IDB WORKING PAPER SERIES No. IDB-WP-441

Energy Intensity

A Decomposition and Counterfactual Exercise for Latin American Countries

Raúl Jiménez
Jorge Mercado

September 2013

Inter-American Development Bank
Infrastructure and Environment Sector
Energy Division

Energy Intensity

A Decomposition and Counterfactual Exercise for Latin American Countries

Raúl Jiménez
Jorge Mercado

Inter-American Development Bank
2013

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Jiménez, Raúl Alberto.
Energy intensity : a decomposition and counterfactual exercise for Latin American countries / Raúl Jiménez, Jorge Mercado.
p. cm. — (IDB working paper series ; 441)
Includes bibliographic references.
1. Energy consumption—Measurement—Latin America. I. Mercado Díaz, Jorge Enrique. II. Inter-American Development Bank. Energy Division. III. Title. IV. Series.
IDB-WP-441

http://www.iadb.org

1300 New York Ave. N.W., Washington, D.C., 20577

Raúl Jiménez (rjimenez@iadb.org); Jorge Mercado (jorgem@iadb.org)

Energy Intensity

A Decomposition and Counterfactual Exercise for Latin American Countries

Raúl Jiménez **Jorge Mercado**

Abstract*

This paper investigates trends in energy intensity in Latin American countries over the last 40 years. It applies the Fisher Ideal Index to decompose the energy intensity into the relative contributions of energy efficiency and the activity mix, and then analyzes the determinants of these energy indexes through panel data regression techniques. Finally, the paper compares the performance of Latin American countries to that of a similar set of countries chosen through the synthetic control method. The authors find that the energy intensity in Latin American countries has decreased about 20 percent, closing the gap with respect to its synthetic counterfactual. In both Latin American countries and its synthetic control, efficiency improvements drive these changes, while the activity mix component does not represent a clear source of change. The regression analysis shows that per capita income, petroleum prices, fuel-energy mix, and GDP growth are main determinants of energy intensity and efficiency, while there are no clear correlations with the activity component.

Keywords: energy intensity; decomposition; panel data; synthetic control method.

JEL Code: O5; O13; Q40; Q43

* The authors, both working in the Energy Division of the Inter-American Development Bank (IDB), are grateful for the support of Ramon Espinasa and the Research Department at the IDB, as well as for the helpful comments and suggestions of Lenin Balza, Alberto Elizalde, Diego Margot, Juan Jose Miranda, Tomas Serebrisky, Rodolfo Stucchi and an anonymous peer reviewer. We also thank to Jennifer Doherty-Bigara, who performed a careful reading.

Corresponding author: rjimenez@iadb.org, address: 1300 New York Avenue, N.W. Washington, DC 20577; phone: 1-202-623-2170.

1. INTRODUCTION

As both energy prices and concerns about global warming continue to increase, energy intensity measures have become important components of energy policy at the country and international organization levels. In particular, there is a focus on identifying factors that influence change in energy intensity and distinguishing the contribution of energy efficiency from other relevant factors. This information is useful as it provides a basis for policy decisions and evaluation. Further, energy efficiency is internationally recognized as one of the most cost-effective strategies to address crosscutting issues such as energy security, climate change, competitiveness, and the promotion of technology transfers (IDB, 2012).

In this context, the general objective of this working paper is to investigate trends in energy intensity in the Latin American and Caribbean (LAC) region over the last four decades. In particular, the aim is to identify the main drivers of trends in energy intensity at the country level. Since energy issues are of increasing interest in the policy agendas of LAC countries, this paper also evaluates the region's relative performance in terms of energy intensity and efficiency.

A key limitation in pursuing these goals is the limited availability of data on energy efficiency measures. However, a rich branch of methodological literature describes ways of estimating energy efficiency measures based on aggregate data. These methods are mostly based on decomposing energy intensity into different components depending on the availability of information. At that point, changes in energy intensity could be decomposed into the variation attributable to energy efficiency, economic activity structure, production levels, and/or fuel sources. The more disaggregate the data, the more accurate the efficiency contribution estimations would be. The election of the specific method to be used depends on the objectives and data availability. However, there seems to be a certain degree of academic consensus that using price index numbers is preferred when dealing with aggregate data at the country level. Some extensive methodological studies and surveys on decomposition methods can be found in Boyd, Hanson, and Sterner (1988); Ang and Lee (1994); Ang and Liu (2003); Ang (2004); Boyd and Roop (2004); and Ang, Huang, and Mu (2009).

Previous empirical studies suggest a downward trend in energy intensity, with the efficiency effect as its most important source of variation. The magnitudes of the improvements tend to be heterogeneous, since those studies analyze different countries and periods using different methodologies. In particular, a large body of literature decomposes and examines the trend in energy intensity based on disaggregate classifications of industrial activity. Some well-studied cases are China, India, and the United States.

In the case of China, the efficiency effect explains 30 percent of the energy savings in industrial energy consumption between 1996 and 2010.[1] In contrast, studies of the Indian industrial sector found mixed results from 1981 to 2005, showing only slight improvement in energy intensity (see Reddy and Ray, 2011). Interesting cases where both efficiency and activity have played a role in reducing the overall energy intensity index are found in studies of the United States and California. Hasanbeigi, Rue du Can, and Sathaye (2012) show that in California, from 1997 to 2008, the energy intensity ratio decreased 43 percent, mainly explained by two events: (i) a shift in value added participation from the oil and gas extraction sector to the electric and electronic manufacturing sector, which uses less energy per value added; and (ii) an escalation in energy prices that led the industries to improve efficiency in order to reduce energy costs. Over a similar period, Huntington (2010) analyzes 65 U.S. industries in the commercial, industrial, and transportation sectors, showing that an estimated 40 percent of reduction in aggregate energy intensity was due to structural change.

In one of the few studies available on energy intensity at the state/country level, Metcalf (2008) performs an exact decomposition exercise at the state level in the United States for the period between 1970 and 2001. He finds a reduction in energy intensity of approximately 75 percent as a result of efficiency improvements. Further, through a panel data analysis, he shows that rising per capita income and higher energy prices play an important part in lowering energy intensity.[2] In one of the few sector-level studies, Bhattacharya and Shyamal (2001) use an exact decomposition approach on energy intensity for multiple sectors (e.g., agriculture, industry, and transport, among others) in India for the period between 1980 and 1986. They find that the intensity effect contributed significantly to energy conservation.

[1] Different studies on China, such as, for example, Sinton and Levine (1994); Zhang (2003); Ma and Stern (2008); and Ke et al. (2012), show a sustained decrease in industrial energy intensity between 1980 and 2010, with efficiency explaining most of this variation.
[2] Bernstein et al. (2003) analyze a similar period using a sample of 48 states in the United States. They find that certain variables, such as population, prices, climate temperatures, and indicators of sector activities, are strongly correlated with energy intensity.

This study contributes to available literature by performing a comparative analysis of the composition and trends in energy intensity, with a particular focus on LAC countries, one that appears to be lacking in previous studies. Following previous literature, this paper bases the decomposition exercise on Fisher's method, which is complemented by a panel data analysis of 75 countries over 40 years. A methodological contribution to this specific literature is the comparison analysis using the synthetic control method of Abadie and Gardeazabal (2003) in order to overcome heterogeneity issues in the benchmark exercise.

The current study focuses on energy intensity indicators at broad end-use sectors at the country level. This implies the observation of (aggregate) energy indexes (i.e., the indicators of energy intensity and its decomposition into efficiency and the activity mix) at the country level. For this purpose, we adopt the monetary-based definition, where energy efficiency improvement generally means using less energy to produce the same amount (value added) of services or output.

In working with aggregate end-use data, it will not be possible to detect shifts between subsectors in each broad activity. Thus, the current study does not capture structural changes between subindustries with high-energy intensity versus low-energy intensity within the industrial sector. To identify specific trends in each subsector, or in products and services, it would be necessary to use more detailed information.

A potential drawback to this strategy is that the estimations herein could be sensitive to the degree of data disaggregation. For example, within a broad activity, changes from more energy-intensive sub-activities to less energy-intensive sub-activities could lead one to overestimate the gains in energy efficiency (and vice versa). That is, it is possible to interpret a result as an energy efficient effect when it is really an activity effect within a broad activity. In general, it is preferable to have more disaggregated good quality data to obtain better estimates. In the case of California industry, an interesting finding by Metcalf (2008) is that a higher level of disaggregation did not significantly affect his estimations. However, Huntington (2010) found contrasting results using a more detailed dataset.[3] In any case, the present exercise

[3] It is important to mention that both authors use different datasets and analyze different periods. In their study of the energy intensity trend in China, Ma and Stern (2008) provide another example where the data disaggregation could affect the decomposition results. They found that the contribution of the industry mix goes from positive to negative, after performing the decomposition with more detailed data.

suggests a starting point for identifying broad trends in the LAC region. Further research should take advantage of available information to perform similar exercises with more disaggregated data.

The paper is structured as follows. The next section provides methodological strategies for (i) the decomposition of aggregate energy intensity, (ii) the specification of the panel data analyses, and (iii) the synthetic control method used to construct a comparison set of countries. Section 3 presents the empirical results of these methodologies, and Section 4 concludes.

2. EMPIRICAL STRATEGIES

2.1. Decomposition through the Fisher Ideal Index

The method applied herein to perform the decomposition is the Fisher Ideal Index Method. Its main advantage is that it does not have residual terms, which make it difficult to interpret the relative importance of compositional and efficiency effects. Specifically, Ang, Mu, and Zhou (2010) emphasize that perfect decomposition methods should be adopted in the case of cross-country/region studies. In addition, as mentioned by Ang (2004; 2006), Boyd and Roop (2004), and Ang and Liu (2003), these methods are also preferred in the case of two-factor decomposition due to their theoretical foundation and their adaptability, as well as the ease in interpreting their results. In this case, energy intensity is decomposed into its efficiency and activity components.

Following those previous contributions, the problem is set in terms of total energy consumption (E) and total production (Y), as well as sub-indexes for economic sector (i) and years (t). Thus, the aggregate energy intensity (e) can be written as:

$$e_t = \frac{E_t}{Y_t} = \sum_i^n \frac{E_{it}}{Y_{it}} \frac{Y_{it}}{Y_t} = \sum_i^n e_{it} s_{it} \text{ (1).}$$

Expression 1 indicates that a change in e_t may be due to changes in the sector energy intensity (e_{it}) and/or the product mix (s_{it}). One of the main operative/practical advantages of this approach is that, by construction, the energy uses in the different sectors need to form a partition (i.e., they must not overlap), but the measures of economic activities do not need to satisfy this condition. In fact, they do not even need to be in the same units. This facilitates the identification of good indicators to account for the activity mix (s_{it}).

Following the index number theory, dividing equation (1) by the aggregate energy intensity for a base year (e_0) allows a perfect decomposition of the aggregate energy intensity index into economic efficiency (F^{eff}) and activity (F^{act}) indexes with no residual. This result is the Fisher Ideal Index, which is a geometric mean of the Laspeyres and Paasche price indexes.

The Laspeyres indexes are:

$$L_t^{act} = \frac{\sum_i^n e_{i0} s_{it}}{\sum_i^n e_{i0} s_{i0}} \text{ (A.1) } \quad L_t^{eff} = \frac{\sum_i^n e_{it} s_{i0}}{\sum_i^n e_{i0} s_{i0}} \text{ (A.2),}$$

and the Paasche indexes are:

$$P_t^{act} = \frac{\sum_i^n e_{it} s_{it}}{\sum_i^n e_{it} s_{i0}} \text{ (A.3) } \quad P_t^{eff} = \frac{\sum_i^n e_{it} s_{it}}{\sum_i^n e_{i0} s_{it}} \text{ (A.4).}$$

Thus, the Fisher Ideal Indexes are given by:

$$F_t^{act} = \sqrt{L_t^{act} P_t^{act}} \dots \text{ (2.1) } \quad F_t^{eff} = \sqrt{L_t^{eff} P_t^{eff}} \dots \text{ (2.2).}$$

They reflect the components that could be attributed to the activity mix and to efficiency changes.

$$\frac{e_t}{e_0} \equiv I_t = F_t^{act} F_t^{eff} \text{ (3).}$$

By taking the logarithm of (3), it is possible to observe the additive contribution of the activity-mix effect and the energy efficiency effect to the total variation in energy intensity.

2.2. Panel Data Determinants Analysis

In line with previous literature (Bernstein, et al., 2003; Metcalf, 2008), the current paper relies on a dynamic panel data specification to analyze the determinants of the energy indexes. In equation 4, the dependent variable (y) refers to intensity, efficiency, or the activity index, which we estimate as explained in Section 1.1. The matrix (X) represents the set of variables of interest. As suggested by the literature, it includes per capita income, energy prices, population growth, fossil fuel energy consumption, and the investment capital ratio. We also include growth rate and rent from natural resources.[4] The proposed specification is as follows:

$$y_{it} = \beta X_{it} + \gamma y_{it-1} + \sum_i \alpha_i co_i + \sum_i \theta_i tr_i + \varepsilon_{it} \dots \text{ (4).}$$

[4] See Annex 1 for a detailed explanation of the variables and sources.

With respect to the expected relationship between the explanatory variables and the energy indexes, there is a certain degree of consensus about the effect of energy prices on intensity and efficiency. However, there is no conclusive evidence about the effects of the other variables. In the case of prices, higher prices would lead to reduced intensity through improving efficiency and/or turning to less intense activities.[5] Sue Wing (2008) emphasizes three channels through which prices would influence energy intensity: (i) production input substitution due to changes in relative energy prices, given constant technology; (ii) innovation, capturing both secular scientific progress and inducement effects of high energy prices; and (iii) changes in the composition of the stock of quasi-fixed inputs to production.[6]

The effects of per capita income on the energy indexes are not clear. On one hand, it is expected that income would put pressure on the demand for energy, increasing intensity. On the other, as income broadly reflects the stage of development, it is expected that it would correlate positively with the degree of efficiency, reducing energy intensity. This usually justifies considering the square of per capita income to allow nonlinearities that capture both effects.

The effects of new investments (measured through the investment capital ratio) on energy indexes are also not certain. While they would improve energy intensity and efficiency by making the stock of available capital more productive, they could also be targeted primarily at enhancing production capacities without significant effects on energy savings. Further, investments oriented toward improving energy efficiency are usually very specific, and not necessarily aligned with other types of investments.

With respect to the population dimension, fast-growing population rates may be associated with agglomeration economies that tend to make energy use more efficient. However, these economies of scale depend on infrastructure growing fast enough to cover the needs of the growing population. For example, a direct consequence of population and infrastructure growing at different rates is traffic congestion, which leads to greater use of fossil fuels per the same unit of distance traveled.

---

[5] In the empirical exercise, since there is no uniform data on energy prices for all countries, we use international petroleum prices in real terms from 2005 as a proxy.

[6] In a study of 35 industries in the United States during the period 1958–2000, Sue Wing shows that the energy prices influenced a decline in energy intensity, mainly due to the quasi-fixed variable costs, particularly vehicle stocks and disembodied autonomous technological progress.

The fossil fuel mix, measured as the ratio of fossil fuel energy consumption to total energy use, does not have a clear influence on the energy indexes. For example, in the case of Australia, available studies suggest an inverse relationship (see, for example, Shahiduzzaman and Khorshed, 2012). It can also be argued that high fuel consumption makes a country sensitive to price variation, providing an incentive for increased efficiency. However, it is important to note that there is little evidence of the mechanism by which this relationship operates. For example, the level of fossil fuel consumption could be endogenous, resulting from abundance in resources, which could provide a perverse incentive to maintain a high use of fossil fuels without improving efficiency.

For this reason, we include as a regressor the rent from natural resources, which is expected to capture the effects of being a country with relative abundance in extractive resources over the energy indexes. Based on the literature on natural resources and economic growth (e.g., Sachs and Warner, 1995), one could argue that a country rich in fossil fuels, with subsidized energy prices, would not have an incentive to change its fuel mix or invest in more energy efficient technologies, leading it to maintain a high level of energy intensity.

Moreover, to take into account the performance of the economy, we include the Gross Domestic Product (GDP) growth rate as another co-variable. It is expected that a country's economic growth will encourage energy efficient investments and/or boost other sectors in the economy that have differing energy intensities.

To account for invariable characteristics specific to each country, we include the fixed country effect (co). In addition, to account for effects that change over time, the specification contains a trend by country (tr). Finally, we include the lagged dependent variable to account for the fact that the energy indexes could react slowly to changes in the explanatory variables. Having the lagged dependent variable makes it possible to estimate the elasticity of the short and long run, where γ is interpreted as the speed of the adjustment to the long-run equilibrium relationship. However, a disadvantage is that the lagged variable is endogenous, which could introduce bias in the estimations.

A set of techniques has been suggested in order to address this potential threat. See for example Bond (2002), Judson and Owen (1999), and Wooldridge (2011). However, they also highlight the within-group estimator as an asymptotically valid method when the time dimension of the panel gets large. Empirically, it is expected that the LSDV estimator would perform well in a sample with T>30 (Judson and Owen, 1999; Galiani and Gonzalez-Rozada, 2002), which is true for the case herein, since we restrict our exercise to the countries with the largest sets of information.

2.3. Synthetic Control Method for the Average Latin American Country

In order to perform a credible comparison of the energy indexes of Latin American countries, it is necessary to construct a similar set of countries. As Abadie, Diamond, and Hainmueller (2010) emphasize, a shortcoming of cross-country regressions is that they compare countries side by side, regardless of whether they have similar or radically different characteristics. Even after controlling for such differences, the relative contribution of each comparison unit to the average comparison country is not clear.

The synthetic control approach (Synth) is a data-driven procedure that allows us to construct a comparison unit as a weighted average from the available comparison countries. That is, since it is often difficult to find a single country that approximates the most relevant characteristics of Latin American countries, this procedure allows for combining countries in order to provide a better comparison unit. The advantages of this method are: (i) as a data-driven procedure, this method reduces discretion in the choice of peers, forcing researchers to demonstrate affinities between the comparison units; (ii) it makes explicit the weights used to build the comparison unit; and (iii) because the weights can be restricted to be positive and sum to one, this method provides a safeguard against extrapolation. Further, Abadie, Diamond, and Hainmueller (2010) demonstrate that the conditions of Synth are more general than the conditions under which linear panel data or difference-in-differences estimators are valid. That is, Synth generalizes the traditional fixed effects model by allowing the effects of unobserved, confounding characteristics to vary over time.

Here we apply Synth to build a unit comparable to the Latin American region in terms of energy indexes. Synth, as described in Abadie, Diamond, and Hainmueller (2011), is applied when multiple units are exposed to an intervention. Examples of the application of this technique to cross-country data can also be found in Abadie, Diamond, and Hainmueller (2010). In particular, our strategy considers the characteristics of the average Latin American country to build a convex combination of non-Latin American countries with similar characteristics, and provides equal weights to each country to avoid over-representing a given country. This is because three countries (Brazil, Mexico, and Argentina) represent more than 60 percent of the GDP and the total energy consumption in the LAC region (see Annex 2). Thus, searching for a synthetic for the aggregate LAC region would over-represent those countries.

The selection of the characteristics (or predictors) by which the comparison unit is chosen is usually based on literature standards. Given that we are primarily interested in the behavior of the energy indexes, the validity of their predictors is a key factor in this synthetic control comparison method. This exercise was performed in the previous section when selecting the set of variables in X. The panel data estimation also provides some insights into the relevance of each variable and the final variables to be considered as predictors (see equation 4). Following Abadie and Gardeazabal (2003) X is partitioned into X_1 and X_0 to refer to Latin American and non-Latin American countries, respectively. Then, we use the optimal vector of weight ($W*$) to minimize $(X_1 - X_0W)'V(X_1 - X_0W)$ subject to $w_j \geq 0$ and $\sum_j w_j$=1. These two conditions restrict the problem to find a comparison unit only if X_1 lies in the predictors' support, avoiding extrapolations. V represents a diagonal matrix, whose elements reflect the importance of each predictor. Following Abadie, Diamond, and Hainmueller (2011), an optimal choice of V assigns weights that minimize the mean square error of the synthetic control estimator—that is, the expectation of $(X_1 - X_0W)'(X_1 - X_0W)$.

Synth is usually applied when an event affects one or more units, but not others. It is important to choose a control group based on pre-event characteristics, and to attribute post-outcome differences only to the occurrence of that event. Our strategy does not have such a source of temporal variability, but only the distinction between Latin American and non-Latin American countries. This means that we must choose a year in which we assume an event occurs. This arbitrary decision makes the results potentially sensitive to the year chosen. The results could also be sensitive to the time window in which we restrict the algorithm to match the predictors—that is, changing the time window in which we match the predictors could change the gap between Latin America and its synthetic control. This would occur because each possible window would return a different set of comparison countries and/or weights. To address this problem, we apply Synth recursively, which allows us to capture the average gap-trend of Latin American energy indexes, taking into account different time windows. Under this approach, the pool of countries and weights used to construct the synthetic counterfactual could change depending on the period analyzed. We use the three following strategies to choose the time windows:

a) *Enlarging matching periods*, where the windows are chosen from (1972) to $(1972 + \mathrm{p})$, with $p\epsilon[3\ (3)27]$. For each window, the energy index trends are evaluated after moving the cut-off $(1972 + p)$, weighting the sets of countries that resemble Latin America from the early 1970s to the whole period (1972–1999).
b) *Reducing matching periods*, with windows from year $(1972 + \mathrm{q})$ to (1999), with $q\epsilon[0\ (3)\ 24]$. Here, we gradually reduce the period of years with which the average synthetic country is constructed, each time taking a set of counterfactuals that resemble the characteristics of the average Latin American country more closely, continuing through the late 1990s.
c) *Moving matching periods* with windows chosen from year $(1972 + \mathrm{r})$ to $(1981 + \mathrm{r})$, with $r\epsilon[0(6)18]$. Each window has nine years to construct a synthetic average Latin American country. In each case, the energy indexes are evaluated after $(1981 + r)$. The windows move every 6 years (r) until the matching period of $(1990 - 1999)$. This strategy captures a set of counterfactuals representative of the characteristics of the average Latin American country in a given period.

We arbitrarily choose values for p, q, and r. In all cases, the time windows extend until the year 1999, which gives us 11 years to perform the comparison exercise. In the next section, we average and present the results of the recursions of each of the above strategies.

3. EMPIRICAL RESULTS

This section presents the main results of the strategies previously described. Annex 1 provides details about the data used for the exercise, which focuses on the evolution of energy intensity in Latin American countries compared to the evolution in other sets of countries.

3.1. Energy Intensity Trends

In absolute terms, Latin America is one of the least energy-intensive regions in the world. By income classification, the region is mainly composed of middle-income countries that, on average, use 165 kg of oil equivalent per US$1,000 GDP (at constant 2005 PPP), just above high-income countries and far below middle- and low-income countries (see Figure 1). This fact could suggest that, even for its stage of development, Latin America can be characterized as a low-intensity region. However, despite its absolute ratio of energy intensity, the economic dynamics of the region raise questions about its performance compared to a similar region.

Figure 2 presents the trends in energy indexes, contrasting the Latin American region with others. In general, and in accordance with previous analysis, it shows that energy intensity has decreased in all regions, mainly led by the efficiency effect. In general, the activity effect has less impact for all income levels; however, it is notoriously more relevant in high-income countries, especially those belonging to the Organisation for Economic Co-operation and Development (OECD).[7]. The activity mix contributes to a 10 percent decrease in energy intensity only in the high-income countries. In contrast, the structural effects of medium-income countries contribute to an 8 percent increase in energy use. We observed that all income classifications, with the exception of those in Latin America, consistently reduced energy intensity (and efficiency) by between 40 and 60 percent during this period. The literature of convergence in energy intensity has already identified this peculiar behavior, whereby the differences in intensity levels within a region have tended to decrease over the last four decades, except in Latin American countries (Duro and Padilla, 2011; Liddle, 2010).

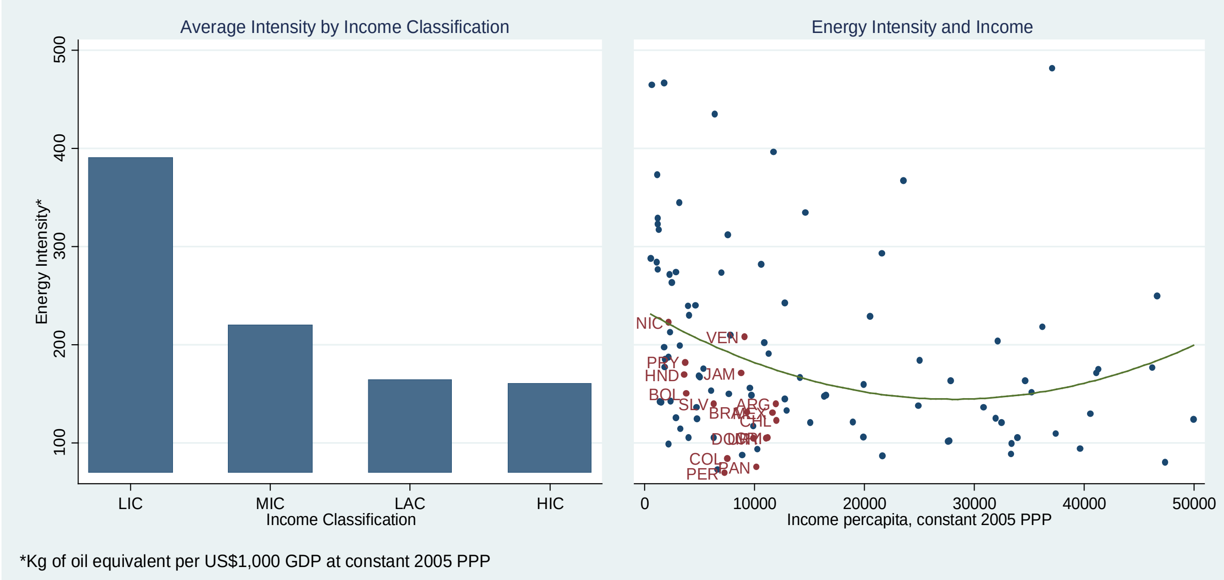
In the case of Latin American countries, we have observed a 17 percent decrease in energy intensity over the last 40 years. During the 1970s, the intensity decreased by about 8.5 percent; between 1980 and 2000, it slightly increased, showing great volatility; and between 2000 and 2010, energy intensity decreased by another 10.6 percent (with respect to the 1970 level). In general, the efficiency effect explains all the changes, while the activity effect remained almost invariable.[8]

However, we should be careful in interpreting these results, since they hide great heterogeneity at the country level. For example, Annex 4 presents decomposition trends by Latin American countries, showing the different paths and variances inside the region. In particular, we observe that during the period 1980–2000, the LAC region in aggregate was

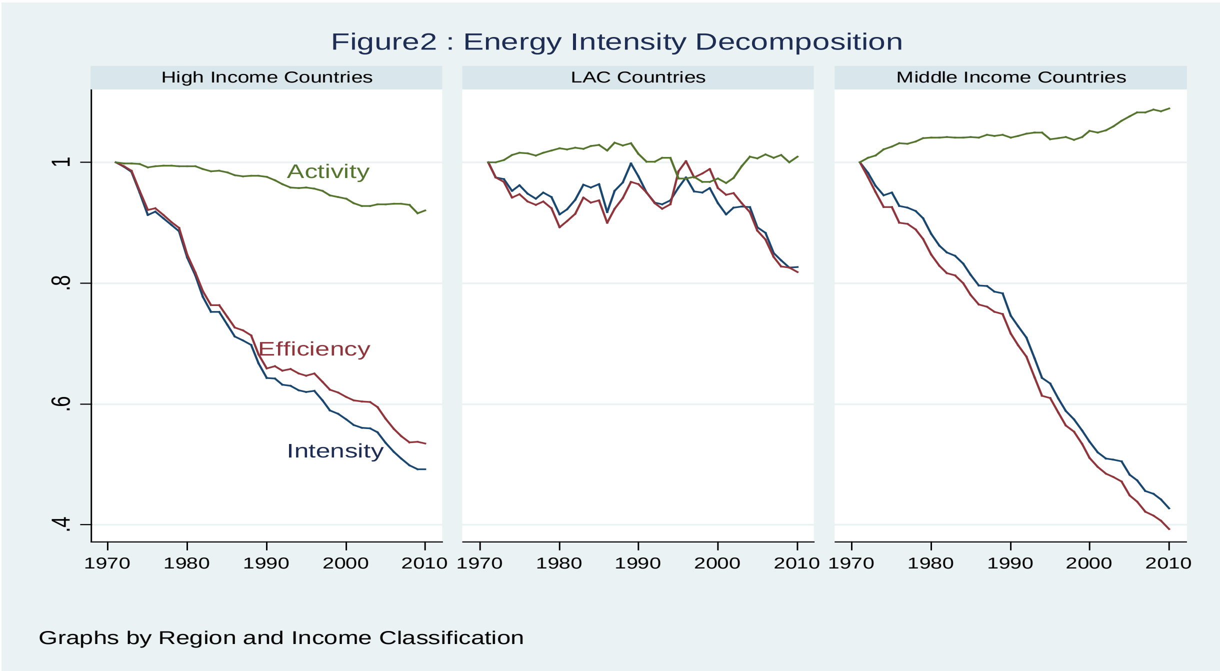
[7] This result is conservative, but still is in line with previous literature (e.g., Duro, Alcántara, and Padilla, 2010; Mulder and de Groot, 2012).
[8] Annex 3 shows the energy indexes expressed in additive variation.

mainly influenced by similar trends in Argentina, Brazil, Mexico, and Venezuela. That is, those aggregate measures tend to over-represent the biggest economies. This is a result of the relative weight of those economies in terms of GDP and energy consumption. Note that the four countries mentioned account for 76 percent of those variables (see Annex 2). This fact illustrates the importance of finding a set of similar countries to perform appropriate comparisons, as well as to perform an analysis of the average Latin American country from the final indexes and predictors. In the next section, we aim to identify the main drivers of variability in the energy indexes.

Figure 1: Energy Intensity and Income, 2010



Source: Authors' elaboration.
Notes: LIC = low-income countries; MIC = medium-income countries; LAC = Latin American Countries; HIC = high-income countries.



Source: Authors' elaboration.
Note: LAC = Latin American countries.

3.2. Determinants of Energy Intensity

This section applies regression analysis in order to identify the main drivers of the energy indexes. Table 1 shows the main results.[9] We start by noting that the lag of the energy indexes as an explanatory variable is always statistically significant, through a dynamic panel specification. This intuitively supports the argument that energy indexes do not respond immediately to changes in economic variables, although these have effects that materialize over time.

Income is also statistically significant, both at level and its square, suggesting some degree of concavity, as expected from Figure 1. Intuitively, energy intensity declines as income increases, but at a decreasing rate. On the other hand, real petroleum prices have a significant influence on increasing efficiency and reducing intensity. This suggests that increasing petroleum prices over the last two decades have been a strong incentive for improving energy use, as shown in the previous section.

[9] In addition, we performed the same regressions, correcting for bias of the lagged dependent variable through the Kiviet, Arellano-Bond, and Blundell-Bond estimators. All of these robustness checks returned similar results.

The energy mix is closely related to energy intensity and efficiency, but not to the activity component. This suggests that countries that consume a higher proportion of fossil fuels in terms of total energy consumption tend to be more energy-intensive and less efficient. Specifically, keeping everything else constant, a 1 percent increase in fossil fuel consumption is often related to an increase in both the intensity and the efficiency indexes by an estimated 0.14 percent.

The rents from natural resources and the GDP growth rate are both relevant in explaining the variability of the energy indexes. The former tend to increase intensity and reduce efficiency, without a strong relationship with activity. The economic growth rate tends to reduce energy intensity and increase efficiency, probably by increasing the use of fixed assets oriented toward production, converging to an optimal point of energy use.

Neither population growth nor the investment capital ratio has a statistically significant influence on the energy indexes. However, it is important to carefully consider the results with respect to investment, since this variable is estimated by constructing the series on stocks of capital (see Annex 1). What is more, we assumed a common depreciation rate across time and across countries. Nonetheless, these results are in line with the specificity of energy-efficient investment, supporting the fact that investments do not necessarily reduce energy intensity at the aggregate level.

Table 1 presents the income and price elasticities. An increase of 1 percent in per capita income tends to reduce the intensity and efficiency indexes by about 1.9 and 1.7 percent respectively. Equivalently, a 1 percent increase in real petroleum prices tends to reduce intensity and efficiency by 0.05 and 0.04 percent, respectively. The low impact of energy prices is notable, probably because we use international petroleum prices instead of energy prices, which could lead to some bias. In general, energy tariffs have some subsidies, so variations in international energy prices do not correspond exactly across countries. In this sense, we could be underestimating the conditional correlations between prices and energy indexes.

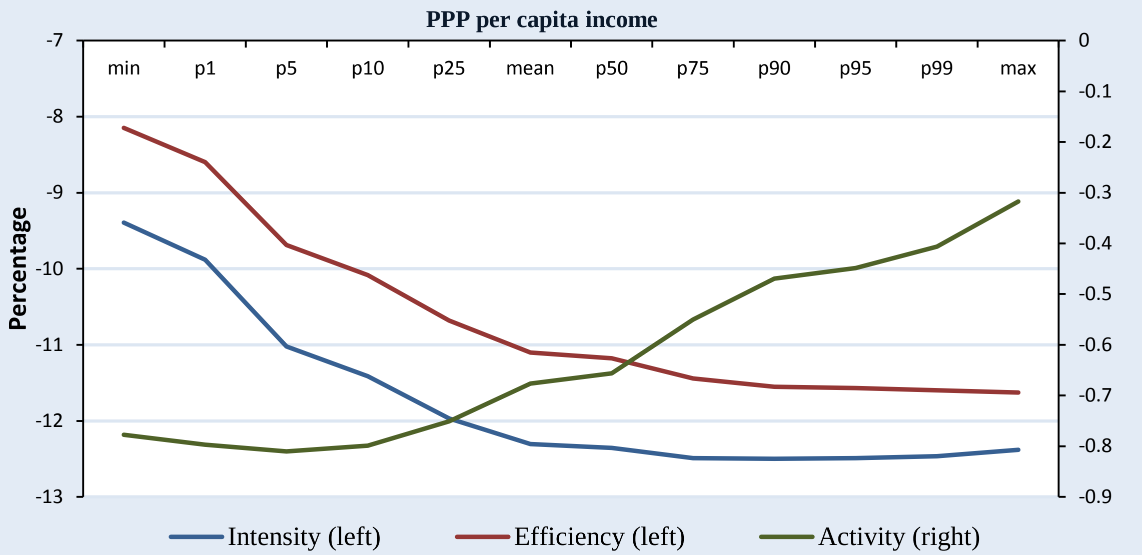
Table 1: Energy Indexes Regressions

	ln(intensity)	ln(efficiency)	ln(activity)
Adjustment parameter	0.764**	0.734**	0.670**
	(0.0183)	(0.0267)	(0.0398)
ln(GDP per capita, constant 2000 PPP)	-0.549**	-0.515**	-0.0846*
	(0.109)	(0.118)	(0.0436)
ln(GDP per capita sq., constant 2000 PPP)	0.0266**	0.0224**	0.00658**
	(0.00654)	(0.00729)	(0.00308)
ln(petroleum prices)	-0.0123**	-0.0109**	-0.00112
	(0.00307)	(0.00365)	(0.00117)
Population growth (%)	0.226	0.363	-0.150
	(0.240)	(0.309)	(0.115)
Natural resources rents (%)	0.179**	0.172**	0.00833
	(0.0416)	(0.0683)	(0.0035)
Fossil fuel energy consumption (%)	0.139**	0.142**	0.00170
	(0.0477)	(0.0523)	(0.0123)
Investment/capital ratio (%)	0.00456	0.000626	0.00367
	(0.000228)	(0.000184)	(0.0000602)
GDP growth rate	-0.466**	-0.447**	-0.00838
	(0.0411)	(0.0495)	(0.0226)
Country fixed effect	Yes	Yes	Yes
Trend effect	Yes	Yes	Yes
Constant	3.76**	3.89**	1.77**
	(0.503)	(0.558)	(0.286)
Income elasticity	-1.898	-1.714	0.036
Price elasticity	-0.052	-0.041	-0.003
Observations	2845	2845	2845
Adjusted R-squared	0.940	0.923	0.781

Source: Authors' elaboration.
Notes: Standard errors in parentheses.
* Coefficient is statistically significant at the 10 percent level; ** at the 5 percent level.
When %, read the coefficients as variation %.

Figure 3 shows the marginal effects of per capita income on the energy indexes. We estimate the marginal effects from the above regressions over the percentiles of the per capita income distribution of our sample of countries. As expected, an increase in per capita income tends to reduce the intensity and efficiency indexes, but at decreasing rates. In the case of the activity component, however, the second effect tends to dominate along the income distribution. An increase of per capita income at the left of the distribution has a greater marginal effect than the same increase at the right of this distribution.

Figure 3: Marginal Effects of Income on Energy Indexes



Source: Authors' elaboration.

Even as this analysis allows us to identify the main drivers of the energy indexes, it does not allow us to distinguish the relative performance of Latin American countries. The next section addresses this limitation by comparing the average Latin American country with another set of countries with similar characteristics thought to drive the energy indexes.

3.3. Synthetic Comparisons in Latin American Countries

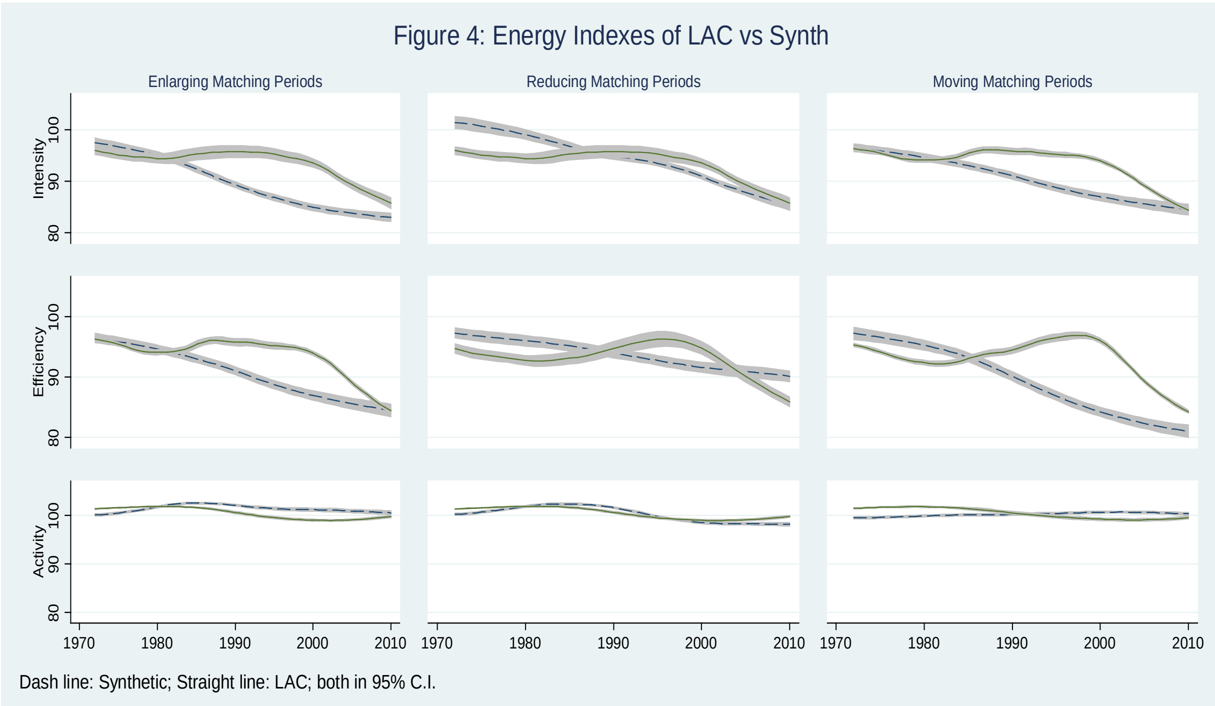
This section returns to the comparison exercise, searching in each window of time for a set of countries with characteristics similar to those of the average Latin American country.[10] It is necessary to choose those characteristics in terms of their ability to predict the outcomes' variables—in this case, the energy indexes, which we tested in the previous section. Taking a conservative position, we take the whole set of variables in X and apply the synthetic control method under each of the strategies described in the methodological section. Figure 3 compares the trends between the average and synthetic Latin American country.. The synthetic Latin American country represents the average of the sets of countries that best resemble Latin America in each strategy.[11]

The three strategies adopted show similar results. The enlarging strategy allows for the introduction of more memory each time—that is, starting from early 1970s, the window in which we look for a synthetic Latin America gradually increases. As shown in Figure 4, Latin America underperformed in terms of intensity and efficiency, but closed the gap between 2000 and 2010. We find similar results when we reduce the window by starting the matching exercise from a later year each time. However, in this case, the energy intensity index of the average Latin American country and its synthetic counterfactual tend to be more similar. Moreover, the efficiency index in Latin America shows a sharp improvement between 2005 and 2010 in relation to its synthetic counterfactual. When we move the entire period of matching forward, the results are more similar to the first exercise, showing a significant increase of the intensity and efficiency indexes over the 1985–2000 period and then a decrease over the next 10 years. The differences between Latin America and its synthetic counterfactual are not statistically significant in terms of the activity-mix index over the last few decades.

[10] The synthetic control method is usually applied when there is an exogenous source of variability affecting some units, but not others. The unaffected units are used to construct the synthetic control. In appendix 5, as an example, we perform a similar exercise. Since we do not have an external source of variability, we arbitrarily choose the year 2010 and the average Latin American country as our treatment unit—that is, we restrict the algorithm to find a synthetic control by matching the co-variants in the period 1972–1999, a period long enough to construct a credible synthetic Latin American country. We changed the variable after 2000 in order to have at least a period of 10 years to evaluate. The results show that Latin America decreased its intensity and efficiency by almost 20 percent, but its synthetic counterfactual would have done so by about 30 percent.

[11] Upon request, the authors can provide the list of countries and weights used to construct the synthetic counterfactual in each strategy.

In general, the main finding of this approach is that Latin America underperformed in energy intensity and efficiency during the period 1985–2000. However, the gap closed over the next 10 years, showing a sharp improvement.



Source: Authors' elaboration.
Note: LAC = Latin American countries.

4. CONCLUSIONS AND POLICY IMPLICATIONS

Energy intensity has shown a decreasing trend in all sets of countries, regardless of income level. The main components explaining this variation are improvements in energy efficiency, although those improvements seem to be less pronounced in Latin America than in other regions. Over the last 40 years, the Latin American region reduced its energy intensity by about 20 percent, while other regions decreased theirs by between 40 and 60 percent. The main drivers behind these general trends are per capita income, petroleum prices, and economic growth. These variables have statistical strength in explaining the improvement in energy use over the last four decades. On the other hand, the fuel mix and the abundance of extractive natural resources are directly correlated with the energy indexes. In particular, these results help to explain stagnant energy intensity in the Latin American region between the mid-1980s and mid-

1990s, a period characterized by difficult economic conditions and relatively low international oil prices.

However, the comparative exercise shows that Latin America is not behind other regions in terms of energy intensity and efficiency: the 20 percent improvement in the Latin American region is similar to the improvement in its synthetic counterfactual. Even when we observe an increase in energy intensity between the mid-1980s and mid-1990s, the analysis shows that Latin America gradually closed the gap between 2000 and 2010. Since no major measures were taken in the region in terms of energy efficiency, this suggests that market signals were enough to correct the trends in energy indexes.

Further studies could perform a more detailed decomposition. For example, components such as the type of fuel and/or production level could be added. When the information is available, it would be useful to perform a detailed analysis by sector (i.e., industry).

REFERENCES

Abadie, A., and J. Gardeazabal. 2003. "Economic Costs of Conflict: A Case Study of the Basque Country." *American Economic Review* 93(1): 113–132.

Abadie, A., A. Diamond, and J. Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association* 105(490): 493–505.

———. 2011. "Synth: An R Package for Synthetic Control Methods in Comparative Case Studies." *Journal of Statistical Software* 42(13): 1–17. Available at http://www.jstatsoft.org/v42/i13/paper.

Ang, B. W. 2004. "Decomposition Analysis for Policymaking in Energy: Which is the Preferred Method?" *Energy Policy* 32: 1131–39.

———. 2006. "Monitoring Changes in Economy-wide Energy Efficiency: From Energy-GDP Ratio to Composite Efficiency Index." *Energy Policy* 34(5): 574–82.

Ang, B. W. and S. Y. Lee. 1994. "Decomposition of Industrial Energy Consumption: Some Methodological and Application Issues." *Energy Economics* 16(2): 83–92.

Ang, B.W. and F. L. Liu. 2003. "Eight Methods for Decomposing the Aggregate Energy-intensity of Industry." *Applied Energy* 76(1–3): 15–23.

Ang, B.W., and N. Liu. 2007a. "Handling Zero Values in the Logarithmic Mean Divisia Index Decomposition Approach." *Energy Policy* 35(1): 238–46.

———. 2007b. "Negative-value Problems of the Logarithmic Mean Divisia Index Decomposition Approach." *Energy Policy* 35(1): 739–42.

Ang, B. W., H. C. Huang, and A. R. Mu. 2009. "Properties and Linkages of Some Index Decomposition Analysis Methods." *Energy Policy* (37): 4624–32.

Ang, B.W., A. R. Mu, and P. Zhou. 2010. "Accounting Frameworks for Tracking Energy Efficiency Trends." *Energy Economics* 32(5): 1209–19

Balza, L. and R. Jimenez. 2013. "Models for Forecasting Energy Use and Electricity Demand: An Application to Central American Countries, Mexico and Dominican Republic." Washington, DC: Inter-American Development Bank. Unpublished.

Bernstein, M., K. Fonkych, S. Loeb, and D. Loughran. 2003. "State-Level Changes in Energy Intensity and Their National Implications." Monograph Reports. Santa Monica, CA: RAND Corporation.

Bhattacharya, R. and P. Shyamal. 2001. "Sectoral Changes in Consumption and Intensity Energy in India." *Indian Economic Review* 36(2): 381–92

Bond, S. 2002. "Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice." *Portuguese Economic Journal* 1(2): 141–62.

Boyd, G.A., D. A. Hanson, and T. N. S. Sterner. 1988. "Decomposition of Changes in Energy Intensity: A Comparison of the Divisia Index and Other Methods." *Energy Economics* 10(4): 309–12.

Boyd, G.A. and J. M. Roop. 2004. "A Note on the Fisher Ideal Index Decomposition for Structural Change in Energy Intensity." *The Energy Journal* 25(1): 87–101.

Diakoulaki, D., G. Mavrotas; D. Orkopoulos, and L. Papayannakis. 2006. "A Bottom-up Decomposition Analysis of Energy-related CO2 Emissions in Greece." *Energy* 31(14): 2638–51.

Duro, J.A., V. Alcántara, and E. Padilla. 2010. "International Inequality in Energy Intensity Levels and the Role of Production Composition and Energy Efficiency: An Analysis of OECD Countries." *Ecological Economics* 69: 2468–74.

Duro, J. A. and E. Padilla. 2011. "Inequality across Countries in Energy Intensities: An Analysis of the Role of Energy Transformation and Final Energy Consumption." *Energy Economics* 33: 474–79.

Galiani, S. and M. Gonzalez-Rozada. 2002. "Inference and Estimation in Small Sample Dynamic Panel Data Models." Business School Working Papers 02/2002. Buenos Aires, Argentina: Centro de Investigación en Finanzas, Universidad Torcuato Di Tella. Available at www.utdt.edu/departamentos/empresarial/cif/pdfs-wp/wpcif-022002.pdf.

Hall, R. E. and C. I. Jones. 1999. "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *The Quarterly Journal of Economics* 114(1): 83–116.

Hasanbeigi, A., S. Rue du Can, and S. Sathaye. 2012. "Analysis and Decomposition of the Energy Intensity of Industries in California." *Energy Policy* 46.

Huntington, H. G., 2010. “Structural Change and U.S. Energy Use: Recent Patterns.” *Energy Journal* 31: 25–39.

IDB (Inter-American Development Bank). 2012. “Justificación de la intervención del gobierno en el mercado de eficiencia energética.” Serie sobre Eficiencia Energética. Available at http://www.iadb.org/en/publications/publication-detail,7101.html?id=64906.

IEA (International Energy Agency). 2012. “Energy Indicators System: Index Construction Methodology.” Paris, France: IEA.

Ke, J., L. Price, S. Ohshita, D. Fridley, N. Zheng, N. Zhou, and M. Levine. 2012. “China's Industrial Energy Consumption Trends and Impacts of the Top-1000 Enterprises Energy-Saving Program and the Ten Key Energy-Saving Projects.” *Energy Policy* 50: 562–69.

Judson, R. A. and A. L. Owen. 1999. “Estimating Dynamic Panel Data Models: A Guide for Macroeconomists.” *Economics Letters* 65(1): 9–15.

Liddle, B., 2010. “Revisiting World Energy Intensity Convergence of Regional Differences.” *Applied Energy* 87: 3218–25.

Nanduri, M., J. Nyboer, and M. Jaccard. 2002. “Aggregating Physical Intensity Indicators: Results of Applying the Composite Indicator Approach to the Canadian Industrial Sector.” *Energy Policy* 30(2): 151–63.

Ma, C., and D. I. Stern. 2008. “China's Changing Energy Intensity Trend: A Decomposition Analysis.” *Energy Economics* 30: 1037–53.

Metcalf, G. 2008. “An Empirical Analysis of Energy Intensity and its Determinants at the State Level.” *The Energy Journal* 29(3): 1-26.

Greening, L. A., W. B. Davis, L. Schipper, and M. Khrushch. 1997. “Comparison of Six Decomposition Methods: Application to Aggregate Energy Intensity for Manufacturing in 10 OECD Countries.” *Energy Economics* 19(3): 375–90.

Mulder, P. and H. L. F. de Groot. 2012. “Structural Change and Convergence of Energy Intensity across OECD Countries, 1970–2005.” *Energy Economics* 34: 1910–21.

Reddy, B. S. and B. K. Ray. 2011. “Understanding Industrial Energy Use: Physical Energy Intensity Changes in Indian Manufacturing Sector.” *Energy Policy* 39(11): 7234–43.

Sachs, J. D. and A. M. Warner. 1995. “Natural Resource Abundance and Economic Growth.” NBER Working Paper No. 5398. Cambridge, MA: National Bureau of Economic Research (NBER). Available at http://www.nber.org/papers/w5398.pdf.

Shahiduzzaman, M. D. and A. Khorshed. 2012. “Changes in Energy Efficiency in Australia: A Decomposition of Aggregate Energy Intensity Using Logarithmic Mean Divisia Approach.” Australian Centre for Sustainable Business and Development. Queensland, Australia: University of Southern Queensland.

Sinton, J. E. and M. D. Levine. 1994. “Changing Energy Intensity in Chinese Industry: The Relatively Importance of Structural Shift and Intensity Change.” *Energy Policy* 22(3): 239–55.

Sue Wing, I., 2008. “Explaining the Declining Energy Intensity of the U.S. Economy.” *Resources and Energy Economics* 30(1): 21–49.

Wooldridge, J. 2011. *Econometric Analysis of Cross Section and Panel Data*. Second Edition. Cambridge, MA: The MIT Press.

Zhang, Z. X. 2003. “Why Did the Energy Intensity Fall in China's Industrial Sector in the 1990s? The Relative Importance of Structural Change and Intensity Change.” *Energy Economics* 25(6): 625–38.

ANNEXES

Annex 1: Data Sources

This study analyzes the period 1971–2010 and uses a sample of 75 countries (20 from Latin America). The data on energy come from the International Energy Agency (IEA), while the measures of economic activity are based on World Bank Development Indicators. The PPP GDP at constant 2005 prices is taken from the Penn tables. Since those tables only provide data through 2009, we use growth projections from the IMF to complete the year 2010. To account for a balanced dataset, we drop those countries with less than 20 observations in any variable.

In the first step, we calculate the energy intensity series (EI) as the ratio of the total final consumption of energy by sector (from IEA) and the PPP GDP at constant prices of 2005, in thousands (from Penn Tables). We analyze detailed data from the agricultural, industrial, service, and residential sectors (from IEA), which allows us to form a partition for these sectors. Since activity indicators can overlap, appropriate proxies are value added in the agricultural, industrial, and service sectors. For the residential sector, we consider the household final expenditure.

To build the energy indexes, the methodology requires that there be no missing values in economic activity indicator or sector energy use. Thus, we input those missing values with estimations based on the compound growth rate method as described in the next expression:[12]

$$y_t = y_{t-l}(1 + g_y)^l$$

Where y represents the variable with missing/zero values, t the period, l the number of periods from the last not missing/zero value, and g the growth rate of the variable of interest.

We extract other variables from the World Bank Development Indicator (fossil fuel consumption, total labor force, fuel exports, population growth, and gross capital formation) and the International Monetary Fund (petroleum prices). Following Metcalf (2008), we incorporate the ratios (stock of capital/labor force) and (investment/stock of capital). Since the stock of capital is not available for all countries, we construct a proxy based on the perpetual inventory method:

[12] Ang and Liu (2007a; 2007b) evaluate and propose different strategies for the case of zero values. In order to preserve trends, we adopt the compound rate of the growth method, which is a standard practice of IEA to forecast trends. As revised in Balza and Jimenez (2013), this method tends to offer accurate estimations of energy use trends.

$$K_t = (1-\delta)K_{t-1} + GFK_t$$

Where K and GFK represent the stock of capital and the gross capital formation, respectively. The depreciation rate (delta) is assumed to be 6 percent. The initial value K is calculated as $K_0 = {GFK_0}/{(\delta + g_{GFK})}$, with g_{GFK} representing the growth rate in gross fixed capital formation.

Hall and Jones (1999) provide further details on this method.

Annex 2: Relative Weight of Latin American and Caribbean Countries in GDP and Energy Use

Table A2.1: Average GDP and TFC of Energy, 2000–2010

Country	GDP PPP 2005 US$ thousands	Percentage	TFC Kg oil equivalent	Percentage
Brazil	1,580,000	35.4	171,380	36.4
Mexico	1,210,000	27.1	104,637	22.2
Argentina	391,000	8.8	49,549	10.5
Colombia	276,000	6.2	21,797	4.6
Venezuela, RB	218,000	4.9	38,465	8.2
Chile	174,000	3.9	21,660	4.6
Peru	163,000	3.6	11,404	2.4
Cuba	109,000	2.4	7,559	1.6
Dominican Republic	75,500	1.7	5,515	1.2
Costa Rica	42,100	0.9	2,938	0.6
El Salvador	35,600	0.8	3,034	0.6
Bolivia	31,100	0.7	3,555	0.8
Uruguay	29,000	0.6	2,599	0.6
Trinidad and Tobago	27,200	0.6	11,800	2.5
Panama	25,500	0.6	2,293	0.5
Jamaica	24,300	0.5	2,855	0.6
Honduras	23,600	0.5	3,305	0.7
Paraguay	21,000	0.5	3,736	0.8
Nicaragua	11,000	0.2	2,271	0.5

Source: Authors' elaboration.

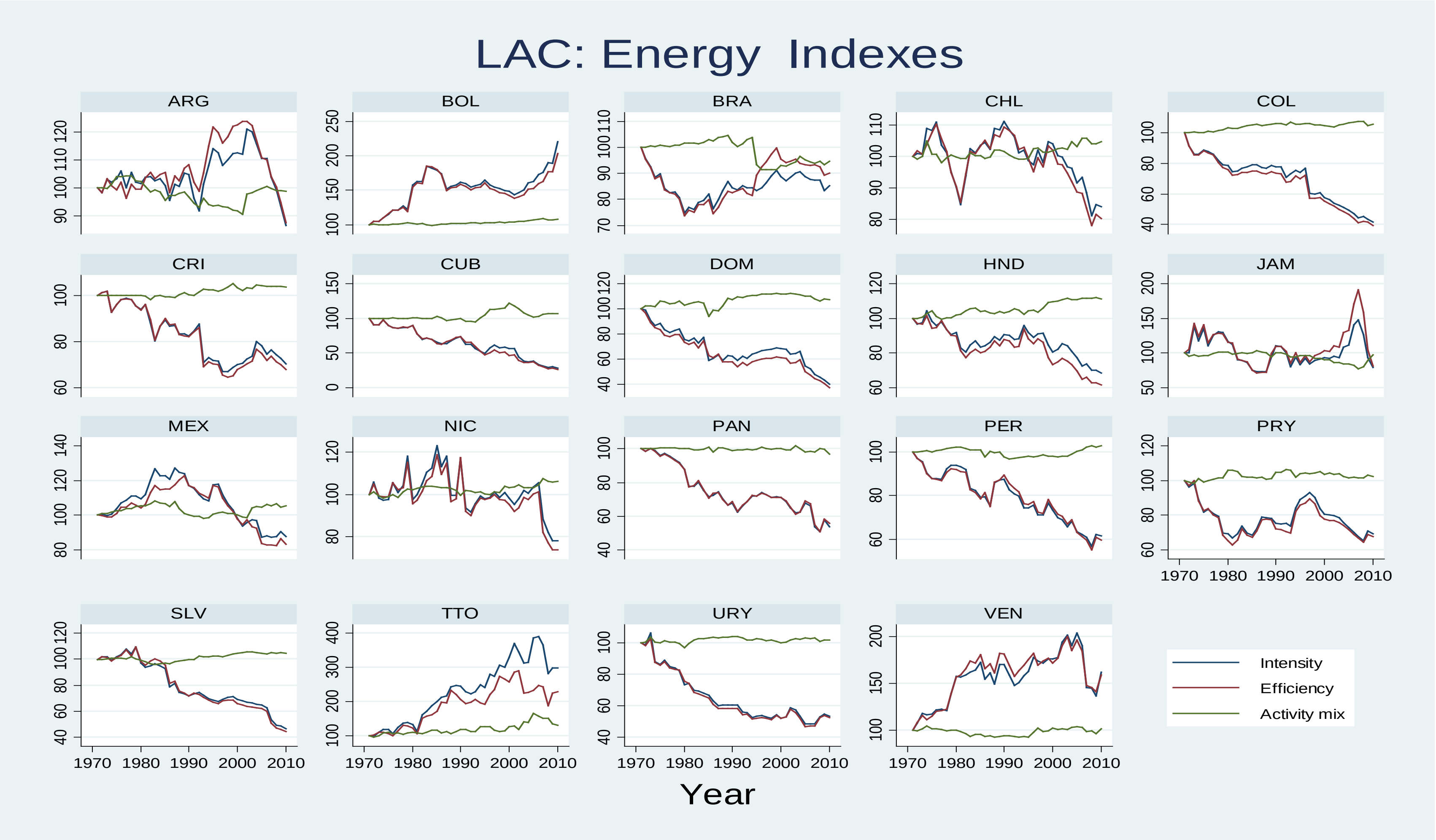
Annex 3: Additive Contribution to Energy Intensity

Table A3.1: Variation Explained by Each Energy index *(by income level)*

Year	Intensity	Activity	Efficiency	Intensity	Activity	Efficiency
	Latin American countries			**Medium-income countries**		
1980	-8.53	2.23	-10.76	-9.88	4.69	-14.57
1990	-2.09	1.31	-3.40	-20.62	4.96	-25.58
2000	-6.57	-2.66	-3.91	-42.46	5.08	-47.54
2010	-17.18	0.78	-17.96	-54.22	6.89	-61.11
	Low-income countries			**High-income countries**		
1980	-12.88	-0.44	-12.45	-15.70	-0.60	-15.10
1990	-24.11	-0.31	-23.80	-35.31	-1.97	-33.34
2000	-29.19	-0.30	-28.89	-42.15	-4.73	-37.42
2010	-42.83	1.28	-44.12	-50.45	-5.96	-44.49

Source: Authors' elaboration.
Note: Base year 1971=100.

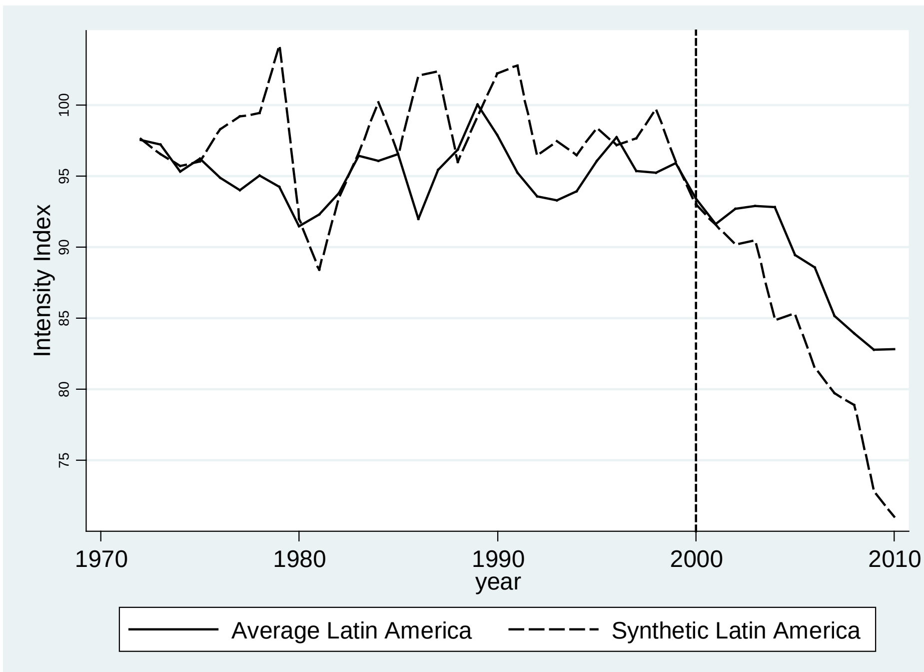
Annex 4. Latin America Energy Indexes



Source: Authors' elaboration.

Annex 5: Example of Synthetic Control Comparison Method

The graph shows that the energy intensity in Latin America's synthetic counterfactual was reduced 10 percent more than in the region itself—that is, the region underperformed in terms of its use of energy. The exercise was performed matching the predictor for the entire period from 1972–1999, so the predictor was well balanced over 30 years, resembling the behavior of Latin America. The problem with the present analysis is that Latin America has several phases that could be unobserved. For this reason, Section 3.3 shows the iteration of Synth for different periods and then presents the average trend, showing that the region closed the gap between 2000 and 2010.



Source: Authors' elaboration.

Table A5.1: Country Weights

Country	Unit weight	Country	Unit weight
Philippines	22.9	Germany	6.7
Japan	13.5	Gabon	6.1
Zambia	11.7	Togo	4.3
Syrian Arab Republic	10.7	Malta	3.6
Italy	9.8	United Kingdom	2.2
Singapore	7.2	Kenya	1.3

Source: Authors' elaboration.

Table A5.2: Balance Pre-treatment

Predictors	Treated	Synthetic
Ln(GDP per capita, const 2000)	8.7	8.7
Population growth	2.0	1.9
Fossil fuel energy consumption	70.6	66.9
GDP growth	0.0	0.0
Natural resources rents	6.4	6.4
Investment / Capital	9.3	9.3

Source: Authors' elaboration.