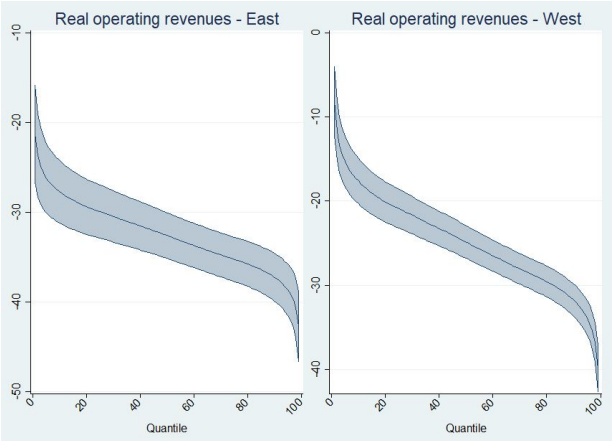
Since not only continents, countries and regions grow at different speed but also firms, one important question in industrial development is whether enterprises converge in company size (Daunfeldt & Elert, 2013). At the aggregated level, the theoretical macroeconomic models by Solow (1956) and Romer (1994) try to explain this phenomenon. At the firm-level, one theory that relates corporate growth to company size is Gibrat's law. It claims that firm growth does not depend on size, since it should be a purely random effect. Gibrat's law was examined by many empirical studies, but the results are ambiguous (Guerzoni *et al.* , 2024; Elston, 2023; Axioglou & Christodoulakis, 2021; Arouri *et al.* , 2020; Distante *et al.* , 2018; Tang, 2014; Daunfeldt & Elert, 2013; Daunfeldt *et al.* , 2012; Lotti *et al.* , 2009; Cefis *et al.* , 2007; Audretsch & Elston, 2006; Calvo, 2006; Bottazzi & Secchi, 2005; Audretsch *et al.* , 2004; Geroski & Gugler, 2004; Lotti *et al.* , 2003; Becchetti & Trovato, 2002; Hardwick & Adams, 2002; Cefis & Orsenigo, 2001; Hart & Oulton, 1996; Dunne & Hughes, 1994; Dunne *et al.* , 1989; Evans, 1987a,b; Hall, 1987; Singh & Whittington, 1975; Samuels, 1965; Hymer & Pashigian, 1962; Simon & Bonini, 1958; Hart & Prais, 1956). Despite the large number of studies, energy sectors are not analysed, although they interesting for various reasons (e.g., capital-intensive production, state-ownership, liberalisation etc.).

This study investigates whether Gibrat's law and its generalised version is supported by employing data on European electricity generators. In particular, it explores the unconditional and conditional

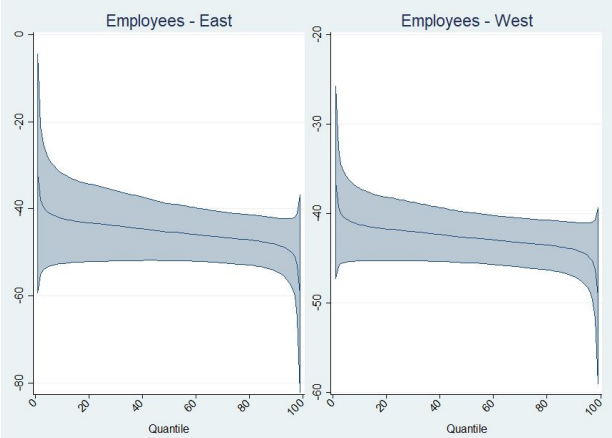
[19] Although the solvency ratio is also included in the regression, the effects across percentiles are not plotted to save space.



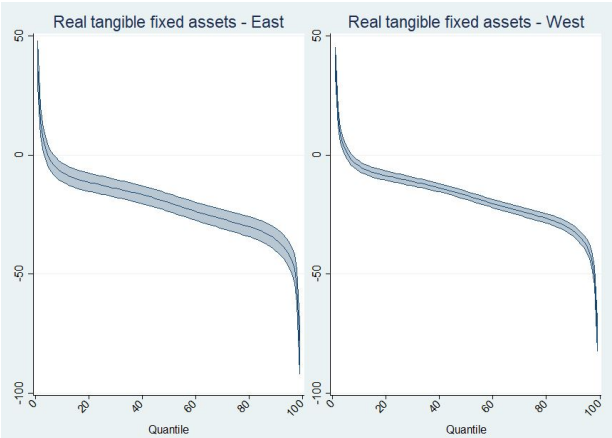
(a) *Real total assets*



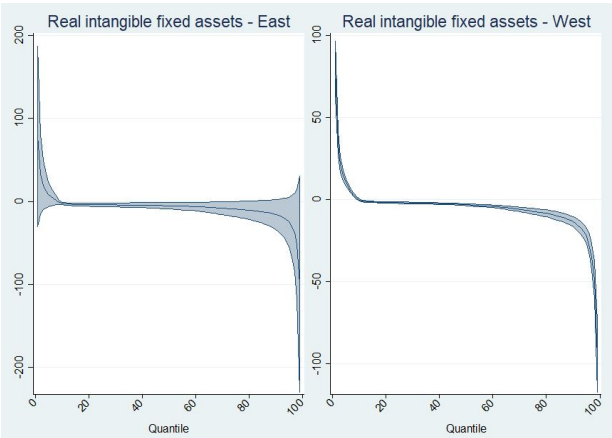
(b) *Real operating revenues*



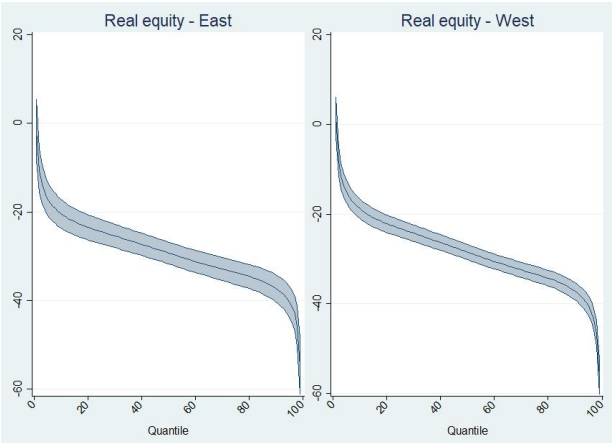
(c) *Employees*



(d) *Real tangible fixed assets*



(e) *Real intangible fixed assets*



(f) *Real equity*

Figure 7: *β coefficients in model examining conditional β-convergence across Eastern and Western Europe*

β-convergence of these companies by applying OLS, fixed effects estimations and quantile regressions. I contribute to the literature in various ways. First, only Tang (2014) explores whether Gibrat's law holds in energy sectors. Nevertheless, only Sweden is analysed. In comparison, my study includes electricity generators from other EU countries to provide more comprehensive results. The reason is that convergence might not be only observed in Sweden but across entire Europe, since governments coordinate economic and energy policies (e.g., EU electricity directives). National electricity mar-

kets are also integrated to some certain degree. European countries have different levels of economic development and historical backgrounds. These differences may substantially influence the speed of convergence that would be otherwise remain unexplored. Next, I check the robustness of the results by employing a variety of different proxies for firm size. Although several different measures of firm size are used in the literature, every study usually relies on a specific measure without comparing results across concepts. As in the literature (Guerzoni *et al.* , 2024; Nakatani, 2023; Castelnovo *et al.* , 2019; Distante *et al.* , 2018; Hanousek *et al.* , 2015; Del Bo, 2013; Schiersch, 2013; Geroski & Gugler, 2004; Dewenter & Malatesta, 2001; Majumdar, 1997), I quantify company size using the measures commonly employed in the literature but also investigate the Gibrat's law using further variables that are more related to particular aspects of capital structures. Besides, my dataset also includes some state-owned companies, which are primarily municipal utilities. As state ownership is still a widely employed tool to overcome problems caused by lacking competition in network industries, governments can provide additional capital to selected firms to accelerate their growth. Last, I investigate the influence of company size on the variance of growth processes by applying a new method to account for the biases implied by omitted variables. The algorith by Machado & Santos Silva (2019) introduces fixed effects in an equation estimated by quantile regression. The development of this new approach makes it necessary to update the research on Gibrat's law. As can be shown the estimates in studies investigating the variance of the growth process might suffer from considerable omitted variable biases.

Overall, the results reject Gibrat's law as in many other studies. Particularly, I observe both, σ-convergence and β-convergence. When investigating β-convergence, the regressions show that electricity generators converge unconditionally and conditionally. This behaviour can be observed for all different measures of company size. Besides, the inclusion of firm-level fixed effects and nested NUTS2 region-year dummies considerably influence the results. Particularly, the estimated β-coefficients turn even more negative, suggesting even faster convergence. Hence, the other studies excluding them may suffer from considerable omitted variable biases. Next, MES do not seem to influence the speed of convergence substantially. This conclusion may suggest that the MES have considerably decreased due to the liberalisation. Last, company size strongly drives the variance of growth processes as suggested by Córdoba (2008). Nonetheless, the generalised version of Gibrat's law is still rejected due to the negative effects of size on the mean growth process. When not accounting for heterogeneity, size can be an advantage and a disadvantage depending on the position in the growth distribution. Hence, divergence and convergence is observed along the distribution. When accounting for unobserved heterogeneity, results and conclusions substantially change. Size is almost always disadvantageous, since it slows corporate growth. In other words, firms converge along the entire growth distribution, implying that policy makers should design policies that especially target small enterprises and support their catch-up.

However, one set of econometric issues is the length of the panel that covers years from 2012 to 2020. Although short panel data sets are more informative on high-frequency variations in corporate growth, they are less informative on low-frequency variations. In other words, corporate growth might appear more random in short panels than it actually is. Hence, estimations employing short data sets risk overlooking relevant long-run processes and secular developments in corporate growth. In other words, short panels struggle with recognising natural life cycles and the systematic evolution of companies (Binder *et al.* , 2005; Geroski *et al.* , 2003). Nevertheless, the time interval analysed has a similar length to the ones in other studies (e.g., Geroski & Gugler (2004)). Since my results are in line with

the literature, this problem seems to be minor.

Another issue is that company size is approximated using deflated monetary values of inputs and outputs instead of quantities. Unfortunately, price indices are only available at some industry-level. Nonetheless, firm-level or even product-level price indices would be required, though mostly not available. Applying industry-level price indices to firm-level variables quantifying company size results in measurement errors and, finally, in biased coefficients. If firms differ in their characteristics such as the access to input and output markets or differences in the structures of these markets etc., firm- or product-level prices will deviate from the development of the industry-level price index. The resulting deviations are captured by the error term (De Loecker & Goldberg, 2014), that will be correlated with lagged company size.
This problem can be weakened but not completely avoided by involving the firm-level fixed effects that capture the permanent measurement errors. These permanent measurement errors are time-invariant differences across firms that will be eliminated by demeaning. The nested NUTS2 region-year dummies also contribute to reduce biases by absorbing all differences that vary across NUTS 2-regions and years. Overall, only smaller parts of the transient measurement errors may survive. They, however, should be dealt with by using 2SLS. 2SLS might be the best approach to solve the issue, since alternative estimators like the ones by Ronning & Rosemann (2008) and Schaalje & Butts (1993)) do not account for the simultaneity between the dependent and explanatory variable. [20]
Besides, the regressions show comparable results across the different measures of company size. The number of employees is the single measure that does not suffer from measurement errors, as it is a physical measure of size. Since the results of the regression quantifying company size using the number of employees resembles the results of the other regressions, the problem caused by deflated variables might be minor as well.

A third issue is the chosen instrument to test the exogeneity of the lagged company size. The literature (Geroski & Gugler, 2004) instruments the company size lagged by one period with the firm size lagged by two periods. I follow the literature, but the instrument might not be perfectly valid. In particular, instrument exogeneity may be violated. If company size is endogenous, then the positive serial correlation in company size may cause a correlation between the company size lagged by two years as an instrument and the error term. Consequently, estimates may still be biased and inconsistent. Nonetheless, the bias would be small given the strength of the instruments, providing informative conclusions even under noteworthy deviations from the instrument exogeneity assumption (Conley *et al.* , 2012; Wooldridge, 2010). Despite the fact that the instrument is strong, the results of the endogeneity test will be biased. Hence, the lagged company size might actually be endogenous, and not exogenous as suggested in *Sections* 3.2.2 and 3.3.2. Nevertheless, the p-values of the relevant tests are usually very high. Even though the instrument is not perfect, the small bias might not be able to push the p-values of the test to such high values.

Although the new algorithm by Machado & Santos Silva (2019) requires to update the estimations investigating the generalised version of Gibrat's law by Córdoba (2008), the estimated β-coefficients in *Sections* 3.3.4 and 3.4 are not consistent. The reason is the involving fixed effects requires functions to

[20] Day *et al.* (2004) show that biases are small, when measurement errors are weakly correlated (below 0.7) and the explanatory variable is exogenous. Although lagged company size is endogenous given the simultaneities, the correlation between the measurement errors, however, will not be large because of the differencing, fixed effects and nested NUTS2 region-year dummies.

be demeaned. Means, however, only go through linear functions but not through non-linear functions. Given the non-linearity of the equations estimated using quantile regressions, the demeaning does not perfectly eliminate the unobserved heterogeneity. Consequently, the estimates will be inconsistent (Machado & Santos Silva, 2019; Wooldridge, 2010).

4 Conclusion and policy implications

In this paper, I want to answer two questions. First, this paper examines whether a common structure between European electricity generation industries is emerging. In other words, I investigate whether European electricity generators are converging in company size. Second, the study explores various properties of the relationship between corporate growth and company size. On the macro-level, the theoretical models by Solow (1956) and Romer (1994) provide guidance on economic convergence and the dynamics of economic growth. On the firm-level, one important theory on this relationship is the model by Gibrat (1931). It claims that firm growth does not depend on size, since it should be a purely random effect. Gibrat's law has been extensively examined in the literature using different approaches ranging from β-convergence to autoregressive models (Distante *et al.* , 2018; Daunfeldt & Elert, 2013; Geroski & Gugler, 2004; Lotti *et al.* , 2003). A lot of them investigate manufacturing sectors, while only a few such as Daunfeldt *et al.* (2012) and Audretsch *et al.* (2004) explore service sectors (Daunfeldt & Elert, 2013). Most of these studies analyse the impacts of size on the average growth process by applying OLS. Owing to this fact, Córdoba (2008) generalises Gibrat's law and hypothesises that size primarily influences the variance of the growth process but not the mean.

In this study, I shed light on whether Gibrat's law applies to European energy sectors, employing panel data on European electricity generators from 2012 to 2020. The European electricity industry is of special interest for many reasons. First, despite substantially supporting market entry, electricity generation sectors are still highly concentrated (Meletiou *et al.* , 2018). Despite the liberalisation, European electricity markets are highly concentrated. Second, state ownership is still a widely employed tool to regulate the industry. State-ownership, however, likely influences the relationship between corporate growth and company such as through performance losses (Steinbrunner, 2023). Third, the industry produces capital-intensively. Network industries are often characterised by increasing returns to scale that promote corporate growth. Fourth, Eastern European countries have transitioned from centrally planned to market economies after the collapse of the Soviet Union, and, therefore, have experienced major institutional changes and liberalisations. Yet, governments still pervasively influence the formerly state-owned companies in these countries. Additionally, poorly implemented privatisations established legal monopolies and strengthened market barriers instead of creating open and contestable markets. These strong entry barriers aggravated the transition to well-functioning market economies (Buccirossi & Ciari, 2018).

To investigate the link between company size and corporate growth, I rely on β-convergence models. Partcicularly, I apply the firm-level panel data to examine unconditional and conditional β-convergence. When analysing unconditional β-convergence, corporate growth is regressed only on company size in the previous year using OLS. Firm-level fixed effects and other controls are added to investigate conditional β-convergence. The endogeneity of the lagged company size is tested using 2SLS. I also explore whether growth processes differ between firms smaller and larger than the MES. Last, the generalised

version of Gibrat's law by Córdoba (2008) is also explored. As suggested by Gibrat (1931), company size does not influence the average growth process. Nonetheless, if affects the variance of growth processes. This hypothesis is examined using quantile regression. Contributing to the literature, company size is quantified employing a large variety of common measures and new approaches: total assets, operating revenues, number of employees, tangible fixed assets, intangible fixed assets and equity.
Overall, I find evidence that electricity generators converge in company size. A first simple investigation of the different proxies for company size reveals σ-convergence. In other words, the differences in company sizes shrink over time. Electricity generators become more and more similar in size. Additionally, the regression models detect β-convergence, i.e.: across the different proxies for company size, β-coefficients are significantly negative. From this observation, two conclusions are drawn. First, this result suggests that European electricity generators converge unconditionally. In other words, smaller companies grow faster than larger enterprises, closing the gap between these groups of corporations. Second, electricity generators converge conditionally, i.e.: enterprises that are relatively farer away from their long-run equilibrium grow faster than firms closer to their steady state. The presence of σ-convergence, and unconditional and conditional β-convergence rejects Gibrat's law, which is generally in line with the literature. Another important conclusion is that introducing fixed effects and nested NUTS2 region-year dummies when exploring conditional β-convergence considerably influences the estimated β-coefficients. In particular, they become even more negative. Hence, empirical studies that exclude them may suffer from considerable omitted variable biases. Next, the MES do not seem to influence the speed of convergence in most specifications. One reason might be that have become less relevant given the liberalisation (e.g., unbundling). Another reason may the concave relationship between productivity and corporate size. Although the impact of firm size on technical efficiency diminish over corporate size, it is still positive for larger enterprises (Steinbrunner, 2024). Thus, larger companies can improve their productivity when growing larger. Moreover, company growth drives the variance of growth processes as suggested by Córdoba (2008). Nonetheless, the generalised version of Gibrat's law by Córdoba (2008) is still rejected due to the negative influence of size on the mean growth process. These regressions show that size is almost never advantageous, implying that firms converge in size almost along the entire growth distribution. Additionally, Eastern European electricity generators tend to converge faster than Western European ones at many points of the growth distribution but not at the mean.

Policy makers, intending to restructure energy markets, should, therefore, continue liberalisation and the elimination of market barriers. Opening markets alleviates market entry and intensifies competition. Especially, small electricity generators should be targeted given their faster growth to accelerate their catchu-up. For instance, investment and R&D subsidies may favour smaller companies as well as feed-in tariffs and taxes. In other words, limited resources should be reallocated towards smaller enterprises European policies should account for the differences between Eastern and Western Europe, since both regions tend to converge at different speeds at many points in the corporate growth distribution. Especially, European policies may be tailored to particular regions to consider their differences. As Eastern and Western European companies appear to form separate convergence clubs, European energy policies should avoid that these to clubs diverge from each other. Particularly, it is important that policies encourage the catch-up of Eastern with Western European energy sectors to reduce the gap in economic development between them. Although supporting small entrants fosters competition, policy makers should not completely forget about the large incumbents. As the results reveal, larger enterprises grow slower than smaller ones. Their slower growth might be problematic. In the worst

case, it may hamper the economic development of the electricity sectors. To accelerate their growth, policy makers may support larger companies by facilitating administrative procedures such as applying and issuing building permits and the assessments of environmental effects, especially permits for larger investment projects (e.g., wind parks, solar farms, grids). In the case that regional governments slow large-scale investment projects, federal governments should be in charge of issuing construction permissions.

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