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Electricity Intensity Convergence in the OECD Countries

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התכנסות עצימות החשמל במדינות ה - OECD

ליאור גאלו

תקציר

מחקר זה מנתח את הדינמיות של עצימות החשמל – כלומר, היחס שבין צריכת החשמל לתוצר המקומי הגולמי – במדינות ה-OECD בין השנים 1990-2017. בפרט, המחקר מנתח את הדינמיות של עצימות החשמל על רקע התפתחות שונה בין תתי קבוצות (או מועדנים) במדינות ה-OECD, שינויים במחירי החשמל, ובמבנה הענפי של הכלכלה. התוצאה המרכזית מהמחקר היא שהתכנסות עצימות החשמל בכל מדינות ה-OECD פחתה בשנים האחרונות, אך התכנסות במועדונים ממשיכה. בנוסף, המחקר מוצא שההשפעה של מחירי החשמל ושל המבנה הענפי על מגמות ההתכנסות של עצימות החשמל מצומצמות. המניע המרכזי לדינמיקה ולהתכנסות של עצימות החשמל היא העצימות ברמת הענף.

Electricity Intensity Convergence in the OECD Countries

Lior Gallo

Abstract

This paper analyzes the dynamics of electricity intensity – i.e., the ratio of electricity consumption to gross domestic product – in the OECD countries for the period 1990–2017. In particular, it analyzes electricity intensity dynamics against the background of different subgroups (or ”clubs”) of the OECD countries, changes in electricity prices, and the industrial structure of the economy. The main results are that general electricity intensity convergence in all OECD countries has decreased in recent years, yet club convergence in subgroups of OECD countries continues, and that the role of the economy’s industrial structure and electricity prices in these trends are negligible. The main driver of the dynamics and convergence of electricity intensity is electricity efficiency at the industry level.

Keywords: Electricity demand, Electricity intensity, Convergence, Club convergence, Decomposition, Structural transformation, Electricity prices.

1. Introduction

Electricity demand is a matter of great importance to prospective energy policy designers, who make policy and infrastructure investment decisions today to meet demand tomorrow. Knowledge of the dynamics of electricity demand and the relation of these dynamics to economic activity facilitates 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 environmental policy designers as well.[2] While this knowledge is relevant to the entire energy industry, it is especially relevant to the electricity industry as the fastest-growing component of energy use. According to WEO (2018), investment in the electricity industry has outpaced investment in the oil and gas industries combined and this trend is expected to continue.

This paper sheds some light on electricity demand by analyzing the dynamics of electricity intensity – i.e., the ratio of electricity consumption to gross domestic product – and the relation of these dynamics to the industrial structure of the economy and electricity prices. The questions that the paper addresses are: Is electricity intensity converging? What is the role of the industrial structure in these dynamics? What part do electricity prices play in these dynamics?

Electricity intensity convergence refers to a situation in which electricity intensity differences between countries decreases over time ; i.e., countries become more similar in their electricity intensity. This type of convergence is referred to in the literature as: σ-convergence. Another type of electricity convergence is when electricity intensity growth rates in countries with low intensity tend to be higher than in those with high electricity intensity, and hence the differences decrease 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 and can be estimated using a simple regression model, hence, it is referred to in the literature as β-convergence.

The paper uses two econometric models that currently serve as the workhorses in the econometric literature to test for electricity intensity convergence, namely, the model of Phillips and Sul (2007) for σ-convergence, and a reduced form of the model of Barro and Sala-i-Martin (1992) for β-convergence.[3] The σ-convergence model is more intuitive as it examine changes in electricity intensity variance over time. The β-convergence model enables us to test the hypothesis of conditional convergence, and I use it here to test for convergence while controlling for the impact of electricity prices. In addition, I will use β-convergence model together with the logarithmic mean divisia index (LMDI) of Ang et al. (1998) and Ang and Liu (2001) to test the hypothesis that changes in economic structure – i.e., structural transformation – impact convergence.

[2] In 2014, 50 percent of global CO2 emissions came from electricity, 20 percent from transport, 20 percent from the manufacturing and construction industries, and 10 percent from residential buildings and commercial and public services combined, according to WDI (2019).

[3] While the econometric literature suggests numerous other models for testing and analyzing the notion of convergence, such as Lee and Strazicich (2003), Kapetanios et al. (2003), and Hansen (2000) the models of Phillips and Sul (2007), and Barro and Sala-i-Martin (1992) remain the most popular.

Past research on the structural transformation of an economy and its impact on electricity intensity dynamics has emphasized consumers' heterogeneity in electricity demand.[4] In line with this research, the present paper explores the electricity intensity dynamics of households and of each of the six economic industries that comprise the GDP: agriculture, mining and quarrying, manufacturing, commercial services, construction, and transport. Specifically, I follow Ang (1987), Ang (1995), Wong (2006), and Mulder and Groot (2012) and decompose electricity intensity into two indices. The first is an index of industrial electricity intensity, which can be viewed as the industrial electricity efficiency. The second is an index of the intensity that emerges from changes of the share of each industry in the economy. For example, as the share of the manufacturing industry – whose electricity intensity is relatively high – shrinks while the share of the services industry – whose electricity intensity is low – expand, total electricity intensity, which is the weighted average of the industries would decrease. To test the impact of the structural transformation on electricity intensity I use the 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 Mulder and Groot (2012) and Wong (2006) and test for β-convergence by regressing each of the two decomposed indices on initial levels of intensity. The results of these methods are the estimates of decomposed βs, which differentiate the effect of the industrial electricity intensity from the effect of the economy's structure on convergence. Estimating these econometric models while controlling for prices and comparing them with the same models without controlling for prices enables us to shed light on the effect of electricity price dynamics on electricity intensity dynamics independently of the dynamics of the industrial structure of the economy.

The paper contributes to the literature on the dynamics of electricity intensity. Past research on this issue found that electricity intensity in countries with similar development levels decreases and converge to one another over time.[5] The present paper shows that electricity intensity in the OECD countries converged for three decades until the financial crisis of 2008, when it began to diverge. The paper tests the hypothesis that this slowdown stems from varying convergence trends of different subgroups (henceforth, "clubs") of OECD countries. For policy makers, the importance this hypothesis for forecasting is straightforward: If electricity intensity within clubs continues to converge, the identification of these clubs can provide empirical support for forecasting; on the other hand if electricity intensity between and within clubs diverges, international comparisons of electricity intensity levels would not improve forecasting because every country would have its unique trajectory. Following Phillips and Sul (2007), the paper identifies two clubs of countries, and finds that within each club, electricity intensity continues to converge, whereas between clubs, electricity intensity diverges.

Another contribution of the paper relates to the impact of industrial structure on energy intensity. Energy researchers have long realized the role of the industrial structure of the economy in energy demand. They decomposes energy intensity into industrial

[4]See, e.g., Ang (1987, 1995, 1999, 2004), Miketa and Mulder (2005), and Mulder and Groot (2012).

[5]See e.g., 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 in more detail.

energy intensity and intensity which is caused by the industrial structure of the economy. However, these researchers explored the impact of the industrial structure of the economy on energy intensity, while overlooking the its impact on electricity intensity which may well be different from energy intensity.[6] A central contribution of the present paper is to extend this line of research from the energy industry to electricity industry. There are three main reasons why it is important to analyze for the importance of industrial structure analysis. First, it is essential to quantify the effect of industrial structure on electricity intensity. If the magnitude of this effect is significant, policies whose objective is to increase electricity efficiency should address structural transformation. On the other hand, if the effect is negligible, such policies would be unnecessary. The second reason is that different industries, or more broadly different consumers, exhibit heterogeneity in electricity demand. For example, the electricity hourly demand curve of the manufacturing industry is often flatter than that of the services industry or that of households, with the latter exhibiting a demand with significant peaks in the early evening. Different demand curves require different supply technologies. Namely, some technologies are better suited to a long-term constant supply level while other technologies are better suited to demand peaks. Hence, forecasts of different types of consumers are an essential input in electricity policy and investment decisions. Third, from the perspective of environmental policy design, analysis of different industries is helpful because it makes it possible to identify industrial bottlenecks and to design appropriate environmentally friendly policies at the industry level.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and some significant trends of electricity intensity. Section 4 describes the σ-convergence test and clusters the OECD countries into clubs. Section 5 examines the effect of the industrial structure of the economy and electricity prices on electricity intensity using the β-convergence test and the LMDI. Section 6 highlights the implication of the results on the Israeli electricity market, and the section 7 concludes.

2. Literature Review

The present paper extend the literature on electricity intensity convergence in several respects. First, it defines electricity intensity as the ratio of electricity consumption to gross domestic product.[7] Second, it uses one database for statistically testing the convergence hypothesis using both σ-convergence and β-convergence tests, each of which has its pluses and minuses. Third, the paper decomposes electricity intensity convergence into industrial efficiency and the industrial structure of the economy and examines the impact of industrial structure and electricity prices on electricity intensity. The paper joins the literature that finds empirical support for electricity intensity convergence by identifying the clubs that exhibit convergence. In line with the literature on energy convergence, the paper finds that the economy's structural transformation has little impact of the structural transformation on electricity intensity convergence.

[6] See: Mohammadi and Ram (2012) for a discussion of the differences.

[7] Most papers define electricity intensity as electricity consumption per capita. Comin and Hobijn (2010) used the ration of electricity consumption to GDP as a technological adoption measure in their exploration of technological diffusion.

While the vast literature on convergence focuses primarily on energy intensity, there is a strand on literature on convergance of electricity intensity. Early papers on the subject used basic econometric and visualization methods to test for convergence. Maza and Villaverde (2008) analyze households' per capita electricity consumption using data from 98 countries between 1980 and 2007. They use β-convergence and σ-convergence models as well as a non-parametric model for ranking and mobility. Their results supports the existence of a slow process of convergence. In their paper, they present a visual illustration that the variance decreases over time. Using linear time trend estimation Liddle (2009) presented evidence for convergence of electricity consumption in the IEA/OECD countries between 1971 and 2005.

Following the specification of Miketa and Mulder (2005), Mohammadi and Ram (2012) estimate β-convergence equations of energy and electricity using a reduced-form version of the test of Barro and Sala-i-Martin (1992). The authors use a sample of 108 countries between 1971 and 2007 and estimate convergence for different periods and different quantiles of the distribution. They find strong support for convergence of electricity intensity but weaker support for energy intensity. The present paper adds to their analysis by estimating electricity intensity convergence at the industry level.

In a more recent paper, Kim (2015) examines the convergence of electricity intensity using data from 109 countries between 1970 and 2009. The author employs the σ-convergence model of Phillips and Sul (2007) for all countries in the database and an additional test for advanced economies. The results show that while electricity intensity converges in all countries, electricity per capita converges only in the advanced economies. By using the algorithm of Phillips and Sul (2007) for clubs identification, Kim (2015) find three clubs in the sample of 109 countries in which electricity per capita converges. Since the present paper is closest to Kim (2015), I will elaborate on the differences. The present paper adds to Kim (2015) by examining the role of the industrial structure of the economy. Also, as noted above, I define electricity intensity differently and report the tests using the model of Barro and Sala-i-Martin (1992) in addition to the model of Phillips and Sul (2007). Third, as mentioned above, I find that electricity intensity in the OECD countries has diverged in recent years. This result emphasizes the need to revisit the results and indicates the limitation of the conventional tests.

Using several convergence tests, Herrerias and Liu (2013) find electricity intensity convergence in three clubs of Chinese provinces.[8] 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 both unit chart and sequential panel selection model (SPSM) test: the unit chart results indicate convergence in all countries, while the SPSM results indicate convergence in 15 of the 19 countries for energy and 17 of the 19 countries for electricity.

The second strand of literature to which the paper relates explores the effect of industrial structure on energy intensity and its convergence. This strand has explored

[8]They test the models of Lee and Strazicich (2003), Kapetanios et al. (2003), Phillips and Sul (2007), and Hansen (2000).

chiefly the structural effect on energy industry, overlooking the possible importance of the structural transformation on electricity industry on its own. A central contribution of the present paper is to extend on this exploration of the effect of industrial structure from the energy to the electricity industry.

To the extent that there are differences in the energy intensity of different industries, a change in the domestic output structure might affect total energy intensity. The most well-known example of this phenomenon is the structural transformation that accompanies the development of nations. Low energy intensity levels characterize the services industries; hence, an increase in their share of the GDP decreases total energy intensity.[9] Past research has decomposed the changes of electricity intensity into the effect of changes in each industry's energy intensity (the energy efficiency effect) and the changes in industrial shares (the structural effect). A prevalently used index for this purpose is the LMDI, developed by Ang et al. (1998) and Ang and Liu (2001), which makes it possible to decompose electricity intensity without residual.

The results regarding the effect of GDP structure on the long-term trend of energy intensity are mixed. Miketa and Mulder (2005) examine the convergence of energy intensity in 10 industries in 56 countries between 1971 and 1995. They find that variation in intensity is particularly evident in less energy-intensive industries. 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 energy intensity and find that their effect is negligible, and energy prices and investment ratios are correlated with intensity.

Mulder and Groot (2012) examine 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. By contrast, the intensity of the services industries decreases more moderately when there is considerable variation in the trend of subindustries. Decomposition of energy intensity changes for structural change and efficiency change shows that structural change explains much of energy intensity dynamics.

In a as study of the heterogeneity in the electricity intensity in the US, Levinson (2016) performs a careful decomposition of the state-level GDP into its sub-industries. The author attributes the heterogeneity in electricity intensity to the long-term trend of efficiency or technical change, where industrial structure, prices, and regulation hav e a relatively small effect. Using a similar methodology, Marrero and Ramos-Real (2013) find that the decline of energy intensity in the EU 15 is also due to energy efficiency.

Torrie et al. (2016) find energy intensity in Canada decreased by 24 percent between 1995 and 2010. Their analysis shows that about 48 percent of the decrease stems from structural change during the sample period. Other reasons for the decline are the GDP per capita increase and the decline in the energy intensity of each subindustry.

[9] This line of research started in the late 1970s; however, it was formalized and developed in the extensive work of Ang (1987, 1995, 1999, 2004).

3. Data

This section describes the data and the primary characteristics of electricity intensity in the sample.[10] The database is an unbalanced panel of the OECD countries for the years 1990 - 2018.[11] For each country, the data include information on GDP and electricity consumption, broken down into six industries of the economy: agriculture, mining and quarrying, manufacturing, construction, commercial services, and transport.[12] In addition, the data include information on the electricity consumption of households. As a measure of the economic activity of the households, the data include information on private consumption from the National Accounts statistics. For industries , electricity intensity is defined as the ratio of electricity consumption of each industry to its GDP. 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. Specifically, electricity intensity (I) of country j in industry k at time t is defined as the ratio of Watt per Hour (WH) electricity consumption (E) to gross domestic product in 2005 USD (Y) for this industry, i.e.,

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

For simplicity, I abstract from the industries' notation and return to it when relevant.

Figure 1 presents the data on total electricity intensity in the OECD countries for the years 1990 – 2017, i.e., total industry and household use of electricity consumption divided by total gross domestic product. The figure shows that, on average, electricity intensity in the past 25 years has been on a downward trend.[13] The second observation from the figure is that the heterogeneity of electricity intensity between countries decreases over time. In 1992, the country with the highest level of electricity intensity was Estonia with 573 Watt-Hours per Dollar (WHD), and the one with the lowest level was Switzerland with 95 WHD. In 2018, the country with the highest level of electricity intensity was Finland with 332 WHD, and the one with the lowest was Switzerland with 81 WHD. Thus, the gap between the countries with the highest and the lowest intensity levels narrowed from 478 to 251 WHD. In other words, according to this simple observation, electricity intensity converged.[14]

Figure 2 shows the annual percentage change in electricity intensity of the OECD countries. In the past three decades, the average decrease in developed countries' electricity intensity has accelerated. In the first two decades, the annual average decrease

[10] For a detailed description of the data construction, see the data appendix

[11] Namely, 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, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

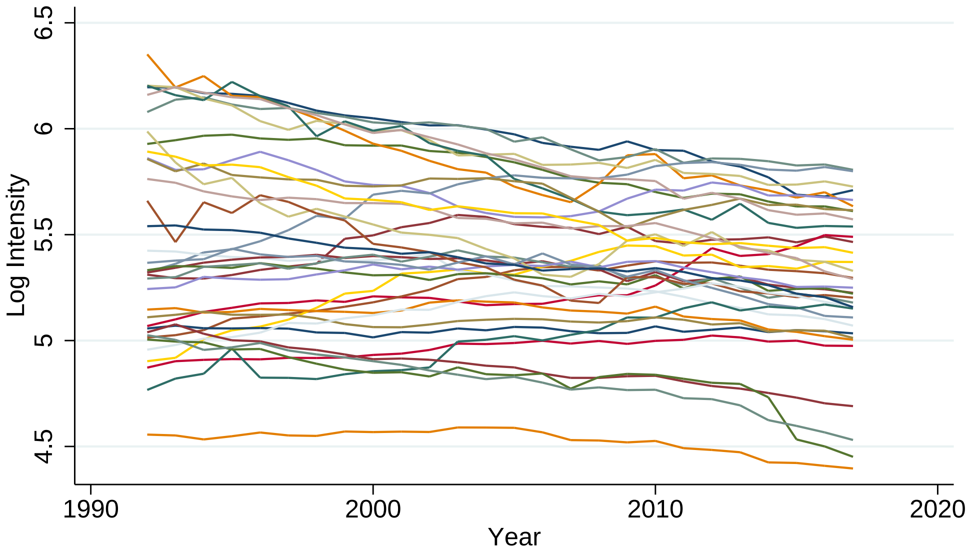
[12] The source of the data on GDP as well as on electricity consumption is UNSTAT.

[13] See Mulder and Groot (2012), Mulder et al. (2014), Levinson (2016), and WEO (2018).

[14] See Mulder and Groot (2012), Mohammadi and Ram (2017), Apergis and Christou (2016), Burnett and Madariaga (2017), Fallahi (2017), and Adhikari and Chen (2014). For a recent symposium on this subject, see Apergis et al. (2017).

was about 0.4 percent, while in the last decade, it reached 1.5 percent. To further examine convergence, one must examine the development of the variance of electricity intensity. An increase in electricity intensity appears mainly in the vicinity of economic crises around 2000 and 2008. This result might stem from the fact that electricity use is related to fixed costs. A crises that decrease production negatively impact economic activity that is related to variable costs more intensively than economic activity related to fixed costs.

Figure 1: Electricity Intensity in the OECD countries



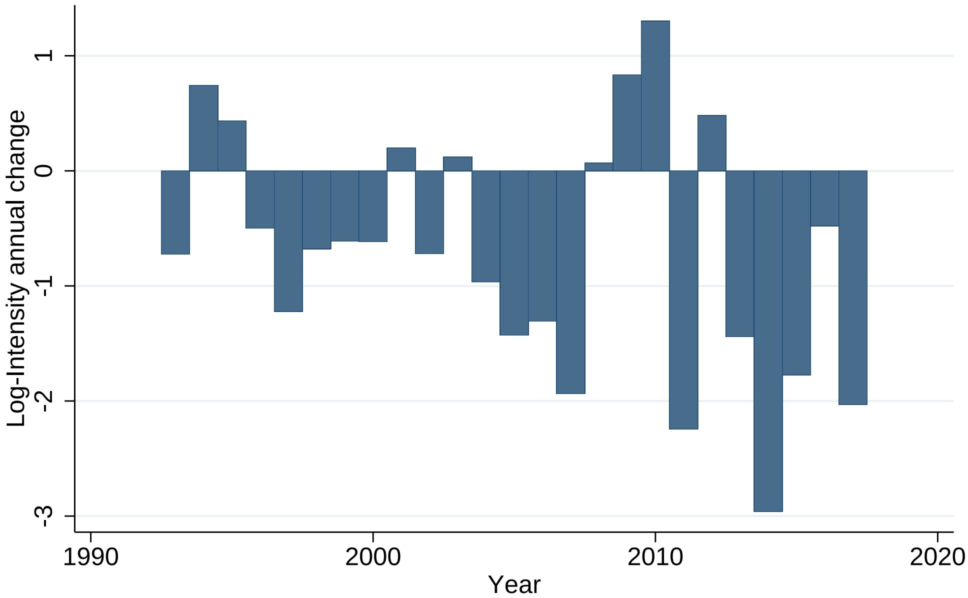
The figure presents log electricity intensity. Electricity intensity is defined as electricity (millions of kilowatts per hour) per GDP (constant 2015 prices in US dollars).

Source: Based on UNSTAT data.

Figure 3 presents the development of three measures of the variance of electricity intensity throughout the sample years.[15] 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 measure is the variance of the log of intensity ($Var(i_{j,t})$), where $i_{j,t} \equiv log(I_{j,t})$. 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 variance measures decrease dramatically between 1990 and 2008, their behavior changes afterward: the first measure remains relatively constant, but the other two start to rise again. Note, that the data in Figure 1 do not indicate that there was a major change after 2008. These results illustrate the limitation of simple visual observation of trends.

[15]The formulation of these three variance measures is presented in the next section.

Figure 2: Change in Electricity Intensity in the OECD



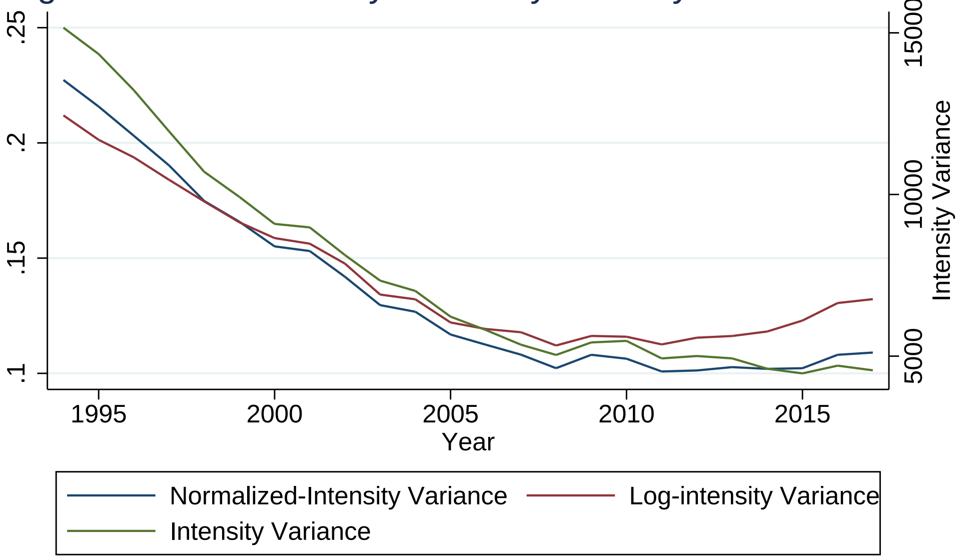
Source: Based on UNSTAT data.

At the end of the sample period, the apparent break in electricity intensity convergence challenges the validity of conducting electricity demand forecasts based on international comparisons. Such forecasts are built on an assumption that our results refute, namely, that the electricity demand of each country will converge over time to some global trend.

4. Testing for Convergence

To formally demonstrate the observed electricity intensity convergence and divergence pattern, this section formulates and estimates the σ-test for convergence. It starts by describing the econometric models with which I analyze the data. Also, the section presents the algorithm of Phillips and Sul (2007) for clustering countries into clubs. The advantage of this convergence approach is that it is intuitive and straightforward, as it directly analyzes the subject under examination:the dispersion of intensity. Its main disadvantage is that it dose not allow to examine other factors' impact on convergence, such as electricity prices or the industrial structure of the country, because the test is conducted on the variance and not on the intensity measure itself. Another disadvantage is that, to the extent that we work with panel data, the number of years is small. This disadvantage leaves us with only a few degrees of freedom in the analysis, which means that the results should be interpreted with caution.

Figure 3: Cross-Country Electricity Intensity Variance Indices



The figure presents three measures of electricity intensity variance: standard variance of electricity intensity, variance of log electricity intensity, and variance of mean normalized electricity intensity.

Source: Based on UNSTAT data.

4.1. Σ-convergence test

In order 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 essentially estimates a non-linear-regression model in which the variance of intensity between countries is a 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. Formally,

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

To the extent that Λ_t is common to all countries, it is possible to remove it by 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 $h_{j,t}$ is one, by definition. In addition, if the transition parameter converges to a constant, then $h_{j,t}$ converges to one and the variance of $h_{j,t}$ like the variance of $\Theta_{j,t}$, converges to zero. Formally, we define the variance of $h_{j,t}$ as $\tilde{\sigma}_t^2 = \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$, i.e.,

$$\Theta_{j,t} \xrightarrow[t\to\infty]{} \Theta \;\Rightarrow\; h_{j,t} \xrightarrow[t\to\infty]{} 1,\; \tilde{\sigma}_t^2 \xrightarrow[t\to\infty]{} 0.$$

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

$$\tilde{\sigma}_t^2 = \frac{\sigma}{log(t+1)t^{\alpha}}. \tag{4}$$

Under this assumption, the variance decreases slowly as $log(t+1)$ increases. If, and only if, α is significantly smaller than zero, then the decrease in 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 would be the one-sided hypothesis that $H_0 : \alpha \geq 0$. In order to test this hypothesis, Phillips and Sul (2007) suggest the following regression and present its asymptotic properties:

$$\begin{aligned} \log\left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_t^2}\right) - 2\log\log(t+1) &= \beta_0 + \beta_\sigma \log(t) + \varepsilon_{j,t} \\ \forall t = rT,\; rT+1,\; ..., & \end{aligned} \tag{5}$$

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 the observation, should be excluded the estimation. A significantly negative $\hat{\alpha}$ indicates a positive correlation of $\hat{\sigma}_t^2$ with time; that is the variance increases over time. Any other result means that the variance decreases over time or that we cannot reject the hypotheses that electricity intensity σ-converges.

Table 1 shows the estimation results of the $\sigma - convergence$ tests as given in equation (5). In addition to the formal test of variance suggested by Phillips and Sul (2007), I present the test using the other two measures of variance, namely, simple variance over intensity ($\sigma_t^2 = \frac{1}{N}\Sigma_j(I_{j,t} - \overline{I}_{j,t})^2$) and the variance of log intensity ($\hat{\sigma}_t^2 = \frac{1}{N}\Sigma_j(\log I_{j,t} - \log \overline{I}_{j,t})^2$).[16] As mentioned above, the statistical test is such that only a significantly negative coefficient implies rejecting the convergence hypothesis. The estimation suggests that the coefficients are positive and significant, regardless of the variance measurements used. Thus, the result implies that we cannot reject the hypothesis that electricity intensity converges according to these tests. 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 3. While the figure illustrates the divergence of electricity intensity at the end of the sample period, the statistical test ignores it.

To provide a statistical test for the observed phenomenon of the increase in variance in the last decade of the sample period, I extend the model of Phillips and Sul (2007). Specifically, I estimate the following model:

[16] Overline sifnifies simple mean, i.e., $\forall X_i, \;\; \overline{X} \equiv \frac{\sum_i X_i}{N}$

$$\log\left(\frac{\hat{\sigma}_1^2}{\hat{\sigma}_t^2}\right) - 2\log\log(t+1) = \tag{6}$$
$$\alpha + \beta_{\sigma_1}\log(t) I_{(year \leq 2007)} + \beta_{\sigma_2}\log(t) I_{(year \geq 2008)} + \phi I_{(year \leq 2008)} + \varepsilon_{j,t}$$
$$\forall t = rT,\ rT+1,\ \ldots$$

The refinement Phillips and Sul (2007) model enables us to identify whether the convergence stems from the variance's behavior before 2008, which is captured by the coefficient β_{σ_1}, or after 2008, which is captured by the coefficient β_{σ_2}.

In Table 2, I present the estimation results of the model given in equation (7), which considers a possible change in the behavior of electricity intensity over time. The coefficients of the first period turn positive and even significant, indicating that before 2008, the electricity intensity of the countries in the sample indeed converges. The coefficients of the second period are mixed. The second period's coefficient of the variance measure of Phillips and Sul (2007) is negative and not significant, the coefficient of the log-variance measure is negative and significant, and the coefficient of the simple variance measure is positive and significant. To test the hypothesis that there has been a change in the convergence pattern change, I use a simple F-test that compares the coefficients before and after 2008. The table reports the test's p-values. As we can see, all the p-values are significant, and so we can reject the hypothesis of equal coefficients in different periods. This result accords with the visual result and suggests that the rate of convergence pace has decreased.

Table 1: Sigma-Convergence Test of Electricity Intensity

	(1) $\tilde{\sigma}_t^2$	(2) $\hat{\sigma}_t^2$	(3) σ_t^2
Log(t)	134.967***	85.067***	262.126***
	(0.000)	(0.000)	(0.000)
Constant	−1028.277***	−649.141***	−1994.444***
	(0.000)	(0.000)	(0.000)
Observation	26.000	26.000	26.000
AdjustedR2	0.892	0.759	0.966

p-values in parentheses
$\tilde{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$
$\hat{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(\log I_{j,t} - \log \overline{I}_{j,t})^2$
$\sigma_t^2 \equiv \frac{1}{N}\Sigma_j(I_{j,t} - \overline{I}_{j,t})^2$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2. Club Classification

The decrease in the rate of of convergence might stem from the divergence of the electricity intensity of specific countries. Alternatively, there may be clubs of countries

Table 2: Sigma-Convergence Test of Electricity Intensity

	(1) $\tilde{\sigma}_t^2$	(2) $\hat{\sigma}_t^2$	(3) σ_t^2
φ	1652.574***	1716.660***	1069.721***
	(0.000)	(0.000)	(0.006)
β_{σ_1}	185.373***	137.928***	306.116***
	(0.000)	(0.000)	(0.000)
β_{σ_2}	−31.912	−87.784***	165.451***
	(0.125)	(0.000)	(0.001)
Constant	−1411.383***	−1050.902***	−2328.787***
	(0.000)	(0.000)	(0.000)
Observation	26.000	26.000	26.000
AdjustedR2	0.986	0.982	0.981
FTest	108.492	202.456	9.404
PValue	0.000	0.000	0.006

p-values in parentheses
$\tilde{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$
$\hat{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(\log I_{j,t}-\log \overline{I}_{j,t})^2$
$\sigma_t^2 \equiv \frac{1}{N}\Sigma_j(I_{j,t}-\overline{I}_{j,t})^2$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

that continue to converge, albeit with different trajectories. To examine these hypotheses, I use the generalized form of the algorithm of Phillips and Sul (2007) in (2), which allows for different clubs of the panel to converge to different levels of intensity. This generalized model clusters countries by the their electricity intensity convergence and identifies potential clubs of countries that converge. In addition, it enables us to identify countries that diverge and separate them from those that converge. Denote the set of all countries by (S) and the set of clubs by (C); then the model can be formulated as follows:

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

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

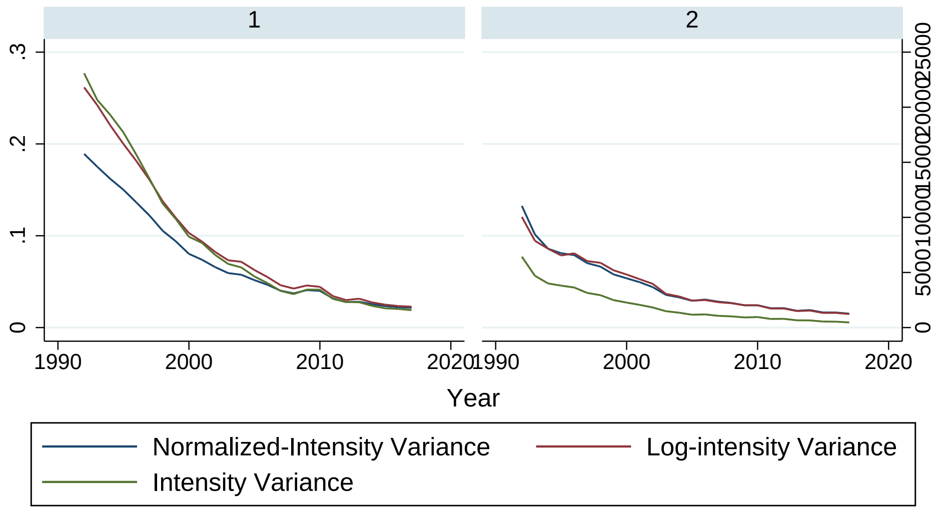
1. Order countries according to the last observation of each.
2. Select a core group with the k highest countries that maximize the $\log t$-test described in the previous subsection.
3. Add each country from the remaining group to the core group and re-test if it still converges, and leave it in the remaining group, otherwise.
4. If both groups converge, the process ends. If the core group converges and no countries can be added to the core group, repeat steps 1-3 for the remaining group.

Table 2 classifies the countries into clubs according to the results of the algorithm. The algorithm identifies two clubs that converge and four countries that diverge from

Clustering the Countries in the Sample into Clubs	
Club 1:	Canada, Chile, Czech Republic, Estonia, Finland, Greece, Hungary, Norway, Portugal, Republic of Korea, Slovak Republic, Slovenia, Sweden, Turkey.
Club 2:	Australia, Austria, Belgium, France, Germany, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Poland, Spain, United States.
Divergent:	Denmark, Ireland, Switzerland, United Kingdom.

all the others. Figure 4 presents the variance indices of the different clubs throughout the sample period. The figure illustrates that although the variance measurements are unstable in the years around the financial crises, they continue their monotonic decrease before and afterward. This result *suggests* that in the last several years the different clubs diverge, while the countries within each club continue to convergence. To test this hypothesis formally, I conduct the same σ-test as in the previous subsection for each club. Tables 3-6 present the results of these tests. As before, the σ-test for the entire period presented in Tables 3 and 5 suggests that we cannot reject the hypothesis that electricity intensity converges. However, when we break the sample years into two periods, presented in Tables 4 and 6, respectively, we find that the coefficients in the second period are larger than those in the first. These results suggest that the rate of convergence is increasing within these clubs, and the F-test that compares the coefficients of the two periods confirms this.

Figure 4: Indices of the Variance of Electricity Intensity in Each Club



The figure presents three measures of electricity intensity variance by clubs: standard variance of electricity intensity, variance of log electricity intensity and, variance of mean normalized electricity intensity.

Source: Based on UNSTAT data.

5. The Effect of Structural Transformation and Electricity Prices on Convergence

The objective of this section is to shed light on possible reasons for electricity intensity convergence. The section tests the impact of the economic structural transformation and electricity prices on electricity intensity convergence. To this end, I adopt the model of Barro and Sala-i-Martin (1992) of convergence in which the electricity intensity of countries with high initial levels increases slower than in countries with low initial levels. To test this, I estimate 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 indicates convergence. This approach is named β-convergence because it manifests itself in the β coefficient of the regression between past levels and current growth. To the extent that this method estimates the regression for the intensity of each country, it is possible to examine the role of structural transformation on electricity intensity. In addition, it enables us to control for country-specific developments on intensity, such as electricity prices.

I formulate a 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).[17] The linearity of this

[17] The linear version is also a prevalent model in the literature, e.g., Mulder and Groot (2012) and Mohammadi and Ram (2012).

Table 3: Sigma-Convergence Test of Electricity Intensity for Club 1

	(1) $\tilde{\sigma}_t^2$	(2) $\hat{\sigma}_t^2$	(3) σ_t^2
Log(t)	639.372***	859.537***	1079.419***
	(0.000)	(0.000)	(0.000)
Constant	−4861.265***	−6534.342***	−8205.251***
	(0.000)	(0.000)	(0.000)
Observation	26.000	26.000	26.000
AdjustedR2	0.952	0.937	0.925

p-values in parentheses

$\tilde{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$

$\hat{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(\log I_{j,t} - \log \overline{I}_{j,t})^2$

$\sigma_t^2 \equiv \frac{1}{N}\Sigma_j(I_{j,t} - \overline{I}_{j,t})^2$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Sigma-Convergence Test of Electricity Intensity for Club 1

	(1) $\tilde{\sigma}_t^2$	(2) $\hat{\sigma}_t^2$	(3) σ_t^2
φ	−4590.685***	−6825.314***	−10603.713***
	(0.000)	(0.000)	(0.000)
β_{σ_1}	497.415***	624.699***	783.800***
	(0.000)	(0.000)	(0.000)
β_{σ_2}	1101.013***	1522.145***	2177.968***
	(0.000)	(0.000)	(0.000)
Constant	−3782.336***	−4749.489***	−5958.416***
	(0.000)	(0.000)	(0.000)
Observation	26.000	26.000	26.000
AdjustedR2	0.986	0.984	0.982
FTest	41.227	41.642	56.734
PValue	0.000	0.000	0.000

p-values in parentheses

$\tilde{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$

$\hat{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(\log I_{j,t} - \log \overline{I}_{j,t})^2$

$\sigma_t^2 \equiv \frac{1}{N}\Sigma_j(I_{j,t} - \overline{I}_{j,t})^2$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Sigma-Convergence Test of Electricity Intensity for Club 2

	(1) $\tilde{\sigma}_t^2$	(2) $\hat{\sigma}_t^2$	(3) σ_t^2
Log(t)	611.460***	574.816***	933.045***
	(0.000)	(0.000)	(0.000)
Constant	−4648.830***	−4370.585***	−7092.612***
	(0.000)	(0.000)	(0.000)
Observation	26.000	26.000	26.000
AdjustedR2	0.972	0.961	0.935

p-values in parentheses
$\tilde{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$
$\hat{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(\log I_{j,t}-\log \overline{I}_{j,t})^2$
$\sigma_t^2 \equiv \frac{1}{N}\Sigma_j(I_{j,t}-\overline{I}_{j,t})^2$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Sigma-Convergence Test of Electricity Intensity for Club 2

	(1) $\tilde{\sigma}_t^2$	(2) $\hat{\sigma}_t^2$	(3) σ_t^2
φ	−2819.828***	−3024.873***	−9133.198***
	(0.00)	(0.00)	(0.00)
β_{σ_1}	521.818***	472.339***	704.237***
	(0.00)	(0.00)	(0.00)
β_{σ_2}	892.582***	870.071***	1905.028***
	(0.00)	(0.00)	(0.00)
Constant	−3967.517***	−3591.725***	−5353.558***
	(0.00)	(0.00)	(0.00)
Observation	26.000	26.000	26.000
AdjustedR2	0.986	0.981	0.987
FTest	17.103	15.820	80.911
PValue	0.000	0.001	0.000

p-values in parentheses
$\tilde{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(h_{j,t}-1)^2$
$\hat{\sigma}_t^2 \equiv \frac{1}{N}\Sigma_j(\log I_{j,t}-\log \overline{I}_{j,t})^2$
$\sigma_t^2 \equiv \frac{1}{N}\Sigma_j(I_{j,t}-\overline{I}_{j,t})^2$
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

model makes it possible to examine the effect of the industrial structure of the economy on electricity intensity convergence as noted by Wong (2006). I use the decomposition method that was developed by Ang (1987) to bifurcate electricity intensity into two indices: an index of the intensity of each industry and an index of the weights of industries with different levels of intensity. I regress each index on initial levels of electricity intensity, which provides me with the estimation of the two decomposed βs. The first coefficient – β_{EFF} – is an estimate of the effect of changes in the electricity intensity of each industry, i.e., the electricity *efficiency* of each industry, on aggregate electricity intensity. The second coefficient – β_{STR} – is an estimate of the effect of the change in the shares of each industries in the GDP, i.e., the *structure* of the GDP, on aggregate electricity intensity. For each index, while controlling for prices, I estimate a linear version of the β-convergence test and extract the coefficient of the efficiency (β_k^{EFF}) and that of the structure (β_k^{STR}). This model allows me to test the joint impact of electricity prices and structural transformation on electricity intensity convergence. To illustrate the impact structure relative to that of the efficiency on electricity intensity convergence, I present the relative structural magnitude index :$RSM = \left(\frac{|\beta_{STR}|}{|\beta_{EFF}|} - 1\right) \cdot 100$. The RSM determines whether the absolute value of the structural coefficient is higher than that of the efficiency coefficient in terms of absolute value. A positive/negative result means that the effect of the structure of the GDP is higher/lower than the effect of the industry efficiency.

As mentioned above, the electricity intensity patterns of different industries are essential for policy designers; hence, I also report each industry's electricity intensity convergence patterns. The previous sections illustrated that convergence is most significant within the clubs that were identified. Hence, the analysis will present the result for the entire set of countries and for each club.

5.1. Formal Representation of Logarithmic Mean Divisia Index (LMDI) for Decomposition Analysis

To put the above issues formally, 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,

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

Here, $\Delta i_{j,t} \equiv i_{j,t} - i_{j,t-1}$. If electricity 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 in intensity, and so in the long run the levels (or change rates) converge. The advantage of the present model is that it allows testing for conditional convergence. By adding independent variables to the model, one can test for convergence after controlling for alternative variables that might affect electricity intensity.[18]

[18]See, e.g., the work of Miketa and Mulder (2005) and Mohammadi and Ram (2012) for analyses of energy intensity.

To examine the effect of the industrial structure of the economy on the convergence of electricity intensity, I follow Miketa and Mulder (2005) and decompose electricity into two indices: industrial intensity and the intensity that ensues from the share of each industry in the economy. For this purpose, I use the 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 formulates electricity intensity as the weighted sum of industrial intensities, where the weights are the shares of the industries 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 industrial 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 at hand, it is easy to show that the change scheme is additive, i.e.,

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

I follow Wong (2006) and Mulder and Groot (2012) who propose a process to estimate a decomposed β in two steps. The first step is to decompose the initial index into two subindices, as was just illustrated. The second step is to estimate a regression of each subindex on the initial year, i.e.,

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

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

Wong (2006) showes that this process yields decomposed β_ks such that the β_L in (7) is their sum, i.e.,

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

In addition to these models, and in order to take into account the impact of electricity prices on electricity intensity convergence, I estimate the following models:

$$D(S_{k,t}, I_{k,t}) \log \frac{I_{k,t}}{I_{k,t-1}} = \alpha + \beta_k^{EFF} i_{j,0} + \gamma_k^{EFF} \log P_{j,t} + \varepsilon_{j,t}, \tag{16}$$

$$D(S_{k,t}, I_{k,t}) \log \frac{S_{k,t}}{S_{k,t-1}} = \alpha + \beta_k^{STR} i_{j,0} + \gamma_k^{STR} \log P_{j,t} + \varepsilon_{j,t}. \tag{17}$$

5.2. Decomposition Analysis Results

Tables 7 and 8 present the estimation results of the decomposed βs for all countries. The first table presents the estimation results of β_{EFF} as formulated in equation (10) and the second table presents the estimation results of β_{STR} as formulated in equation (11). Since the club convergence results of each industry are not qualitatively different from the general convergence results of all countries, the estimation results for each club are presented in the Appendix. The results show that except for the mining and construction industries, the β_{EFF} is negative and significant. These results mean that efficiency plays a significant role in the process of electricity convergence. By contrast, none of the β_{STR} estimations are significantly negative, and some are even positive and significantly different from zero. According to this test, efficiency is the main driver of electricity intensity convergence while the industrial structure does not affect or in some industries partly offsets electricity intensity convergence. Tables 9 and 10 present the estimation results of the decomposed βs while controlling for prices. In estimating the efficiency coefficient, it is possible to see that although prices negatively impact electricity intensity, their coefficient is not significantly different from zero. In addition, controlling for prices did not change the efficiency coefficients' results or those of the structural coefficients.

Table 7: Structure Impact on Convergence - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{STR}	-0.188^{*}	-0.185	2.862^{*}	0.000	0.580^{**}	0.016	-0.045
	(0.061)	(0.138)	(0.062)	(0.976)	(0.047)	(0.777)	(0.919)
Constant	0.762	0.601	-18.428^{*}	-0.036	-3.171^{*}	0.011	0.319
	(0.135)	(0.178)	(0.056)	(0.265)	(0.057)	(0.949)	(0.871)
Observation	827.000	723.000	806.000	617.000	882.000	905.000	932.000
OverallR2	0.008	0.011	0.018	0.000	0.005	0.000	0.000

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Efficiency Impact on Convergence - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{EFF}	-1.229^{***}	0.203	-7.868^{***}	-0.089^{*}	-2.943^{***}	-0.467^{***}	-3.028^{***}
	(0.000)	(0.600)	(0.000)	(0.077)	(0.000)	(0.003)	(0.000)
Constant	6.091^{***}	-0.708	47.814^{***}	0.265^{**}	17.558^{***}	1.445^{**}	13.087^{***}
	(0.000)	(0.601)	(0.000)	(0.047)	(0.000)	(0.017)	(0.000)
Observation	827.000	723.000	806.000	617.000	882.000	905.000	932.000
OverallR2	0.036	0.004	0.053	0.004	0.014	0.018	0.033

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Structure Impact on Convergence Controlling for Electricity Prices - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{STR}	−0.104**	−0.204	1.954**	−0.005	0.233	0.080***	−0.134
	(0.033)	(0.107)	(0.033)	(0.738)	(0.645)	(0.000)	(0.809)
γ_k^{STR}	−0.069	−0.007	−2.053	0.050*	0.284	0.195	−1.194
	(0.672)	(0.947)	(0.119)	(0.083)	(0.632)	(0.158)	(0.208)
Constant	0.721	0.684	−2.263	−0.285**	−2.722	−1.174	6.877
	(0.382)	(0.146)	(0.701)	(0.034)	(0.579)	(0.116)	(0.288)
Observation	741.000	638.000	712.000	557.000	780.000	796.000	718.000
OverallR2	0.004	0.013	0.017	0.007	0.002	0.010	0.006

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Efficiency Impact on Convergence Controlling for Electricity Prices - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{EFF}	-0.602^{**}	0.218	-5.724^{***}	-0.094^{*}	-2.677^{***}	-0.387^{***}	-2.742^{***}
	(0.019)	(0.603)	(0.000)	(0.070)	(0.000)	(0.003)	(0.000)
γ_k^{EFF}	-2.034^{*}	-0.269	-3.162	-0.199	-1.254	-0.695	-0.813
	(0.081)	(0.508)	(0.133)	(0.150)	(0.484)	(0.120)	(0.155)
Constant	13.191^{**}	0.601	50.178^{***}	1.285^{*}	22.388^{**}	4.732^{*}	15.858^{***}
	(0.036)	(0.777)	(0.000)	(0.074)	(0.025)	(0.074)	(0.000)
Observation	741.000	638.000	712.000	557.000	780.000	796.000	718.000
OverallR2	0.048	0.007	0.047	0.030	0.024	0.039	0.024

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To summarize the relative importance of the structure and efficiency coefficient on the convergence of electricity intensity, I define for each industry k in club c the following index for the RSM:$RSM = \left(\frac{|\beta_{STR}|}{|\beta_{EFF}|} - 1\right) \cdot 100$. The simple RSMs presented in Table 11 and the RSMs with controls for prices presented in Table 12 shows similar results. Most of the indices are negative, meaning that, in most cases, the structural coefficient is smaller than the efficiency coefficient. This result means that the dominant factor in the convergence of electricity intensity is industrial efficiency rather than industrial structure of the economy. This result means that in most OECD countries, the effect of the structural transformation on electricity intensity convergence is limited. In addition, it seems that apart from the mining industry, the limited role of structural transformation covers all industries.

Table 11: Relative Structural Magnitude (RSM)

	Total	Club1	Club2
Agriculture	-84.68	-86.34	-80.59
Mining	-8.51	-23.10	924.48
Manufacturing	-63.62	-55.61	-85.35
Construction	-99.53	-70.24	-87.12
Services	-80.30	-88.98	-65.23
Transport	-96.57	-72.67	-77.25
Household	-98.50	-99.50	-89.44

Table 12: Relative Structural Magnitude (RSM) Controlling for Prices

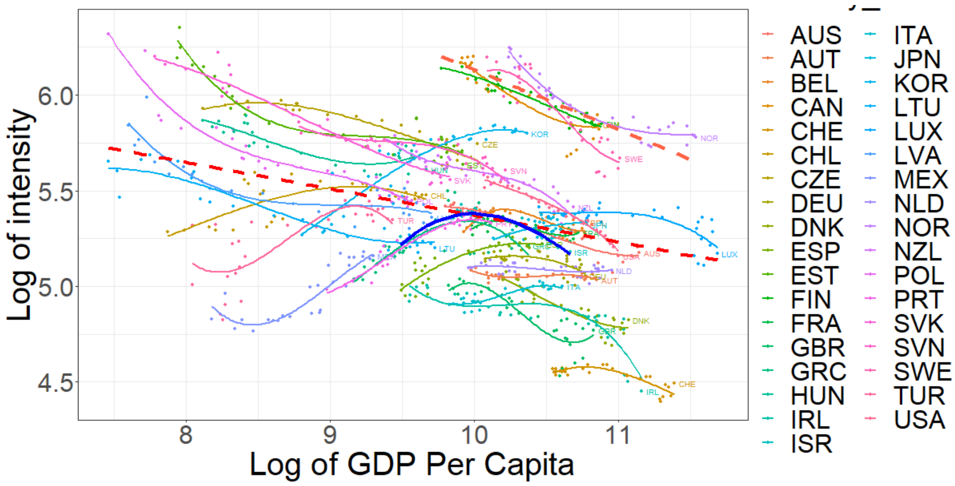
	Total	Club1	Club2
Agriculture	-82.64	-95.96	-54.42
Mining	-6.37	-43.72	132.82
Manufacturing	-65.86	-60.66	-68.06
Construction	-94.93	-66.48	-69.00
Services	-91.31	-99.36	-59.77
Transport	-79.30	-95.83	-76.69
Household	-95.12	-90.17	-99.49

6. A Spotlight on Israel

What will Israel's electricity demand growth rates be in the next few decades? To the extent that electricity production is the greatest consumer of fuels in the energy market, the answer to this question portrays the roadmap to the entire energy industry in Israel; hence, it is essential to prospective energy policy designers, who make policy and infrastructure investment decisions today in order to meet future demand.

The current paper shows that electricity intensity in the OECD countries has decreased for the last three decades. Figure (5) portraits electricity intensity against gross

Figure 5: Domestic Product per Capita and Electricity Intensity in the OECD Countries



domestic products per capita of OECD countries. The figure shows a clear relationship between development level (proxied with GDP per capita) and electricity intensity. Countries with higher GDP per capita also have lower levels of electricity intensity. In addition, the lines in the figure are drawn for each country over the years. It shows that as a country develops, its intensity decreases. If electricity intensity in Israel behaves according to past trends of OECD countries' electricity intensity, one can expect that electricity intensity will decrease in the future. This result implies that electricity demand will increase at lower rates than GDP. The current paper addresses the similarity between the trends in Israel and the OECD countries and finds a club of countries that Israel's electricity intensity resembles.

The paper finds that after a few decades of convergence, and ever since the financial crisis of 2008, electricity intensity in the OECD countries has stopped converging. However, using (Phillips and Sul, 2007)'s algorithm, the paper finds electricity intensity clubs in the OECD countries, where the electricity intensity of countries within the clubs continues to converge. Israel belongs to the second club that was identified. The electricity intensity of Israel's club is lower than that of the other club, which means Israel's electricity intensity is relatively low. Within this club, Israel's electricity intensity is at the center of the distribution, as can be seen in Figure (**??**), where Israel is painted in blue. Throughout the examined period, Israel's electricity intensity is in the middle of the other countries in the club. The electricity intensity dynamics in Table (14) show that while Israel's electricity intensity at the first period increased, at the end of the period, it has converged to the rates of the second club. According to this result, Israel's electricity intensity has decreased annually by about 1.5 percent in recent years, meaning that Israel's electricity demand is expected to increase at a rate that is 1.5 percent lower than that of its GDP.

Table 13: Electricity Intensity Levels

	All	Club1	Club2	Israel
1990-2000	252.93	336.06	213.11	211.04
2001-2010	230.81	301.06	199.40	213.95
2011-2017	213.93	280.03	185.64	187.05

Table 14: Electricity Intensity Dynamics

	All	Club1	Club2	Israel
1990-2000	-0.40	-0.17	-0.39	1.44
2001-2010	-0.38	-0.58	-0.16	-1.01
2011-2017	-1.49	-0.92	-1.59	-1.67

The result of this paper provides a low forecast for electricity demand relative to other forecasts. Using local data, Gallo (2017) estimated correlation coefficients between electricity demand and gross domestic product, electricity prices, structural transformation, temperature, and other relevant variables. The main reason for the higher foretasted electricity demand in is that in Gallo (2017) electricity elasticity to GDP is estimated as constant during a period of increase intensity, while in the current paper it is the changes in intensity, end hence in elasticity are estimated. Under some assumption on these variables' future development, Gallo (2017) found that electricity demand is expected to grow at a rate of 2.7, which is slightly above that of GDP. This forecast stands at odds with the OECD countries' past trends, as shown in the current paper.

7. Summary

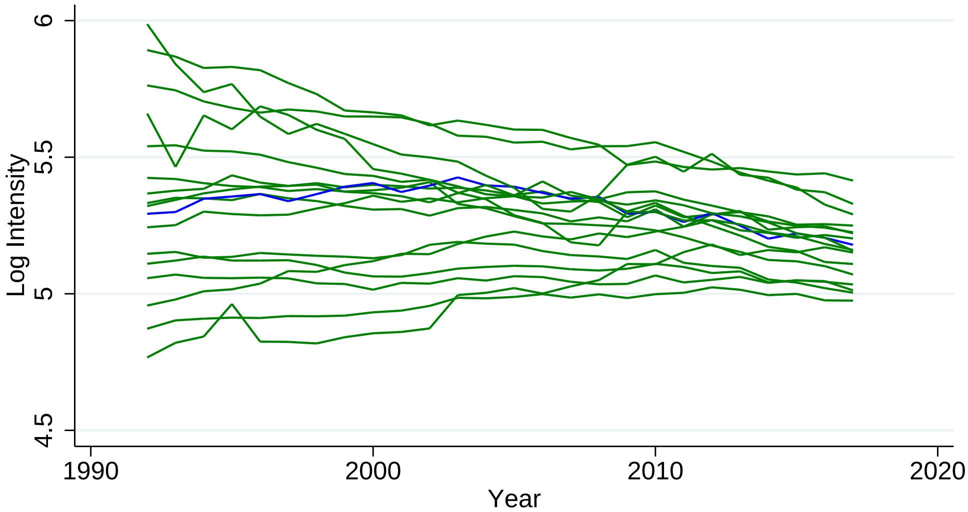
This paper sheds some light on the demand for electricity by analyzing the dynamics of electricity intensity – i.e., the ratio of electricity consumption to the gross domestic product – and the relation of these dynamics to the industrial structure of the economy. The questions that the paper addresses are: Does electricity intensity still converge? What are the drivers of convergence and divergence? What is the role of the industrial 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, while emphasizing the advantages and disadvantages of each approach.

The analysis in the present paper shows that electricity intensity of countries in the OECD converged for three decades until the financial crisis of 2008, when it started to diverge. The paper tests and confirms the hypothesis that this increase in the variance of electricity intensity stems from the divergence of the trends of different clubs of countries, even though within these clubs convergence persist.

In addition to the electricity intensity of the entire economy, the paper analyzes the electricity intensity of households and each of the six economic industries that make

Figure 6: Electricity Intensity in Club 1 of the Advanced Economies



The figure presents log electricity intensity. Electricity intensity is defined as electricity (millions of Kilowatts per hour) per GDP (constant 2010 prices in US Dollars).

Source: Based on UNSTATS data.

up the GDP, namely, agriculture, mining and quarrying, manufacturing, commercial services, construction, and transport. I follow Ang (1987), Ang (1995), and Wong (2006) and decompose electricity intensity into two indices: industrial electricity intensity, which can be viewed as industrial electricity efficiency, and the intensity that emerges from the share of each industry in the economy. For this purpose, I use the LMDI that was developed by Ang et al. (1998) and Ang and Liu (2001).

The results show that the main driver of the dynamics and convergence of electricity intensity electricity efficiency at the industry level rather the industrial structure of the economy.

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Appendices

A. Data Appendix

In order to conduct this analysis, we collected data and created a balanced panel dataset for the following OECD 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 the United States.

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

A list of the data collected:

1. Electricity consumption and its breakdown by industry in millions of Kilowatts per hour, as published by UNSTATS. Covering 1990-2017.
2. GDP and its breakdown at constant 2010 prices in US Dollars, as published by the UNSTATS National Accounts Main Aggregates Database. Covering 1970-2017.
3. Per capita GDP at current prices – US dollars as published by the UN statistics division. Covering 1970-2017.

A.0.1. Sources Limitations

our dataset is limited in several aspects:

1. UNSTATS breakdown to industries of electricity consumption was not paralleled to UNSTATS breakdown to industries 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. To have a balanced panel dataset for each industry, we had to ensure that we have continuous series for each country in each industry. Due to this, we had to remove from our dataset the following states in the following industries:
   (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.

(f) Turkey was removed from the price analysis due to very low inflation.

B. Analysis Appendix

Table B1: Efficiency Impact on Convergence - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{EFF}	-1.131^{***}	0.420	-13.225^{***}	-0.351^{***}	-4.026^{***}	-0.617^{***}	-3.574^{***}
	(0.006)	(0.583)	(0.002)	(0.000)	(0.000)	(0.005)	(0.000)
Constant	5.480^{***}	-1.559	86.372^{***}	1.290^{***}	25.512^{***}	2.123^{**}	16.466^{***}
	(0.009)	(0.571)	(0.003)	(0.000)	(0.000)	(0.013)	(0.000)
Observation	345.000	292.000	286.000	212.000	370.000	370.000	370.000
OverallR2	0.036	0.012	0.062	0.008	0.017	0.014	0.042

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Structure Impact on Convergence - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{STR}	−0.155	−0.323	5.870	0.104***	0.444	−0.169	0.018
	(0.324)	(0.134)	(0.102)	(0.000)	(0.366)	(0.128)	(0.976)
Constant	0.573	1.122	−39.042	−0.424***	−2.736	0.634	−0.261
	(0.448)	(0.158)	(0.110)	(0.001)	(0.378)	(0.103)	(0.925)
Observation	345.000	292.000	286.000	212.000	370.000	370.000	370.000
OverallR2	0.006	0.016	0.025	0.015	0.002	0.010	0.000

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Efficiency Impact on Convergence Controlling for Electricity Prices - All Countries - Club 1

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{EFF}	-0.409^{***}	0.561	-7.126^{***}	-0.443^{***}	-4.438^{***}	-0.352^{***}	-3.316^{***}
	(0.000)	(0.502)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
γ_k^{EFF}	-0.128	0.234	-1.383	-0.179	4.116	0.034	-0.197
	(0.306)	(0.318)	(0.726)	(0.366)	(0.104)	(0.815)	(0.870)
Constant	2.831^{***}	-3.219	51.102^{**}	2.541^{**}	8.058	1.045	16.384^{*}
	(0.003)	(0.197)	(0.031)	(0.020)	(0.561)	(0.245)	(0.068)
Observation	289.000	252.000	240.000	180.000	314.000	314.000	287.000
OverallR2	0.036	0.015	0.037	0.063	0.053	0.056	0.026

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Structure Impact on Convergence Controlling for Electricity Prices - All Countries - Club 1

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{STR}	-0.017	-0.316	2.803	0.149^{***}	-0.029	0.015	0.326
	(0.776)	(0.163)	(0.193)	(0.000)	(0.971)	(0.535)	(0.702)
γ_k^{STR}	0.365^{**}	0.163	-2.451	0.124^{*}	0.038	-0.010	-0.646
	(0.011)	(0.401)	(0.271)	(0.082)	(0.967)	(0.815)	(0.587)
Constant	-1.844^{**}	0.274	-5.590	-1.243^{***}	-0.485	0.055	1.526
	(0.028)	(0.810)	(0.608)	(0.004)	(0.953)	(0.794)	(0.858)
Observation	289.000	252.000	240.000	180.000	314.000	314.000	287.000
OverallR2	0.010	0.019	0.020	0.042	0.006	0.001	0.003

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5: Efficiency Impact on Convergence - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{EFF}	-1.642^{***}	-0.006	-7.986^{***}	-0.093	-2.828^{***}	-0.612^{**}	-3.670^{***}
	(0.004)	(0.958)	(0.000)	(0.172)	(0.003)	(0.012)	(0.000)
Constant	8.193^{***}	0.042	49.665^{***}	0.246	16.169^{***}	2.047^{**}	15.714^{***}
	(0.006)	(0.900)	(0.000)	(0.155)	(0.004)	(0.035)	(0.000)
Observation	374.000	377.000	412.000	297.000	404.000	427.000	454.000
OverallR2	0.045	0.000	0.037	0.021	0.022	0.030	0.031

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B6: Structure Impact on Convergence - All Countries

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household	(8) -	(9) Club
β_k^{EFF}	-0.409^{***}	0.561	-7.126^{***}	-0.443^{***}	-4.438^{***}	-0.352^{***}	-3.316^{***}		
	(0.000)	(0.502)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)		
γ_k^{EFF}	-0.128	0.234	-1.383	-0.179	4.116	0.034	-0.197		
	(0.306)	(0.318)	(0.726)	(0.366)	(0.104)	(0.815)	(0.870)		
β_k^{STR}								-0.319^{***}	-0.057
								(0.000)	(0.321)
Constant	2.831^{***}	-3.219	51.102^{**}	2.541^{**}	8.058	1.045	16.384^{*}	1.431^{***}	0.153
	(0.003)	(0.197)	(0.031)	(0.020)	(0.561)	(0.245)	(0.068)	(0.000)	(0.426)
Observation	289.000	252.000	240.000	180.000	314.000	314.000	287.000	374.000	377.000
OverallR2	0.036	0.015	0.037	0.063	0.053	0.056	0.026	0.018	0.004

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B7: Efficiency Impact on Convergence Controlling for Electricity Prices - All Countries - Club 2

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{EFF}	-0.559	-0.034	-7.177^{***}	-0.072	-2.378^{***}	-0.543^{***}	-3.744^{***}
	(0.454)	(0.715)	(0.000)	(0.119)	(0.000)	(0.000)	(0.000)
γ_k^{EFF}	-3.379	-0.332	-3.138	-0.267	-3.745^{*}	-1.109^{*}	-1.182^{**}
	(0.135)	(0.373)	(0.256)	(0.168)	(0.087)	(0.076)	(0.014)
Constant	19.477^{**}	1.811	60.356^{***}	1.535	32.552^{***}	7.464^{**}	21.873^{***}
	(0.047)	(0.394)	(0.000)	(0.114)	(0.002)	(0.031)	(0.000)
Observation	344.000	332.000	364.000	269.000	358.000	374.000	381.000
OverallR2	0.064	0.004	0.043	0.055	0.045	0.053	0.032

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B8: Structure Impact on Convergence Controlling for Electricity Prices - All Countries - Club 2

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Construction	(5) Services	(6) Transport	(7) Household
β_k^{STR}	−0.255	−0.079*	2.292	−0.022**	0.957	0.126***	−0.019
	(0.145)	(0.072)	(0.118)	(0.039)	(0.110)	(0.001)	(0.988)
γ_k^{STR}	−0.147	−0.160	−2.302	0.065**	0.245	0.301	−1.654
	(0.701)	(0.180)	(0.190)	(0.049)	(0.700)	(0.150)	(0.291)
Constant	1.851	1.022	−4.088	−0.301**	−6.139**	−1.855*	8.768
	(0.113)	(0.155)	(0.549)	(0.034)	(0.021)	(0.072)	(0.500)
Observation	344.000	332.000	364.000	269.000	358.000	374.000	381.000
OverallR2	0.017	0.016	0.012	0.021	0.019	0.014	0.009

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$