ELECTRICITY INTENSITY IN THE DEVELOPED COUNTRIES: GLOBAL DIVERGENCE, CLUB CONVERGENCE AND THE ROLE OF THE STRUCTURE OF THE ECONOMY

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Abstract. This paper presents an empirical analysis of the dynamics of electricity intensity—the ratio of electricity consumption to gross domestic product—in advanced economies for the period 1990–2015. It analyzes electricity intensity dynamics against the background of different behavior of subgroups/clubs of countries and changes in the sectoral structure of the economy. The paper tests for global and club convergence of electricity intensity and decomposes the convergence into sectoral efficiency vs. economic structure. The novelty of the paper is twofold: First, it demonstrates that while electricity intensity diverges between the developed countries, the electricity intensity of sub-groups of developed countries continues to converge; Second, the paper illustrates the role of the structure of the economy in the convergence process of electricity intensity. The results show that the dominant source of the dynamics and convergence of electricity intensity is the intensities at the sectoral level—that is, the sectoral electricity efficiency rather than economic structure.

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1. Introduction

The demand for electricity is a matter of great importance to prospective energy policy designers, who make policy and infrastructure-investment decisions today in order to meet future demand. Knowledge of past dynamics of electricity demand and its relation to the development of economic activity facilitates the task of forecasting and may clarify effective incentives for policy design. To the extent that electricity production remains the largest source of greenhouse gas emissions, knowledge of these issues impacts on environmental policy designers as well.[1] The prominence of electricity production within the energy sector manifests itself in electricity having been the fastest-growing element of energy use and investment in this sector having outpaced that in the oil and gas sectors combined. In addition, according to WEO (2018), these trends are expected to continue.

This paper sheds some light on these issues by analyzing the dynamics of electricity intensity—the ratio of electricity consumption to gross domestic product—and the relation of these dynamics to the sectoral structure of the economy. The questions that the paper addresses are: Is electricity intensity still converging? What are the drivers of convergence or divergence? What is the role of the sectoral structure of the economy in these dynamics?

The most straightforward way to consider the convergence of electricity intensity is by reflecting on a situation in which the dispersion of electricity intensity of different countries decreases over time. To the extent that this type of convergence relates to the variance of intensity over time, it is named: $\sigma - convergence$. A different perspective to think about convergence is to consider a situation in which growth rates of those countries with low levels of intensity tend to be higher than those with high levels of intensity. These high growth rates tend to decrease as electricity intensity increases over time. This type of convergence manifests itself in the data when initial levels or past levels of electricity intensity are negatively correlated with current growth rates. To the extent that this type of convergence can be estimated using a simple regression model, it was named: $\beta - convergence$. To test for convergences, I estimate two well-known econometric models, namely: Phillips and Sul (2007)'s $\sigma - convergence$ test and Barro and Sala-i Martin (1992)'s $\beta - convergence$ test emphasizing the advantages and disadvantages of each approach.

Electricity intensity varies over time and between countries. Past research on this issue found that when examined among countries with relatively similar development

[1] In 2014, 50 percent of the global CO2 emissions came from electricity, 20 percent from transport, 20 percent from the manufacturing and construction industries, and ten percent came from residential buildings and the commercial and public services combined. WDI (2019)

levels, electricity intensity decreases and converges over time.[2] The analysis in the current paper shows that after three decades of convergence, and right after the financial crises of 2008, the electricity intensity of these countries started to diverge. The paper tests the hypothesis that this phenomenon, of increase in the variance of electricity intensity, stems from the divergence of the trends of different sub-groups/clubs of countries, while within these clubs, convergence continues. The importance of testing this hypothesis for forecasting is straightforward: If the electricity-intensity clubs of countries continue to converge, their identification can provide empirical support for forecasting; yet at the same time, if electricity intensity diverges, international comparisons of intensity levels would have a minor contribution for forecasting because every country would have its unique trajectory. Using the method of Phillips and Sul (2007), the paper identifies three clubs of countries. The electricity intensity of the countries within each club continues to converge, in contrast to the average clubs' trends that diverge from each other.

Energy researchers have long realized the importance of the structure of the economy on energy demand.[3] The analysis in this path decomposes energy intensity to the sectoral energy intensity and the intensity that is caused by the sectoral mix of the economy. However, this strand of literature explored the structural effect on energy intensity, overlooking the possible importance of the effect on the electricity sector on its own. A central contribution of the current paper is to elaborate on this exploration from energy to electricity. Hence, despite being avowed, it would be instructive to mention three central reasons for the importance of such analysis: First, it is essential to identify the effect of sectoral structure on electricity intensity. If the magnitude of this effect is significant, policies whose objective is to increase electricity efficiency should address structural transformation.[4] Otherwise, if the effect is negligible, such policies would be useless. The second reason relates to the fact that different sectors, or more broadly different types of consumers, exhibit different demand schemes. For example, the hourly demand curve of the manufacturing sector is often flatter than the hourly demand curve of the services sector or that of households, with the latter exhibiting a demand scheme with significant demand peaks in the early evening. Different demand curves require different supply technologies. For example, some demand schemes fit technologies that cope better with a long-term constant level of supply, as opposed to demand schemes that fit technologies that cope better with demand peaks. Hence, forecasts of different types of consumers are a critical input in the design of electricity

[2] Notable papers on this issue are: Maza and Villaverde (2008), Liddle (2009), Mohammadi and Ram (2012), Herrerias and Liu (2013), Kim (2015) and Le et al. (2017). The next section describes the literature on this subject in more detail.

[3] See for example: Miketa and Mulder (2005); Mulder and Groot (2012) as well as the work of Ang (1987, 1995, 1999, 2004).

[4] Algebraically, electricity efficiency is the inverse of electricity intensity.

policy and the investment decision. Third, from the perspective of environmental policy design, sectoral analysis is useful because it makes it possible to identify sectoral bottlenecks and design appropriate energy efficiency policies at the sectoral level. This paper analyzes the electricity intensity dynamics of each of the abovementioned sectors and the effect on the total electricity intensity of the sectoral shares in the economy.

In addition to the analysis of electricity intensity of the overall economy, the paper analyzes the electricity intensity of households and of each of the five economic sectors that comprise the GDP, namely: Agriculture, mining and quarrying, manufacturing, commercial services, and construction. To analyze the role of the sectoral structure of the economy on electricity intensity, I follow Ang (1987), Ang (1995) and Wong (2006) and decompose electricity intensity into two indices: sectoral electricity intensity—that can be viewed as the sectoral electricity efficiency, and the intensity that emerges from the share of each sector in the economy. For this purpose, I use the Logarithmic Mean Divisia Index (LMDI) that was developed by Ang et al. (1998) and Ang and Liu (2001). Their index makes it possible to decompose electricity intensity without residual. Then, I follow Wong (2006) and test for β-convergence by regressing each of the two decomposed indices on initial levels of intensity. The result of this method is the estimation of decomposed βs, which enables us to differentiate the role of the sectoral electricity intensity from the role of the structure of the economy on convergence.

The remainder of this paper is organized as follows. The next section provides a review of the relevant literature. The third section formulates the analytical framework—that is, the econometric models with which I analyze the data. The fourth section presents the data, the fifth the analysis, and the sixth summarizes.

2. Literature Review

The convergence of electricity intensity has been examined in the past. The current paper contributes to previous studies in several respects: First, it defines electricity intensity as the ratio of electricity consumption to gross domestic product.[5] Second, it uses one database for statistically testing the convergence hypothesis using both σ and β tests, each of which has its advantages and shortcomings. Third, the paper reports the results of electricity intensity convergence tests at the sector level. Fourth, the paper decomposes the electricity intensity convergence process into sectoral efficiency and economic structure.

While the vast literature on convergence focuses on (primary) energy intensity, the literature on electricity intensity is narrower. Early papers on this subject used basic econometric and visualization methods to test for convergence. Maza and Villaverde

[5]Rather than electricity consumption per capita. Comin and Hobijn (2010) used electricity to GDP as a technological adoption measure in their exploration of technological diffusion.

(2008) analyzed households' per capita electricity consumption using data from 98 countries between 1980 and 2007. They examined β and σ convergence indices as well as a non-parametric test for ranking and mobility. Their estimation supports the existence of a slow process of convergence. In their paper, they present a visual illustration that the variance decreases over time. Liddle (2009) also presents visual illustration that the variance of electricity intensity decreases over time. In addition, Liddle (2009) presented estimation of linear time trend to tests for the convergence of electricity consumption in the IEA/OECD countries between 1971 and 2005 and found evidence for convergence.

Following Miketa and Mulder (2005)'s specification, Mohammadi and Ram (2012) estimated β-convergence equations of energy and electricity using a reduced-form version of the test of Barro and Sala-i Martin (1992).[6] The authors used a sample of 108 countries between 1971 and 2007 and estimated convergence for different periods and different quantiles of the distribution. They found strong support for convergence in electricity intensity, but weaker support for energy intensity. In their estimation, the authors consider the role of urbanization and found it significant. The current paper adds to their analysis by estimating the electricity intensity at the sectoral level. The importance of their results is worth noting. The research on the drivers of electricity intensity is relatively new, and many of the usual suspects are found to be insignificant. For example, Gutiérrez-Pedrero et al. (2018) analyzed the data of the non-residential sector in the European Union and found that while prices had only limited influence on electricity intensity, the capital stock had a major influence. Hence, the importance of the results of Mohammadi and Ram (2012) is in identifying urbanization as a major driver for electricity intensity.

In a more recent paper, Kim (2015) examined the convergence of electricity intensity using data from 109 countries between 1970 and 2009. Kim (2015) estimated Phillips and Sul (2007)'s σ-convergence tests for all countries in the database and another test for developed countries. The results showed that while electricity intensity converges for all countries, electricity use per capita converges only for the developed countries. Using Phillips and Sul (2007)'s algorithm for clubs, Kim (2015) found three clubs in the sample of the entire 109 countries to which the electricity per capita converges. To the extent that the current work is closest to Kim (2015), I elaborate on the differences. The current paper adds to Kim (2015)'s analysis by examining the role of the structure of the economy. Also, as noted above, I define electricity intensity differently and report the tests using Barro and Sala-i Martin (1992)'s model in addition to that of Phillips and Sul (2007). Third, as mentioned above, I find that in recent years, electricity intensity

[6]Below I formulate both Barro and Sala-i Martin (1992)'s model as well as the reduced form version.

in the developed countries diverged. This result emphasizes the need for revisiting the results and indicates the limitation of the conventional tests.

Using several convergence tests, Herrerias and Liu (2013) found electricity intensity convergence in Chinese provinces.[7] They identify three clubs to which the provinces converge. Le et al. (2017) examine the convergence of per capita energy and per capita electricity in the APEC countries using annual data between 1989 and 2012. They use Unit Chart and Sequential Panel Selection Model (SPSM). When using Unit Chart, their results indicate convergence in all countries. The SPSM test indicates convergence in 15 of the 19 countries for energy and 17 out of 19 for electricity.

The second strand of literature to which the paper relates explores the structural effect on energy intensity and its convergence. So far, this strand has mostly explored the structural effect of energy intensity, overlooking the possible importance of the electricity sector on its own. A central contribution of the current paper is to elaborate on this exploration from energy to electricity.

To the extent that there are differences in the energy intensity of different sectors, a change in the national output structure might affect total energy intensity. The most well-known example of this phenomenon is the structural change that accompanies the development of nations. Low energy intensity levels characterize the services sectors; hence, the increase in their share decreases total energy intensity.[8] Past papers in this strand decomposed the effect on electricity intensity into two: an effect of each sector's energy intensity—or energy efficiency effect; and an effect of sectoral shares—or the structural effect. A prevalent index for this purpose is the Logarithmic Mean Divisia Index (LMDI), developed by Ang et al. (1998) and Ang and Liu (2001) and makes it possible to decompose electricity intensity without residual.

The results regarding the effect of GDP structure in the long-term trend of energy intensity are mixed. Miketa and Mulder (2005) examine the convergence of energy intensity in 56 countries in 10 industries between 1971 and 1995. They find that variation in intensity is particularly evident in industries that are less energy-intensive. They study the theory of traceability and find that a low starting point indeed accompanies an increase in energy intensity. They also examine the factors that influence the intensity and find that while energy prices and investment ratios are correlated with intensity, their effect is negligible.

[7] They presented tests from the models of: Lee and Strazicich (2003), Kapetanios et al. (2003), Phillips and Sul (2007) and Hansen (2000).

[8] Indeed, this line of research started in the late 1970s; however, it was institutionalized by the extensive work of Ang (1987, 1995, 1999, 2004).

Mulder and Groot (2012) examined the energy consumption data of 50 industries in 18 OECD countries from 1970 to 2005. They find a downward trend in the intensity of energy consumption in most industries. In contrast, the intensity of the services industries decreases more moderately when there is a great variation in the trend of sub-industries. Decomposition of intensity for structural change and technological change shows that structural change explains much of the dynamics of energy intensity.

In a search for possible reasons for the heterogeneity in the electricity intensity in the US, Levinson (2016) performs a careful decomposition of the state-level GDP into its subsectors. Levinson (2016) finds that output composition contributes little to the decrease in electricity intensity. Prices and regulations also contribute little to the intensity decrease, while most of the decrease is attributed to the long-term trend of technical changes. Using a similar methodology, Marrero and Ramos-Real (2013) found that the decline of energy intensity in the EU 15 is also due to technical changes.

Torrie et al. (2016) find a decline of 24 percent in the intensity of energy consumption (energy to GDP) in Canada between 1995 and 2010. Their analysis shows that about 48 percent of the decline stems from the structural change during the period reviewed. The other reasons for the decline were the increase in GDP per capita and the decline in the intensity of each subsector.

3. Analytical Framework

This section formulates the econometric models with which I analyze the data. It presents the two econometric models that currently serve as the workhorses in the economic literature to test for convergence, namely the models of Phillips and Sul (2007) for σ-convergence and the model of Barro and Sala-i Martin (1992) for β-convergence.[9] Also, it presents Phillips and Sul (2007)'s algorithm to cluster countries into clubs of convergence.

In searching for possible drivers of convergence I also formulate a second well-known test for β-convergence, which can be described as a reduced form or linear version of the model of Barro and Sala-i Martin (1992).[10] The linearity of this model makes it possible to examine the role on convergence of the structure of the economy as suggested by Wong (2006). I use the decomposition method that was developed by Ang (1987)

[9] Indeed, the econometric literature suggests numerous other models to test and analyze the notion of convergence, each using a different specification to deal with different econometric challenges. For example: Lee and Strazicich (2003), Kapetanios et al. (2003), and Hansen (2000). Nevertheless, the models of Phillips and Sul (2007) and Barro and Sala-i Martin (1992) remain the workhorses of the field.

[10] The linear version is also a very prevalent model in the energy economic literature, for example in the papers of Mulder and Groot (2012) and Mohammadi and Ram (2012)

to bifurcate electricity intensity into two indices: an index of the intensity of each sector, and an index of the weights of sectors with different levels of intensity. I regress each index on initial levels of intensity, which provides me with the estimation of a decomposed βs, namely, β_{EFF} that stems from the estimation the electricity intensity of each sector and can be interpreted as the sectoral electricity *efficiency*, and β_{STR}, which stems from the change in the shares of these sectors in the economy or in other words the *structure* of the economy.

Define electricity intensity (I) of country j in sector k at time t as the ratio of Watt per Hour (WH) electricity consumption (E) use and gross domestic product in 2005 dollar (Y) of this sector:

$$I_{j,k,t} \equiv \frac{E_{j,k,t}}{Y_{j,k,t}} \tag{1}$$

To ease the notation, I abstract for now from the sectors' notation and will return to it when it is relevant.

3.1. **A Test for σ-Convergence.** The first approach to analyze convergence relies on the intuition that electricity intensity convergence describes a situation in which the dispersion or differences in electricity intensity between countries decreases over time. To the extent that this approach analyzes the dynamics of the variance of intensity, it is called the σ-convergence. The advantage of this approach is that it is intuitive and straightforward, as it analyzes the subject directly under examination—the dispersion of intensity. The main disadvantage is that when using this method, it is not possible to examine the role of other factors on convergence, such as the structure of the economy, because the test is conducted on the variance and not the intensity process itself. Second, in the field of economics, we usually work with panel data where the number of years is limited. This disadvantage leaves us with only a few degrees of freedom in the analysis, which might be a significant problem if we wish to examine changes in the trend of the variance.

To test for σ-convergence, the economic literature usually uses the model of Phillips and Sul (2007). These authors developed a model known as the $\log(t)$-test to test the σ-convergence hypothesis. Their method boils down to an estimation of a regression model in which the variance of intensity between countries is a negative-non-linear function of time. In the remainder of this subsection, I present their model, which will be estimated later.

Equation (2) presents the dynamics of the electricity intensity process $I_{j,t}$ as comprised of two components: Λ_t which represents a global process as it is a common component to all countries; and $\Theta_{j,t}$ which represents an idiosyncratic component of economy j or a process of the distance of the economy from the global process.

$$I_{j,t} = \Theta_{j,t}\Lambda_t \tag{2}$$

To the extent that Λ_t is common to all countries, it is possible to remove it with the following scaling:

$$h_{j,t} \equiv \frac{I_{j,t}}{\frac{1}{N}\sum_j I_{j,t}} = \frac{\Theta_{j,t}}{\frac{1}{N}\sum_j \Theta_{j,t}} \tag{3}$$

The cross sectional mean of $h_{i,t}$ is one, by definition. In addition, if the transition parameter converges to a constant than $h_{i,t}$ converges to one and the variance of $h_{i,t}$ like the variance of $\Theta_{j,t}$ converges to zero. Formally, define the variance of $h_{j,t}$ as $\sigma_t^2 = \frac{1}{N}(h_{i,t}-1)^2$:

$$\Theta_{j,t} \xrightarrow[t\to\infty]{} \Theta \;\Rightarrow\; h_{i,t} \xrightarrow[t\to\infty]{} 1,\; \sigma_t^2 \xrightarrow[t\to\infty]{} 0$$

.

To test for convergence Phillips and Sul (2007) assume the variance has the following parametric representation:

$$\sigma_t^2 = \frac{\sigma_i}{log(t+1)t^{\alpha}} \tag{4}$$

Under this assumption the variance decreases slowly with the increase in $log(t+1)$. If and only if α is significantly smaller than zero, then the decrease in the variance due to the increase in $log(t+1)$ is offset by the increase in variance due to the decrease in t^{α}. Hence, a valid test for the decrease in variance or for the convergence would be the one sided hypothesis that: $H_0 : \alpha \geq 0$. In order to test this hypothesis, Phillips and Sul (2007) suggested the following regression and presented its asymptotic properties:

$$\log\left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_t^2}\right) - 2\log\log(t+1) = \alpha + \beta_\sigma \log(t) + \varepsilon_{j,t} \tag{5}$$
$$\forall t = rT,\; rT+1,\; \ldots$$

where $\hat{\sigma}_t^2$ is the empirical estimation of σ_t^2, $\beta_\sigma = 2\hat{\alpha}$ and r is taken to be 0.3, which means that the first 30 percent of observation should not take part in the estimation. A significantly negative $\hat{\alpha}$ indicates a positive correlation of $\hat{\sigma}_t^2$ with time, or otherwise, that the variance increases with time. Any other results mean that the variance decreases over time or that we cannot reject the hypotheses that the intensity σ-converges.

3.2. **Club Convergence.** A generalized form of the model in (2) allows for different subgroups of the panel to converge to different levels of intensity. This generalised model clusters countries by the convergence of their intensity and makes it possible to identify potential clubs of countries that converge. In addition, it enables us to identify countries that diverge and to separate them from those that converge. Defining the set of all countries as (S) and assuming there are (C) clubs, the model can be formulated as follows:

$$I_{j,t} = \Theta_{j,t}\Lambda_t^c \;\; \forall j \in S^c, \forall c \in \{1, ..., C\}$$

Phillips and Sul (2007) suggested a four-stage algorithm to cluster observations into clubs:

(1) Order countries according to the last observation of each.

(2) Select a core group with the k highest countries that maximize the $\log t$-test that was described in the previous section.

(3) Add each country from the remaining group to the core group and re-test if it still converges, otherwise return it to the remaining group.

(4) If both groups converge, the process ends. If the core group converges and there are no countries that can be added to the core group, repeat steps 1-3 on the remaining group.

3.3. **A Test for β-Convergence.** The second approach is to view convergence as a process in which the intensity of those countries with high initial levels grows slower than those with low initial levels. The tests of this approach are built on a regression in which the dependent variable is the change in electricity intensity, and the independent variable is electricity intensity in an initial year. A negative correlation between initial levels and current growth indicate convergence. This approach was named the β-convergence because its result depends on the β coefficient of the regression between past levels and current growth.

In order to test for β-convergence Barro and Sala-i Martin (1992) suggested the following specification:

$$\frac{i_{j,t} - i_{j,t0}}{t - t_0} = \alpha - \left(\frac{1 - e^{-\beta_{BSM}(t-t_0)}}{t - t_0} \right) i_{j,t_0} + u_{i,t} \tag{6}$$

where $i_{j,t} \equiv log(I_{j,t})$, $u_{i,t}$ is assumed to be white noise and i_{j,t_0} is the intensity in the base year t_0. Equation (6) estimates the cumulative average change rate of intensity as a constant term (α) which is offset by the second term on the right-hand side of the equation. When ($\beta_{BSM} \geq 0$) the second term on the right-hand side is positive, and the minus sign before the parentheses expresses the negative correlation between the initial levels of intensity and the accumulative change. To understand the intuition of this formulation, note that the effect of the second term diminishes with time. To see this, note that: $\left(\frac{1-e^{-\beta_{BSM}(t-t_0)}}{t-t_0}\right) \xrightarrow{t-t_0 \to \infty} 0$. Hence, α here can be interpreted as the average change rate in the long run. As Sala-i Martin (1996) explains the main econometric advantage of the model in (6) relative to a simple time-series model is that (6) overcomes a bias that might be caused due to different time length. [11] In appendix (3) I further discuss the relationship of this model with a simple time series model and with the σ-convergence model.

3.4. **The Logarithmic Mean Divisia Index (LMDI) for Decomposition Analysis.** This subsection presents a linear version of the β-convergence test which enables me to develop a model that identifies the role of the structure of the economy on intensity. The linear model for β-convergence formulates current change in (log) intensity as a linear function of the (log) level of intensity in the initial year. That is:

$$\Delta i_{j,t} = \alpha + \beta_L i_{j,0} + \varepsilon_{j,t} \tag{7}$$

where $\Delta i_{j,t} \equiv i_{j,t} - i_{j,t-1}$. If intensity converges, the coefficient of intensity in the base year will be negative ($\beta_L \leq 0$), i.e., the higher the level of electricity intensity in the base year the slower the rate of change of intensity, so that in the long term the levels (or change rates) converge. The advantage of the current model is that it allows testing for conditional convergence. By adding independent variables to the model, one can test for convergence after controlling for possible alternative variables that might affect electricity intensity, such as electricity prices, investment and capital, the share of economic activity in urban relative to rural areas, etc.[12] In addition, this model allows the examination of the role of the structure of the economy on electricity intensity.

To examine the role of the structure of the economy on the intensity, I follow Miketa and Mulder (2005) and decompose electricity into two indices: sectoral intensity and the intensity that ensues from the share of each sector in the economy. For this purpose,

[11] Another advantage is that the formulation in (6) intimately relate to the economic growth model for which it was built. To the extent that the current work does not deal with the economic growth issue, the relevant advantage is the first. For thorough explanation of these advantages see Barro and Sala-i Martin (1992) and Sala-i Martin (1996) or Durlauf et al. (2005).

[12] See for example the work of: Miketa and Mulder (2005) and Mohammadi and Ram (2012) for the analysis of energy intensity

I use the Logarithmic Mean Divisia Index (LMDI) that was developed by Ang et al. (1998) and Ang and Liu (2001). Their index makes it possible to decompose electricity intensity without residual. In this section, I present the index following the formulation of Ang (2005).

The general index for decomposition analysis identity formulates electricity intensity as the weighted sum of sectoral intensities, where the weights are the shares of the sectors in the economy ($S_k \equiv \frac{Y_k}{Y}$) :

$$I = \frac{E}{Y} = \sum_k \frac{Y_k}{Y}\frac{E_k}{Y_k} = \sum_k S_k I_k \tag{8}$$

To decompose electricity intensity into the part that relates to the sectoral efficiency and the part that relates to the structure of the economy define the following decomposition function:

$$D(S_{k,t}, I_{k,t}) \equiv \frac{S_{k,t}I_{k,t} - S_{k,t-1}I_{k,t-1}}{\log(S_{k,t}I_{k,t}) - \log(S_{k,t-1}I_{k,t-1})} \tag{9}$$

Now define the change of intensity due to *efficiency* as:

$$\Delta\tilde{I}_t^{EFF} = \sum_k D(S_{k,t}, I_{k,t}) \log\left(\frac{I_{k,t}}{I_{k,t-1}}\right) \tag{10}$$

and the change of intensity due to the *structure* of the economy as:

$$\Delta\tilde{I}_t^{STR} = \sum_k D(S_{k,t}, I_{k,t}) \log\left(\frac{S_{k,t}}{S_{k,t-1}}\right) \tag{11}$$

With these definitions, it is easy to show that the change scheme is additive, that is:

$$\Delta I_t = \Delta\tilde{I}_t^{STR} + \Delta\tilde{I}_t^{EFF} \tag{12}$$

I follow Wong (2006) who proposed a process to estimate a decomposed β in two steps. The first step includes a decomposition of the initial index to two sub-indices, where the first relates to the structure of the economy and the second to the efficiency of each sector. The second step includes regression of each sub-index on the initial year, that is:

$$D(S_{k,t}, I_{k,t}) \log\left(\frac{I_{k,t}}{I_{k,t-1}}\right) = \alpha + \beta_k^{EFF} i_{j,0} + \varepsilon_{j,t} \tag{13}$$

$$D(S_{k,t}, I_{k,t}) \log\left(\frac{S_{k,t}}{S_{k,t-1}}\right) = \alpha + \beta_k^{STR} i_{j,0} + \varepsilon_{j,t} \tag{14}$$

Wong (2006) showed that this process yields decomposed β_ks such as the β_L in (7) is their sum, that is:

$$\beta_L = \sum_k \beta_k^{STR} + \sum_k \beta_k^{EFF} \tag{15}$$

4. Data, Global Divergence and Club Convergence - Visual Analysis

This section describes the data and the primary characteristics of electricity intensity in the sample.[13] The database is an unbalanced panel of the OECD countries as well as Bulgaria, Croatia, Cyprus, and Romania for the years 1990—2018.[14] For each country, the data include information on GDP and electricity consumption classified into five branches of an economy: agriculture, mining and quarrying, manufacturing, construction, and commercial services.[15] Also, it includes information on the electricity consumption of households. As a measure of the economic activity of the households, the data includes information on the private consumption from the National Accounts statistics. The current paper defines electricity intensity as the ratio of each branch's electricity consumption to its GDP in each economy. For households, electricity intensity is defined as the ratio of electricity consumption and private consumption from the National Accounts statistics. All electricity measures are in Kwh, while all GDP and consumption measures are PPP adjusted to 2005 USD.

Figure (1) presents the data on total electricity intensity in the developed countries through the years. This is the total use of electricity by all sectors of the economy

[13] For further description of the data construction see the data appendix

[14] Namely: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

[15] The source of the data on GDP as well as on electricity consumption is UNstat.

as well as the electricity consumption of households divided by total gross domestic product. The figure shows that, on average, electricity intensity in the last 25 years had a decreasing trend. The average electricity intensity in each year is presented by the dashed line in the figure. In 1992, the country with the highest level of electricity intensity was Estonia with 0.52 Watt-Hour per Dollar (WHD), while the one with the lowest level was Switzerland with 0.11 WHD. At the end of the period, the country with the highest level of electricity intensity was Korea with 0.39 WHD, and the one with the lowest was Ireland with 0.08 WHD. These simple figures suggest two empirical observations that characterize the dynamics of electricity intensity. The first is that electricity intensity decreases over time.[16] It is easy to see that the major increase in the electricity intensity of Korea, the country with the highest electricity intensity at the end of the period, is at odds with the development of the rest of the countries. Despite this increase, in the last three decades, the average electricity intensity in the developed countries decreased at an annual rate of 0.8 percent. The second observation is that the heterogeneity of electricity intensity between countries shrinks over time. The gap shrank from 0.41 to 0.31 WHD. In other words, according to this simple visual examination, electricity intensity converged.[17] To further examine convergence, one must examine the development of the variance of electricity intensity.

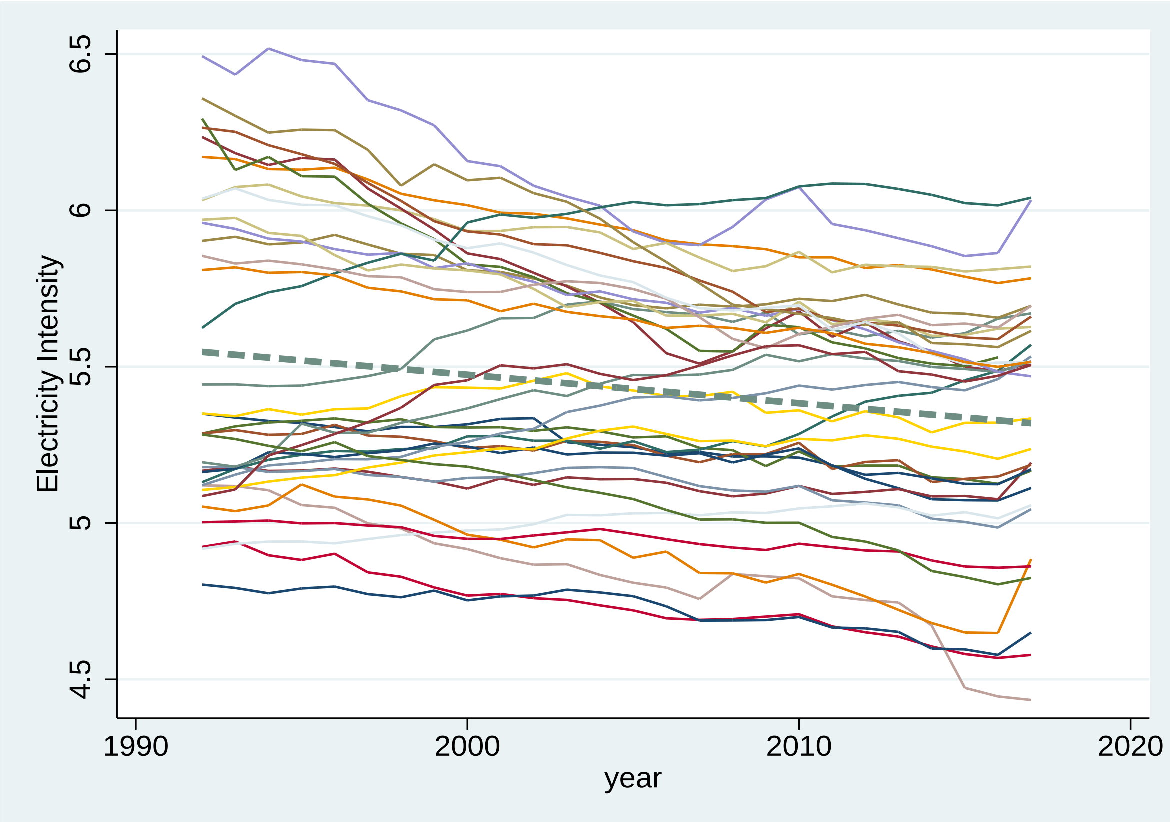
Figure (2) presents the development of three measures of the variance of electricity intensity throughout the years. The first measure is the simple variance between the countries calculated for each year over the actual intensity ($Var(I_{j,t})$). The second measure is the variance calculated over a standardized intensity ($Var(h_{j,t})$)—that is, according to equation (3). The third is the variance of the log of intensity ($Var(i_{j,t})$). The simple variance is larger than the other two and is drawn on a secondary axis. It is apparent from the figure that while all measures of variance decreased dramatically between 1990 and 2008, their behavior afterward changes. While the first measure remains relatively constant, the other two started rising again. The data in figure (1) does not indicate that there was a major change in these years.

The divergence at the end of the period questions the validity of electricity demand forecasts that are based on international comparisons. These forecasts are built on the assumption that the electricity demand of each country will converge with time to some global trend, and this result refutes this assumption. However, this result may stem from the divergence of the electricity intensity of specific countries. Alternatively, there may be subgroups of countries that indeed do converge to different trajectories.

[16] This observation has been documented in the literature for total electricity intensity in : Mulder and Groot (2012), Mulder et al. (2014), Levinson (2016), and WEO (2018)

[17] Notable papers on energy convergence are: Mulder and Groot (2012), Mohammadi and Ram (2017), Apergis and Christou (2016), Burnett and Madariaga (2017), Fallahi (2017) Adhikari and Chen (2014). For a recent symposium on this subject, see: Apergis et al. (2017)

Figure 1. Electricity Intensity in the Developed Countries



To examine these hypotheses, I run the algorithm of Phillips and Sul (2007), which clustered the countries in the sample as listed in table (1). The algorithm identified four clubs within each of the countries converge and one country that diverges from all the others: the Republic of Korea. The largest club has 21 countries, and the smallest has two. Figure (3) presents the average electricity intensity of each club. The first two clubs are close in their average as well as in the dispersion of electricity intensity. The next two clubs have lower intensity while the final club that includes just the Republic of Korea has the highest intensity. Figure (4) presents the variance indices of the different clubs throughout the years. The figure illustrates that although the measurements of variance are unstable in the years at the vicinity of the crises, they continue their monotonic decrease afterword. This result *suggests* that the divergence in the last several years is the result of the divergence of different clubs, while within

Figure 2. Indices of the Variance of Electricity Intensity

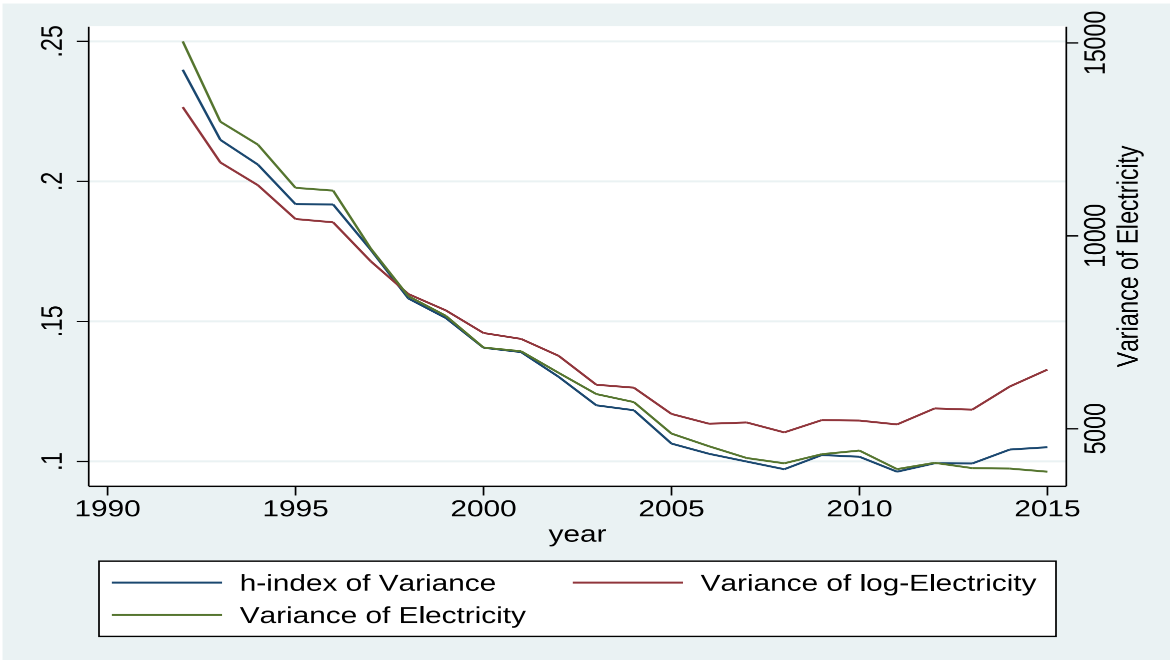


Table 1. Clustering the Countries in the Sample into Clubs

club 1:	Finland, Estonia, Mexico, Greece, Portugal, Turkey.
club 2:	Canada, Slovenia, Chile, Hungary, Czech Republic, Slovakia, Norway, New Zealand, Sweden, Poland, Latvia, United States, Lithuania, Israel, Spain, Belgium, Japan, France, Austria, Italy, Germany.
club 3:	Australia, Netherlands.
club 4:	Luxembourg, Switzerland, United Kingdom, Denmark, Ireland.
Divergent:	Republic of Korea.

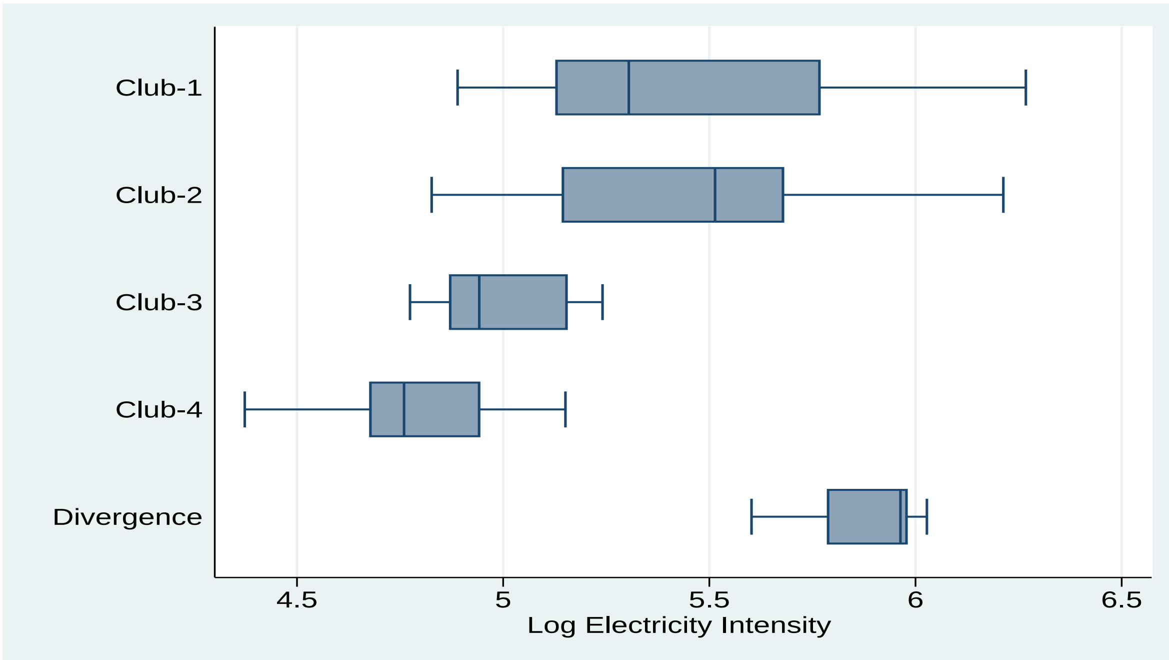
each club convergence remains.[18] In the next section, I present an econometric test for these suggestions.

5. Global Divergence and Club Convergence - Econometric Analysis

To provide a statistical test for the observed phenomenon of increase in the variance I elaborate Phillips and Sul (2007)'s model that was formulated in (6) to consider the

[18]I tested and rejected the hypothesis that the reason for the end of the period divergence is the major increase in the intensity of the Republic of Korea. The variance at the end of the period increases even if we drop the Republic of Korea from the sample.

FIGURE 3. Average Electricity Intensity by Club

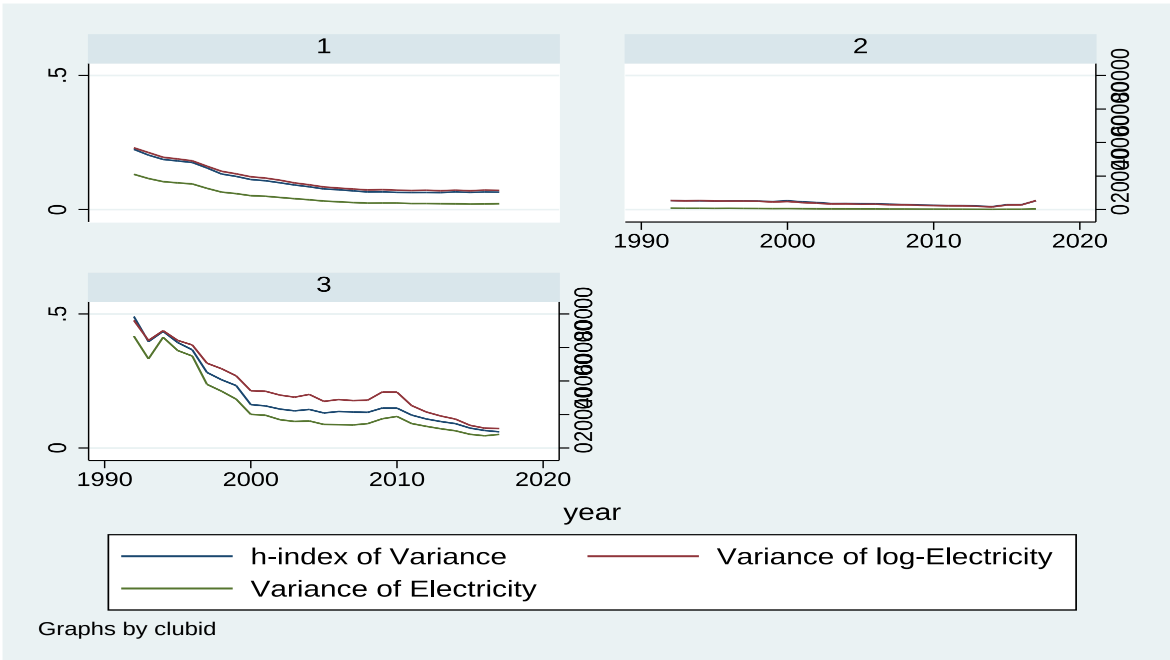


changing behavior of the data through time. Define the right hand side of (6) as $\log\left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_t^2}\right) - 2\log\log(t+1) \equiv g(\sigma_t, t)$, I estimate the following model:

$$
\begin{aligned}
g(\sigma_t, t) &= \alpha + \beta_{\sigma_1}\log(t) I_{(year\leq 2007)} + \beta_{\sigma_2}\log(t) I_{(year\geq 2008)} \\
&+ \phi I_{(year\leq 2008)} + \varepsilon_{j,t} \\
\forall t &= rT,\ rT+1,\ \ldots
\end{aligned} \tag{16}
$$

This refinement of Phillips and Sul (2007) enables us to identify if the convergence stems from the variance behavior before 2008, which is captured by the coefficient β_{σ_1}, or after 2008, which is captured by the coefficient β_{σ_2}. Tables (2) and (3) show the estimation results of the $\sigma - convergence$ tests as formulated in equations (6) and (17), respectively. As mentioned above, the statistical test is such that only a significantly negative coefficient implies a rejection of the hypothesis of convergence. The first column in the table presents the estimation of (6) over the entire sample. The coefficient is positive and significant. This result implies that according to this test, we cannot reject the hypothesis that electricity intensity converges. This result exposes the limitation of the model of Phillips and Sul (2007) and the advantage of a simple visual examination of the data, as presented in figure (2). While the figure illustrates the divergence at the end of the period, the statistical test ignores it. The following

FIGURE 4. Indices of the Variance of Electricity Intensity in Each Club



columns present the convergence test results of the four clubs, in none of which we can reject the hypothesis of convergence.

In table (3) I present the estimation results of the model in (17) which considers possible change in the behavior of electricity intensity. The coefficient of the first period turns positive and even significant, indicating that through the first period, electricity intensity of the countries in the sample indeed converged, or at least we reject the hypothesis that it diverges. The coefficient for the second period turns negative and significant. This means that we cannot reject the hypothesis of divergence in this period — this result accords with the visual result. The next columns present estimation results of the models for each one of the clubs. Despite the possible global divergence, each club converges both in the first period and in the second. To the extent that none of the coefficients is significantly negative, these results illustrate that each club continues to converge after 2008.

The conventional $\sigma - convergence$ test is not adequate for data whose variance exhibits a decrease followed by an increase and needs adjustment, as was suggested by equation(17). However, the models of $\beta - convergence$, such as the one of Barro and Sala-i Martin (1992), are indeed adequate for such data. The reason stands at the heart of the claim that $\beta - convergence$ is not sufficient for $\sigma - convergence$. To see this, note that if the intensity of countries that started with a high level decreases faster than the intensity of countries that started with low levels of intensity at some point, the intensities might converge, and the variance will equal zero. Afterward, if the same pattern continues, we should see that those that started with high intensity continue to decrease faster than the others, and the variance will start to grow, just like the figure illustrates. There are two further advantages of this method over the $Sigma - convergence$ approach. First, this method enables us to evaluate the convergence speed—the rate at which the index reaches its steady-state—and the dispersion's half-life—the time at which half of the variance vanishes. This is done by the following formula: $\Lambda = -\frac{ln(1+\beta T)}{T}$ for the convergence rate and $H = -\frac{ln(2)}{ln(1+\beta)}$ for the half-life.[19] Additionally, to the extent that this method estimates the regression for the intensity of each country, it is also possible to control for country-specific developments on intensity such as electricity prices, capital per worker and temperature.

Table (4) presents the estimation results of the $\beta - convergence$ by Barro and Sala-i Martin (1992). The first panel presents the original specification of the test of Barro and Sala-i Martin (1992). According to this test, electricity intensity converges in the full sample. It also converges in most clubs with a highly significant coefficient. The average half-life is about one percent a year, which means that it takes about 50 years for the dispersion of electricity intensity to shrink in half. Notably, there are major differences between the clubs where the half-life of the first clubs is smaller than 40, and the half-life of the third is 173 years. According to this test, the electricity intensity of the fourth club does not converge.

5.1. **The Sectoral Structure of the Economy and Electricity Intensity.** The objective of this sub-section is two-fold: First, it sheds some light on the relation between electricity intensity and the sectoral structure of the economy. Second, it reports the electricity intensity convergence patterns of each sector. As mentioned above, the pattern of different sectors is an important input for policy designers. I follow Wong (2006) and decompose the change in electricity intensity into two: sectoral intensity and economic structure. The first can be interpreted as the efficiency of the sector or its technological progress. I estimate the linear version of the β convergence test for each index and extract the coefficient of the efficiency (10) and one of the structures (11). To illustrate the role of structural transformation on electricity intensity, I present the ratio of the coefficients of these models, namely $\frac{\beta_k^{STR}}{\beta_k^{EFF}}$. Tables (B1) - (B4) presents the estimation results of the decomposed β for each club respectively. Wong (2006) Each table is divided into two panels, where the first presents the estimation results of $\beta_E FF$ as formulated in equations (10) and the second of β_{STR} as formulated in equations (11).

[19]Indeed, these statistics can also be calculated using the Phillips and Sul (2007); however, they require stronger assumptions, such as the assumption on the functional form of the variance.

Table 2. Sigma Convergence Test for All Countries and Each Club

VARIABLES	(1) All Countries	(2) Club 1	(3) Club 2	(4) Club 3	(5) Club 4
β_σ	134.7***	748.1***	230.7***	167.7***	134.2***
	(9.829)	(43.10)	(8.402)	(22.30)	(14.99)
α	-1,026***	-5,687***	-1,756***	-1,277***	-1,023***
	(74.72)	(327.7)	(63.88)	(169.6)	(114.0)
Observations	23	24	24	24	24
R-squared	0.899	0.932	0.972	0.720	0.785

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: This table presents the results of the estimation of the following model:
$\log\left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_t^2}\right) - 2\log\log(t+1) = \alpha + \beta_\sigma \log(t) + \varepsilon_{j,t}$

To summarize the relative importance of the structural development vis-à-vis the importance of the development of the efficiency on the convergence of electricity intensity, I define for each sector k in club c the following index for the relative structural magnitude (SRM):$SRM = \left(\frac{|\beta_{STR}|}{|\beta_{EFF}|} - 1\right) \cdot 100$. The estimated SRM are presented in table (5). It is easy to see that most of the indices are negative, meaning that, in most cases, the structural coefficient is smaller than the efficiency coefficient. The meaning of this result is that the dominant factor in the development of electricity intensity is the sectoral intensity rather than the economic structure. The exception here is the third club, which, as listed above, is made up of only two countries. This result means that in most countries, the role of the structural transformation on electricity intensity is limited. In addition, it seems that apart from mining and utilities, the limited role of structural transformation covers all sectors. As for the magnitude of the coefficients differences, it ranges (in absolute terms) between 1 percent and 4 percent, except for the coefficient of agriculture in the third club. To the extent that this club covers only two countries, I put less weight on its results and consider it mostly as a club of countries in which the development of their electricity intensity does not accord with the global trend.

6. Discussion and Future work

This paper sheds some light on the demand for electricity by analyzing the dynamics of electricity intensity—the ratio of electricity consumption to the gross domestic product—and the relation of these dynamics to the sectoral structure of the economy.

TABLE 3. Sigma Convergence Test for All Countries and Each Club

VARIABLES	(1) All Countries	(2) Club 1	(3) Club 2	(4) Club 3	(5) Club 4
β_{σ_1}	185.5***	630.5***	244.3***	92.32***	88.09***
	(6.500)	(73.58)	(12.25)	(29.34)	(25.83)
β_{σ_2}	-34.16*	1,073***	101.3***	499.3***	201.0**
	(17.70)	(210.6)	(35.06)	(83.99)	(73.93)
ϕ	1,671***	-3,366*	1,087***	-3,095***	-858.7
	(143.4)	(1,697)	(282.5)	(676.7)	(595.6)
α	-1,412***	-4,794***	-1,859***	-704.4***	-672.4***
	(49.40)	(559.2)	(93.11)	(223.0)	(196.3)
Observations	23	24	24	24	24
R-squared	0.989	0.946	0.984	0.869	0.828

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: This table presents the results of the estimation of the following model:

$$\log\left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_t^2}\right) - 2\log\log(t+1) =$$
$$\alpha + \phi I_{(year\leq 2008)} + \beta_{\sigma_1}\log(t) I_{(year\leq 2007)} + \beta_{\sigma_2}\log(t) I_{(year\geq 2008)} + \varepsilon_{j,t}$$

The questions that the paper addresses are: Does electricity intensity still converge? What are the drivers of convergence and of divergence? What is the role of the sectoral structure of the economy on these dynamics?

To test for convergences, I estimate two well-known econometric models, namely: Phillips and Sul (2007)'s $\sigma - convergence$ test and Barro and Sala-i Martin (1992)'s $\beta - convergence$ test, emphasizing the advantages and disadvantages of each approach.

The analysis in the current paper shows that after three decades of convergence, and right after the financial crises of 2008, the electricity intensity of these countries started to diverge. The paper tests the hypothesis that this phenomenon, of increase in the variance of electricity intensity, stems from the divergence of the trends of different sub-groups/clubs of countries, while within these clubs, convergence continues.

In addition to the analysis of electricity intensity of the entire economy, the paper analyzes the electricity intensity of households and of each of the five economic sectors that make up the GDP, namely: Agriculture, mining and quarrying, manufacturing, commercial services, and construction. I follow Ang (1987), Ang (1995) and Wong

Table 4. Beta Convergence Test for All Countries and Each Club

VARIABLES	(1) All Countries	(2) Club 1	(3) Club 2	(4) Club 3	(5) Club 4
β_{BSM}	0.0131***	0.0208**	0.0134***	0.00402**	0.00256
	(0.00283)	(0.00643)	(0.00232)	(0.000300)	(0.0108)
α	0.0593***	0.103***	0.0600***	0.0150	0.00165
	(0.0133)	(0.0234)	(0.0106)	(0.00331)	(0.0527)
Observations	816	144	504	48	120
R-squared	0.265	0.487	0.317	0.125	0.022
Half Life	53.23	33.75	52.25	172.9	270.7
Convergence Rate	-0.0114	-0.0168	-0.0116	-0.00384	-0.00249

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents the results of the estimation of the following model: $\frac{i_{j,t}-i_{j,t0}}{t-t_0} = \alpha - \left(\frac{1-e^{-\beta_{BSM}(t-t_0)}}{t-t_0}\right) i_{j,t_0} + u_{i,t}$

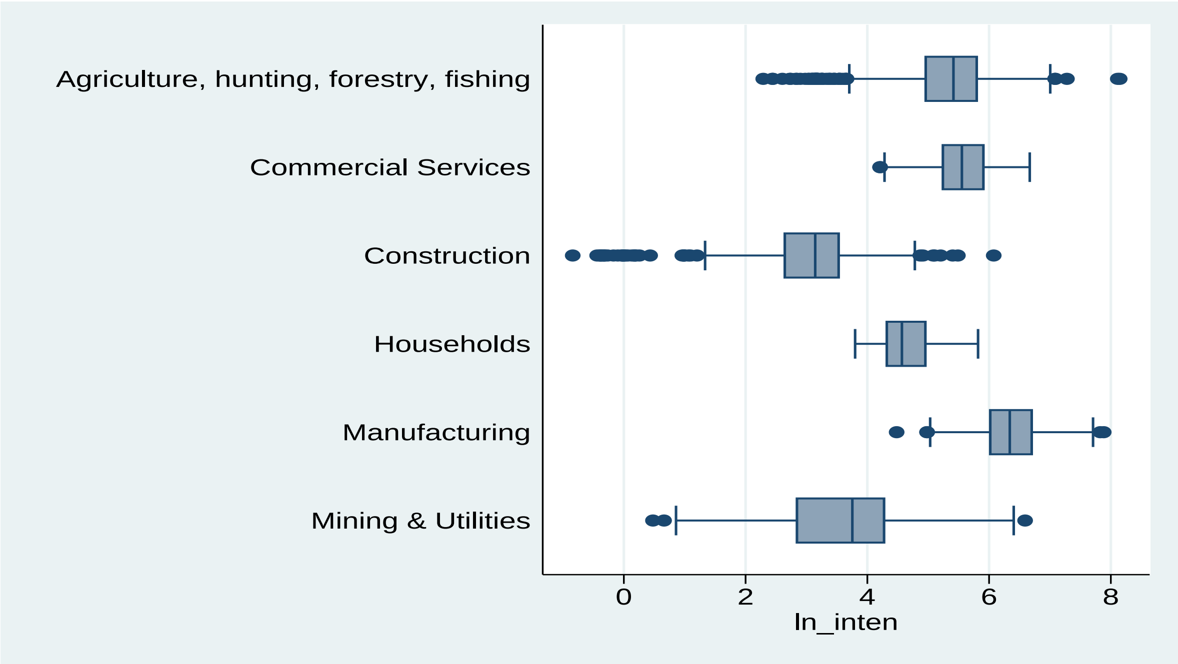
Table 5. Beta Ratio

$$SRM \equiv \left(\frac{|\beta_{STR}|}{|\beta_{EFF}|} - 1\right) \cdot 100$$

	Club - 1	Club - 2	Club - 3	Club - 4
Agriculture	-0.034	-0.041	0.127	-0.023
Mining and Utilities	0.038	0.025	0.014	-0.014
Manufacturing	-0.037	-0.027	0.019	0.007
Construction	-0.040	-0.017	-0.006	-0.021
Commercial Services	-0.014	-0.022	0.025	-0.036
Household	-0.021	-0.015	-0.018	-0.026

(2006) and decompose electricity intensity into two indices: sectoral electricity intensity, which can be viewed as the sectoral electricity efficiency, and the intensity that emerges from the share of each sector in the economy. For this purpose, I use the Logarithmic Mean Divisia Index (LMDI) that was developed by Ang et al. (1998) and Ang and Liu (2001).

FIGURE 5. Average Electricity Intensity in Each Sector



The results show that the dominant source of the dynamics and convergence of electricity intensity is the intensities at the sectoral level; or, in other words, the sectoral electricity efficiency rather than economic structure.

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Appendices

A. Data Appendix

	Final Database Observation Summery						
	Total	Households	Agriculture	Mining	Manufacturing	Construction	Services
Countries	35	36	32	28	35	24	34
Years	24	24	24	23	24	24	24
Observations	840	864	768	644	840	576	816

In order to conduct this analysis, we collected data and created a balanced panel dataset for the following countries (36): Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Republic of Korea, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States.

For each of the following countries, we collected data on six branches of the economy: Agriculture, Mining and Quarrying, Manufacturing, Commercial Services and Construction. In addition, we included consumption by Households and Gross Consumption.

A list of the data collected:

(1) Electricity consumption and its breakdown by sectors in millions of Kilowatts per hour, as published by UNSTATS. Covering 1990-2016.

(2) GDP and its breakdown at constant 2010 prices in US Dollars, as published by the UNSTATS National Accounts Main Aggregates Database. Covering 1970-2016.

(3) Per capita GDP at current prices – US dollars as published by the UN statistics division. Covering 1970-2016.

A.0.1. *Sources Limitations.* our dataset is limited in several aspects:

(1) UNSTATS breakdown to sectors of electricity consumption was not paralleled to UNSTATS breakdown to sectors of states' GDP (ISIC Rev. 4). therefore, we used the UNSTATS "Guidelines for the 2016 United Nations Statistics Division Annual Questionnaire on Energy Statistics" in order to correspond to ISIC Rev. 4.

- **Total:** ”Final energy consumption” (CL12)
- **Mining:** ”Mining and quarrying” (CL1214e)
- **Construction:** ”Construction” (CL1214i)
- **Households:** ”Households” (CL1231)
- **Agriculture:** ”Agriculture, forestry and fishing” (CL1232)
- **Services:** ”Commerce and public services” (CL1235)
- **Manufacturing:** We took the ”Manufacturing, Construction, and non-fuel mining industry” (CL121) minus the Mining (CL1214e) and Construction (CL1214i) industries.

(2) In order to have a balanced panel dataset for each sector, we had to make sure that we have continuous series for each country in each sector. Due to this, we had to remove from our dataset the following states in the following sectors:

  (a) In the Agriculture industries, we removed the following countries:
    (i) Belgium, due to lack of data for 1990-1996
    (ii) Germany, no data at all
    (iii) Slovenia, no data at all
    (iv) United States, due to lack of data for 1990-2001
  (b) In the Commercial Services industries, we removed the following countries:
    (i) Latvia, due to lack of data for 1998-2006
    (ii) Lithuania, due to lack of data for 1990-2006
  (c) In the construction industry we removed the following countries:
    (i) Slovenia, due to lack of data for 1997-1999
    (ii) Canada, No data at all
    (iii) Chile, No data at all
    (iv) Germany, due to lack of data for 2003-2015
    (v) Greece, due to lack of data for 2015
    (vi) Israel, due to lack of data for 2013-2015
    (vii) Latvia, due to lack of data for 1990-2006
    (viii) Lithuania, due to lack of data for 1990-2006
    (ix) Luxembourg, due to lack of data for 1990-1999
    (x) Republic of Korea, No data at all
    (xi) Slovakia, due to lack of data for 1992
    (xii) United States, due to lack of data for 1990-2002

(d) In the Mining industries, we removed the following countries:

   (i) Latvia, due to lack of data for 1990-2006
   (ii) Lithuania, due to lack of data for 1990-2006
   (iii) Luxembourg, due to lack of data for 1990-1999
   (iv) Slovakia, due to lack of data for 1990-1994
   (v) Slovenia, due to lack of data for 1990-1996
   (vi) Sweden, missing data for 2014
   (vii) Switzerland, no data at all
   (viii) the United Kingdom, due to lack of data for 1990-2009

(e) Iceland was removed from both the Manufacturing industries and the Total groups, due to dramatic changes in the Icelandic economy, further discussion on the Icelandic case will follow.

B. Decomposing Convergence to Structure and Efficiency

Table B1. Decomposition of the Convergence Effect - Club 1

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Sector - 1	Sector - 2	Sector - 3	Sector - 4	Sector - 5	Sector - 6
			Efficiency Effect			
β_{EFF}	-0.0341***	0.0379***	-0.0374***	-0.0399***	-0.0135**	-0.0215***
	(0.000478)	(0.0135)	(0.00400)	(0.00471)	(0.00588)	(0.00419)
α	0.640***	-0.166**	6.082***	0.163**	3.003**	2.957***
	(0.120)	(0.0828)	(1.003)	(0.0663)	(1.465)	(0.701)
# Obs	138	132	138	115	138	138
# Countries	6	6	6	5	6	6
			Structural Effect			
β_{STR}	-0.00855***	-0.0174***	0.00755**	0.00791**	-0.00845***	-0.00622***
	(0.000137)	(0.00502)	(0.00371)	(0.00371)	(0.00252)	(0.00171)
α	-0.0691**	0.0578*	-1.687**	-0.0723	0.805**	0.424
	(0.0303)	(0.0337)	(0.807)	(0.0593)	(0.345)	(0.379)
# Obs	138	132	138	115	138	138
# Countries	6	6	6	5	6	6

TABLE B2. Decomposition of the Convergence Effect - Club 2

VARIABLES	(1) Sector - 1	(2) Sector - 2	(3) Sector - 3	(4) Sector - 4	(5) Sector - 5	(6) Sector - 6
			Efficiency Effect			
β_{EFF}	-0.0411***	0.0253	-0.0270***	-0.0169**	-0.0217***	-0.0148***
	(0.00133)	(0.0181)	(0.00901)	(0.00779)	(0.00359)	(0.00145)
α	0.594***	-0.273**	2.886	0.136***	2.815***	1.045***
	(0.157)	(0.132)	(2.023)	(0.0300)	(0.417)	(0.376)
# Obs	391	352	483	276	437	483
# Countries	17	16	21	12	19	21
			Structural Effect			
β_{STR}	0.000785	-0.0108***	0.00197	-0.0242***	-0.0108***	-0.00581
	(0.00229)	(0.00103)	(0.00866)	(0.00702)	(0.00297)	(0.00554)
α	-0.233**	0.0221	-0.911	0.0185	1.154***	0.635
	(0.0955)	(0.0160)	(1.944)	(0.0256)	(0.321)	(0.723)
# Obs	391	352	483	276	437	483
# Countries	17	16	21	12	19	21

TABLE B3. Decomposition of the Convergence Effect - Club 3

VARIABLES	(1) Sector - 1	(2) Sector - 2	(3) Sector - 3	(4) Sector - 4	(5) Sector - 5	(6) Sector - 6
			Efficiency Effect			
β_{EFF}	0.127***	0.0145***	0.0192***	-0.00599***	0.0251***	-0.0181***
	(0)	(0)	(0)	(0)	(0)	(0)
α	-1.469***	0.0328***	-4.630***	0.0225***	-3.135***	1.328***
	(0)	(0)	(0)	(0)	(0)	(0)
# Obs	46	44	46	46	46	46
# Countries	2	2	2	2	2	2
			Structural Effect			
β_{STR}	-0.00373***	0.00187***	-0.0632***	-0.0202***	-0.0577***	-0.0116***
	(0)	(0)	(0)	(0)	(0)	(0)
α	-0.120***	-0.0153***	8.483***	0.00284***	6.315***	0.185***
	(0)	(0)	(0)	(0)	(0)	(0)
# Obs	46	44	46	46	46	46
# Countries	2	2	2	2	2	2

Table B4. Decomposition of the Convergence Effect - Club 4

VARIABLES	(1) Sector - 1	(2) Sector - 2	(3) Sector - 3	(4) Sector - 4	(5) Sector - 5	(6) Sector - 6
			Efficiency Effect			
β_{EFF}	-0.0227***	-0.0139***	0.00689**	-0.0209*	-0.0365***	-0.0262***
	(0.00650)	(0)	(0.00328)	(0.0112)	(0.00661)	(0.00377)
α	0.189***	0.00933***	-2.516**	0.0488*	2.340***	1.585***
	(0.0683)	(0)	(1.176)	(0.0271)	(0.766)	(0.374)
# Obs	115	44	115	92	115	115
# Countries	5	2	5	4	5	5
			Structural Effect			
β_{STR}	0.00247	-0.00557***	-0.0280***	-0.00760**	0.0251***	0.00420
	(0.0121)	(0)	(0.00251)	(0.00351)	(0.00836)	(0.0126)
α	-0.217*	-0.0108***	2.824***	-0.0143***	-1.965*	-0.935
	(0.132)	(0)	(0.892)	(0.00438)	(1.064)	(1.171)
# Obs	115	44	115	92	115	115
# Countries	5	2	5	4	5	5