Executive Summary

The improvement of energy efficiency is one of the most promising measures to meet emission targets set by climate policy. Beside this effect, it may also help to reduce the dependence on fossil fuels as well as it can foster the competitiveness of industries. In this paper, we will introduce and employ the new World Input Output Database (WIOD) in order to tell a story about the development of the energy intensity in Europe. The purpose of our work is to determine the economic and political factors which have driven the development of energy intensity in Europe between 1995 and 2009.

In our analysis we consider Europe for various reasons: First, the European Union regards itself as a leading actor in international climate policy, and as improving energy efficiency is a central pillar of Europe's strategy, we want to investigate the development in this particular region. Second, the data we are using for our analysis allows us to consider an interesting period of time in Europe. Our sample starts shortly after the fall of the iron curtain and includes periods without and with climate policy. Finally, and most important for our work, the European integration process is an outstanding example for structural change. While other studies focussed mainly on e.g. the impacts of the North-American free trade agreement NAFTA and how the increased trade affected the environment in the United States, we consider large structural shifts causing enormous opening to international trade.

Our analysis consists of two interrelated parts. In the first part we describe the different data sources we have used and we use an index decomposition framework to describe the development of energy intensity in Europe between 1995 and 2009. We show measures for the EU 27 aggregate and individual countries with additional sectoral disaggregation. Our analysis reveals the large heterogeneity within Europe. While some countries experienced a clean-up due to structural change, most countries have benefited from technology improvements. In the second part of the paper, we use the obtained index values and construct potentially relevant variables that drive the respective developments. We construct variables which are potential drivers of the different effects, such as an estimate for total factor productivity, trade openness, income per capita, environmental regulation, energy prices and country characteristics. Then we use panel econometrics to identify causalities that would be unable to be found within an IDA framework.

Our conclusions are optimistic. Structural change is less important for the clean-up of energy intensity, against the background of the fall of the iron curtain a surprising fact. Instead, technological change is the key driving force. This is an optimistic conclusion, as the development is replicable in currently less developed regions, such as Brazil, China or India. We can show that energy prices are less important than in the United States and that energy efficiency regulation does not matter. The major contributors to the positive development are the rising income per capita, a proxy for employed technologies, and improvements in total factor productivity as a measure for technological progress.

Das Wichtigste in Kürze

Die Steigerung der Energieeffizienz ist eine der vielversprechendsten Politikmaßnahmen um vereinbarte Klimaschutzziele zu erreichen. Darüber hinaus kann sie die Abhängigkeit von fossilen Energieträgern verringern und die Wettbewerbsfähigkeit einzelner Industriezweige erhöhen. In dieser Arbeit verwenden wir die neue „World Input-Output Database“ (WIOD) um den Verlauf der Energieintensität in Europa im Zeitraum von 1995 bis 2009 darzustellen und die treibenden ökonomischen und politischen Kräfte hinter der Entwicklung zu erklären.

Wir legen das Augenmerk aus mehreren Gründen auf Europa: Erstens, betrachtet sich die Europäische Union als Vorreiter der weltweiten Klimapolitik und die Verbesserung der Energieeffizienz stellt eine tragende Säule der europäischen Politik dar. Ein weiterer Grund für eine rein europäische Betrachtung ist der interessante Betrachtungszeitraum unserer Studie. Dieser erstreckt sich von kurz nach dem Fall des Eisernen Vorhangs über eine Zeit ohne Klimapolitik bis zu der Zeit nach dem Inkrafttreten des Kyoto-Protokolls. Und schließlich, als einer der Hauptgründe für unsere Entscheidung, ist, dass der Prozess der Europäischen Integration ein herausragendes Beispiel für Strukturwandel ganzer Volkswirtschaften darstellt. Während andere Studien zum Beispiel die Auswirkungen des nordamerikanischen Freihandelsabkommens NAFTA auf Handel und Umwelt untersuchen, sehen wir den europäischen Fall als besonders gravierendes Beispiel für strukturellen Wandel an.

Unsere Analyse besteht aus zwei miteinander verwobenen Teilen. Im ersten Teil beschreiben wir die verschiedenen verwendeten Datenquellen und bedienen uns einer „Index Decomposition Analysis“ (IDA) um die Entwicklung der Energieintensität in Europa und den einzelnen Länder zu illustrieren. Die IDA ermöglicht es uns auch, die Gesamtentwicklung in zwei Komponenten zu zerlegen: der durch Strukturwandel erklärte Anteil und der Beitrag des technologischen Fortschritts. Besonders auffällig ist dabei die Heterogenität in Europa. Während einige Länder durch den Strukturwandel profitieren, haben viele Länder ihre eingesetzte Technologie erneuert. Im zweiten, empirischen Teil der Arbeit verwenden wir die erhaltenen Indexwerte der IDA und konstruieren potentiell relevante erklärende Variablen, die die Entwicklung der Indexwerte treiben. Mit Hilfe von Panel-Ökonometrie versuchen wir Kausalitäten zu identifzieren, die von der einfachen IDA nicht zu finden wären.

Die Ergebnisse unserer Arbeit sind optimistisch. Der Strukturwandel spielt für die Entwicklung der Energieintensität in Europa eine eher untergeordnete Rolle, weit wichtiger sind die Variablen die mit technologischem Wandel in Verbindung gebracht werden. Das Ergebnis ist deshalb optimistisch, da die europäische Entwicklung in gegenwärtigen Entwicklungs- und Schwellenländern wie Brasilien, China oder Indien wiederholbar ist. Unser empirisches Modell zeigt auch, dass Energiepreise im Vergleich zu den Vereinigten Staaten weniger relevant sind und die energiepolitischen Interventionen keine große Rolle spielen. Der Hauptanteil der Energieeffizienzsteigerung wird erklärt durch ein steigendes Pro-Kopf-Einkommen, stellvertretend für Präferenzwechsel hin zu einer sauberen Umwelt und für verwendete Technologien und Verbesserungen bei der Totalen Faktorproduktivität als Maßstab für den technologischen Fortschritt.

Peeling the Onion: Analyzing Aggregate, National and Sectoral Energy Intensity in the European Union

An Application of the WIOD Database

Michael Schymura*and Andreas Löschel†

Abstract

One of the most promising ways of meeting climate policy targets is improving energy efficiency, i.e. reducing the amount of scarce and polluting resources needed to produce a given quantity of output. This study undertakes an empirical exercise using the World Input-Output Database (WIOD), a harmonized dataset comprising time-series input-output tables along with environmental satellite accounts and socioeconomic information. The paper consists of two parts. In the first part we begin with an aggregated picture of EU27 energy intensity and its evolution between 1995 and 2009. Then we dig deeper and introduce sectoral detail to identify the economic changes that occurred during the same period. Finally, we disaggregate the EU27 into countries for regional analysis and perform a sectoral disaggregation for a fine-grained picture of energy intensity in Europe. In the second part of the study we take our findings from index decomposition analysis and subject them to panel estimations in a manner similar to the approach used by Metcalf (2008) for the United States. The objective is to control for factors that may have shaped the evolution of energy intensity in the European Union. In particular, we investigate the impact of technological change, structural change, trade, environmental regulation and country-specific characteristics.

Keywords: Environmental and Climate Economics, Energy Intensity, Structural Decomposition
JEL-Classification: Q0, Q50

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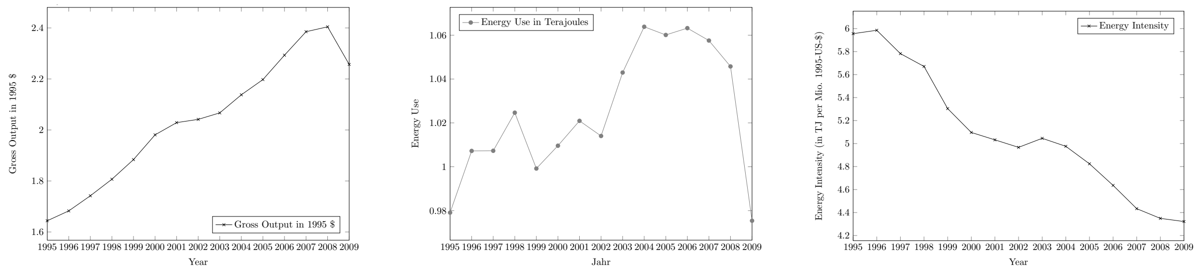
I. Introduction

Improving energy efficiency is one of the most promising ways of meeting the emission targets set by climate policy. What is more, it may also help reduce dependence on fossil fuels and foster industrial competitiveness (Ang et al., 2010). In this paper, we introduce and employ the new WIOD to tell a story about the evolution of energy intensity in Europe between 1995 and 2009. As the graphs below show, the gross aggregate output of the EU 27 increased by 37.2 % (Figure 1a) and total energy use decreased by 0.4 % (Figure 1b) in this period. As a result of both, energy intensity declined steadily by 27.4 % (Figure 1c).[1]



(a) Gross Output (b) Energy Use (c) Resulting Energy Intensity

Figure 1: Gross Output, Energy Use and Energy Intensity in the EU27 1995-2009

These three figures appear to tell us everything, and yet in reality they reveal nothing. Is the decline in energy intensity due to a shift in the composition of the European economy as a whole as it moves away from energy-intensive production towards less energy-intensive production? Or are more fundamental improvements to energy utilization responsible for the decline? And how did individual countries perform during the same time? What are the main economic and political drivers?

This paper seeks to understand the decline of energy intensity by using index decomposition analysis to differentiate between structural changes (*composition effects*), the effects of efficiency improvements (*technology effects*) and their regional and sectoral patterns (*spatial effects*).

The questions posed above have fundamental import: if the decline in energy intensity could be obtained simply by structural improvements and increasing imports of energy-intensive goods from outer Europe, the pattern in Europe would not be replicable in other, less developed regions.[2] But if the decrease in energy intensity is due to increased efficiency, the trajectory would be replicable in other regions of the world. (Indeed, thanks to technology transfers, spillover effects, economies of scale, and learning-by-doing, achieving the same trajectory elsewhere might even be easier.) As Wolfram et al. (2012) argue, energy consumption in OECD and non-OECD countries was almost equal in 2007, "[...] but from 2007 to 2035, it [the U.S. Energy Information Administration] forecasts that energy consumption in OECD countries will grow by 14 percent, while energy consumption in non-OECD countries will grow by 84 percent" (Wolfram et al., 2012, p. 119). Given this information, the investigation of the replicability of the European

[1]The WIOD takes into account the effects of the financial crisis as well as its impact on gross output and energy use. Accordingly, between 2008 and 2009 gross output declined by 5.9 % and energy use by 6.2 %, the latter even dipping below 1995 levels.

[2]For a similar argument applied to the impact of international trade on pollution in U.S. manufacturing between 1987 and 2001, see Levinson (2009).

decline assumes tremendous importance. Indeed, a key finding of this paper is that a substantial share of the decrease of energy intensity can be attributed to various facets of technological change. In other words: energy intensity is replicable in less developed countries.

We focus our analysis on Europe for a variety of reasons. First, the European Union regards itself as a leading actor in international climate policy and improving energy efficiency is a central pillar of its strategy. Second, the data we use allows us to consider an interesting period in Europe.[3] Our sample starts shortly after the fall of the Iron Curtain and includes periods with climate policy and without.[4] Finally, and most important, the European integration process is an outstanding example of structural change at work. While other studies have focused mainly on the impact of NAFTA and increased environment trade in the United States, we consider large structural shifts associated with enormous openings in international trade. For instance, Grossman and Krueger (1991) analyzes the impact of the NAFTA free trade agreement on pollution; others look at countries in which structural changes have occurred. But no case examined so far involves large charges to the openness of cross-country trade (see Antweiler et al. (2001); Cole (2006); Cole and Elliott (2003) and Managi et al. (2009)). Cornillie and Fankhauser (2004) investigate the development of energy intensity for transitional economies, but their time frame is brief (six years) and spans the years in which structural break took place: 1992 to 1998. We too will investigate the consequence of economic transition.

Our study consists of two interrelated parts and is organized as follows. In the first part we describe the different data sources we employ. Next we perform an index decomposition analysis of the energy intensity in Europe between 1995 and 2009. We show measures for the EU 27 aggregate and for individual countries with additional sectoral disaggregation. Our analysis reveals a large heterogeneity within Europe. While some countries experienced a decline in energy intensity due to structural change, most countries benefited from technology improvements. We then construct variables for the potential drivers behind the different effects, including estimates for total factor productivity, trade openness, income per capita, environmental regulation, energy prices and country characteristics. We then present the results of our empirical exercise and discuss their robustness. Finally we draw some conclusions in section V.

II. Data Issues

A. The WIOD

Our analysis relies on data from the World Input-Output Database (WIOD),[5] a comprehensive, unified dataset that permits comparison of specific environmental indicators like energy intensity over the years covered by the database (1995 to 2009). The WIOD is based on national

[3]In its cost-benefit analysis of the new European Energy Efficiency Directive, the European Commission concludes optimistically that the annual cost of 24 billion euros estimated for the period of 2011 to 2020 will be outweighed by the annual benefits, projected at 44 billion euros (European Commission, 2012).

[4]The time-series character of our data allows us to investigate evolved changes. Alcantara and Duarte (2004), for example, use structural decomposition analysis to investigate the energy intensities in 14 European countries and 15 sectors, though the authors restrict their analysis to 1995.

[5]The WIOD and all satellite accounts are available at http://www.wiod.org. For this paper, we have used data from February 2012.

accounts data harmonized for international comparability. The dataset covers 40 countries (27 EU countries and 13 other major countries), which together account for $\approx 80 - 85\%$ of the world's GDP in 2009. The data is disaggregated into 36 industries (agriculture, manufacturing, services and a private sector[6]). Besides the broad country coverage, the sectoral disaggregation and the time range, the dataset has another key advantage: it contains several unified satellite accounts with the same sectoral classification as the core dataset. The satellite accounts consist of bilateral trade data, socioeconomic data (different skill types of labor, sectoral and total capital stocks, etc.) and, most important for this analysis, a rich set of environmental information. The environmental satellites cover the following data: energy use broke down by several energy carriers (fossil, non-fossil, renewables, etc.), emissions of greenhouse gases ($\mathrm{CO_2, N_2O, CH_4}$), air pollutants relevant for acidification ($\mathrm{SO_2, N_OX, CH_4}$) and tropospheric ozone information ($\mathrm{N_OX, NMVOC, CH_4}$).

B. Used Data

In this subsection we describe the data we have used for both parts of the paper. To perform the index decomposition analysis and the empirical study in the second part of the paper, we have used the following information from the WIOD for all 27 current European Union countries: the Socioeconomic Accounts Files (*SEA*) and the Energy Use Files (Gross (*EU*)). The other data sources are the *Penn World Tables* (Mark 7.0), the *CIA World Fact Book*, the *CEPII* Gravity Data Set, The International Energy Agency and the Barro and Lee database on educational attainment. A complete list of the regions and sectors covered by this analysis is given in Appendix A and the summary statistics in Appendix B.

Energy Use Data

Energy is measured in physical units (TJ) and is aggregated across 26 energy carriers (*EU*). The sectoral classification of energy use is exactly congruent to the socioeconomic data we have used from the WIOD database.

Socioeconomic Data

The variables that we need for our index decomposition analysis are defined for time t and measured on an annual basis. (Sectoral) output is expressed in monetary units in basic prices of 1995 and converted to mio. US-$ (1995) using the supplied exchange rates. One advantage of the WIOD is the availability of sectoral price deflators, so that different price developments can be taken into account, not only on a national level but also on a sectoral one. The measure of sectoral economic activity is gross output (*GO*). We use hours worked by employees as a measure of labor input (*H_ EMPE*). Data on three types of labor quality is also included (low-skilled (*LAB_ LS*), medium-skilled (*LAB_ MS*) and high-skilled (*LAB_ HS*). One major advantage of the WIOD is the capital stock variable. It is generally hard to obtain (physical) capital stock data from official data sources. The WIOD offers information about physical capital stocks and gross fixed capital formation for each country, sector and year (*K_ GFCF* and *GFCF*). We used this information to construct capital-to-labor ratios (*KL*) and to take capital vintaging into account (*VINTAGING*). We have also used information on bilateral trade flows to capture the effect of structural change (*OPENESS*).

[6] We have excluded the private sector from our analysis.

Other Data

Besides the WIOD, we use the *Penn World Tables* (Mark 7.0) to obtain information about real GDP per capita (variable *rgdpch*), population (*pop*), real openness as defined by the sum of imports and exports divided through GDP (*openk*) and real investment as a fraction of GDP (*ki*) (Heston et al., 2011). The information about the geographical country characteristics, such as area, was obtained from the *CIA World Fact Book* and the *CEPII* Gravity Data Set.[7] Information on environmental regulation was collected from the International Energy Agency; from it we constructed an index for the extent and stringency of environmental regulation.[8] In addition, we used the Barro and Lee database (Barro and Lee, 2010) on educational attainment and Psacharopoulos and Patrinos (2004) for estimated social Mincearian returns on education to construct our measure for human capital. Energy prices (*PRICE*) and heating degree days (*HDD*) were collected from Eurostat.

III. Index Decomposition Results

A. Index Decomposition Analysis

In this section we introduce the concept of index decomposition analysis (IDA). The IDA allows changes in energy intensity to be decomposed into their underlying source, be it technological or structural. The IDA compares actual emissions in each sector with hypothetical emissions that would have been emitted had the total economy's size and energy intensity (i.e. technology) remained unchanged over time. In general, there are two broad categories of decomposition methodologies: approaches based on input-output analysis, called structural decomposition analysis (SDA), and disaggregation techniques, which is known as index decomposition analysis (IDA) and is related to index number theory in economics.[9]. Ma and Stern (2008) summarizes the main advantages and disadvantages of each approach. The main advantage of the SDA approach is that it considers the effects of direct and indirect demand.[10] The IDA model we use considers direct energy consumption without factoring in indirect effects. Below we focus on a standard IDA for total, sectoral and national energy intensities as described in Ang and Choi (1997); Ang and Liu (2007); Boyd et al. (1987); Ang et al. (2010), Choi and Ang (2012) and Su and Ang (2012). There are several ways to decompose indicators. One is to distinguish between multiplicative and additive decomposition. For our study, we focus on multiplicative decomposition. Another is to distinguish between indicator types (e.g. Paasche, Laspeyres or Divisia indices). Following Ang and Choi (1997), we calculate our decomposition by means of the log mean Divisia index. It offers very important advantages: it is zero-value robust (Ang et

[7] http://www.cepii.fr/anglaisgraph/bdd/gravity.asp

[8] We thank Enrica de Cian, Elena Verdolini and Sebastian Voigt for providing us with their data on environmental regulation.

[9] The roots of index numbers can be traced back to the Frenchman Nicolas Dutot in 1738 and the Italian G.B. Carli in 1764 (Chance, 1966; Diewert, 1993). See also Diewert (1993) for a technical summary of index number theory. Boyd and Roop (2004) offer a more recent review of different indices in the context of energy intensity and the index number problem in economics.

[10] For an exemplary application of the SDA approach on Chinese carbon emissions, see Zhang and Qi (2011).

al. (2010)) and able to "yield a perfect decomposition" (Ang and Choi (1997, p. 1169)), which leaves no residual term unexplained. Additionally, unlike the arithmetic mean Divisia index, the residual for the arithmetic mean method can be different from zero when the changes in a particular period are substantial, as in our case where we use the IDA for cross-country analysis (Ang and Choi, 1997)).

Our variable for energy intensity at time t for the aggregate economy or for $j = 1, \ldots, 27$ countries is a weighted average of sectoral energy intensity:

$$I_t = \sum_i \frac{GO_{i,t}}{GO_t} \frac{EU_{i,t}}{GO_{i,t}} = \sum_i S_{i,t} I_{i,t} \tag{III.1}$$

where:

- Period: $t \in (1995, 2009)$
- Sectors: $i = 1, \ldots, 35$
- Energy use of the economy in period t: EU_t
- Sectoral energy use of sector i in period t: $EU_{i,t}$
- Gross output as a measure of economic activity in period t: GO_t
- Sectoral gross output of sector i in period t: $GO_{i,t}$
- Share of sector i in total gross output in period t: $S_{i,t} = \frac{GO_{i,t}}{GO_t}$
- Total energy intensity in period t: $I_t = \frac{EU_t}{GO_t}$
- Sectoral energy intensity of sector i in period t: $I_{i,t} = \frac{EU_{i,t}}{GO_{i,t}}$.

The multiplicative decomposition is described by the following formula:

$$D_{E,Tot} = \frac{I_{t+1}}{I_t} = D_{E,Str} D_{E,Int}. \tag{III.2}$$

$D_{E,Str}$ is the estimated impact of *structural change* on aggregate energy intensity. $D_{E,Int}$ is the estimated impact of changes in energy intensity that can be explained by a change in sector efficiency (*technology effect*). The formula for the log mean Divisia index decomposition are:

$$D_{Str} = \exp \sum_i \frac{L(\omega_{i,t+1}, \omega_{i,t})}{\sum_i L(\omega_{i,t+1}, \omega_{i,t})} \ln \left(\frac{S_{i,t+1}}{S_{i,t}} \right) \tag{III.3}$$

$$D_{Int} = \exp \sum_i \frac{L(\omega_{i,t+1}, \omega_{i,t})}{\sum_i L(\omega_{i,t+1}, \omega_{i,t})} \ln \left(\frac{I_{i,t+1}}{I_{i,t}} \right), \tag{III.4}$$

where

$$L(\omega_{i,t+1}, \omega_{i,t}) = \frac{\omega_{i,t+1} - \omega_{i,t}}{\ln(\frac{\omega_{i,t}}{\omega_{i,t+1}})} \tag{III.5}$$

stands for the logarithmic mean – say for the period t and $t+1$ – and serves as a weighting scheme for the index decomposition (Ang and Choi, 1997) and $\omega_{i,t}$ is the country share of energy consumption, $\omega_{i,t} = \frac{EU_{i,t}}{EU_t}$.

Below we present the decomposition results for the entire EU27 region and describe the evolution of sectoral energy intensity between 1995 and 2009. We then disaggregate the EU27-block into individual countries to identify regional differences. Most studies are content with description and stop at this point. One exemption is Metcalf (2008), who investigates the development of U.S. energy intensity on aggregate and state levels between 1970 and 2001. Metcalf also uses index decomposition, but adds an econometric analysis to examine the main economic drivers. In the second part of the paper we build on Metcalf's work as we investigate the European economy. By doing so, we identify causalities that would have gone undetected in an IDA framework.

B. The EU27-Aggregate: Introducing Sectors

As we mention in the introduction, the aggregate picture of European energy intensity tells us everything yet nothing. What fraction of the 28.9 % decline in aggregate energy intensity is due to *structural effects*? How much does *technology* account for the aggregate result? To answer these questions, we have aggregated the economic and environmental data for the individual countries into an "artificial" EU27 block representing the entire European economy and its 35 sectors.[11] For the analysis, we have excluded private households, since we are more interested in structural change than in changes to ultimate demand. We include agriculture and services for in our interpretation structural change can occur not only in manufacturing but also on a larger scale, where it affects the economy's entire composition. Figure 2 summarizes the results of the index decomposition for the EU27 aggregate. The index for total energy intensity began to decline in 1996 and by 2009 had fallen 0.27 (27 %). Changes on the structural level took a different trajectory. While the structure of the aggregated EU27 economy shifted towards less energy-intensive sectors from 1995 to 1999, it trended in the opposite direction from 1999 on. The index for the structural effect increased from 0.93 in 1999 to 1.10 in 2009, or an 18 % increase in the weight of energy-intensive sectors, As the figure indicates, the decline in aggregate energy intensity was mostly due to technology. While the index remained almost constant in the period from 1995 to 1998, it later decreased considerably and by 2009 had reached a value of 0.66.

Figure 10 in the appendix depicts the energy intensity evolution by sector between 1995 and 2009. While some sectors experience an increase in energy intensity – the energy intensity of the wood and cork production ("Sector 20") increased by 33 % – most sectors experienced a decrease. The decline ranged from moderate (-3.8 % in the inland transport, or sector "60") to tremendous (-56.1 % in the coke, refined petroleum and nuclear fuel, or sector "23", an energy-sector correlate).

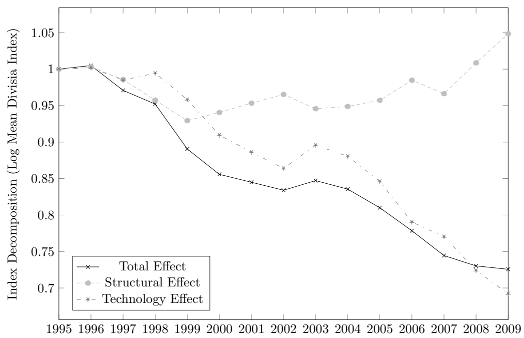


Figure 2: Log Mean Divisia Index Decomposition of Energy Intensity

[11] The aggregation is "artificial" because former Socialist countries joined the EU27 after 1995.

C. Decomposing the EU27-Aggregate: Countries and Sectors

As we noted in the previous section, the inclusion of sectors added considerable explanatory power to the analysis. In this section, we disaggregate the EU27 into individual countries.

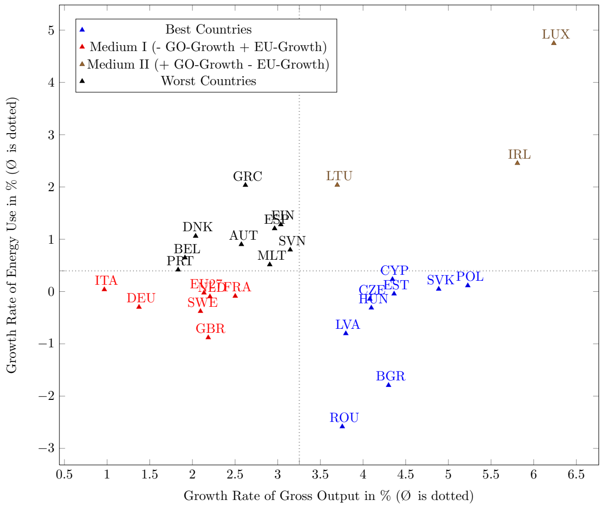


Figure 3: GO- and EU-Growth

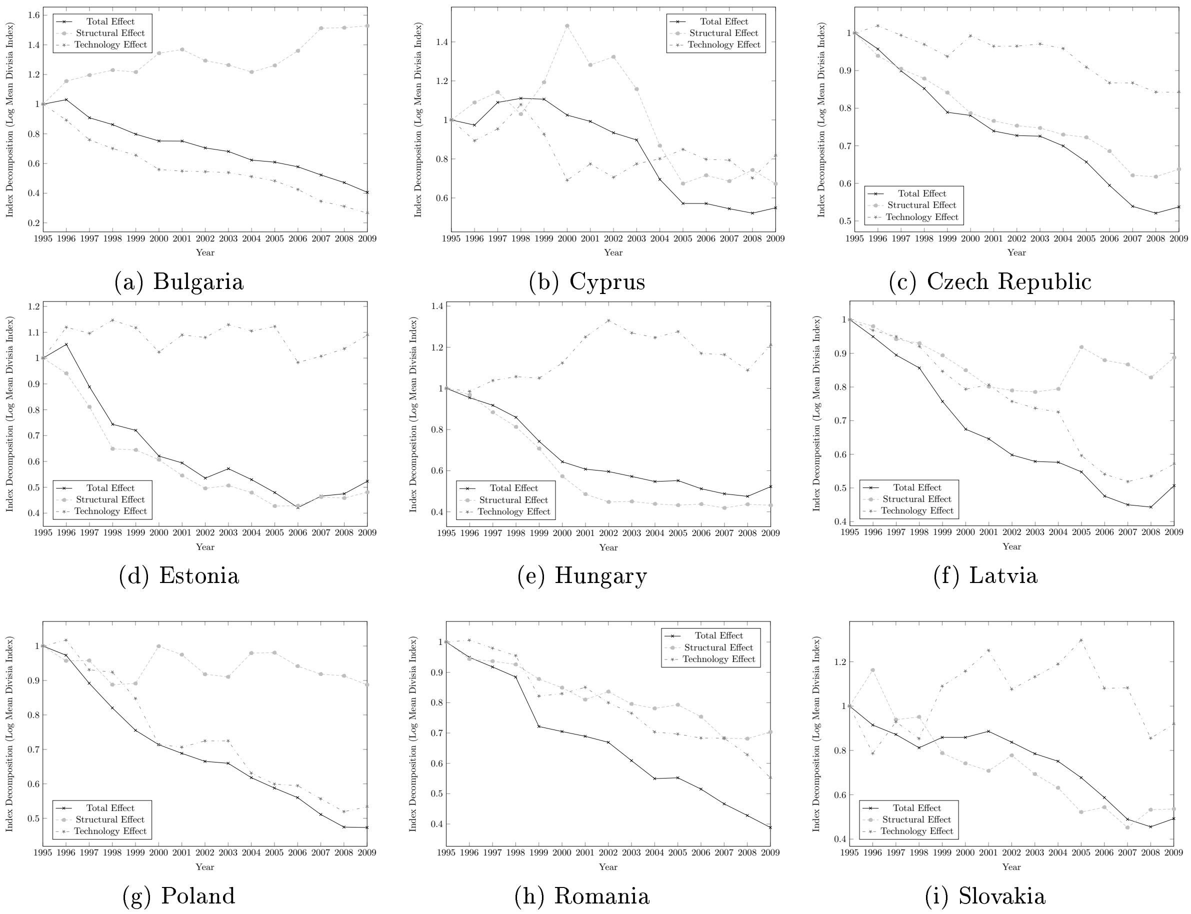
Figure 3 presents the annual growth rates of gross output and energy use (both in %) between 1995 and 2009. The dotted lines represent the EU27 average for both time series. Remarkably, Eastern European countries performed best (located in the lower right corner, implying above-average rises in gross output and below-average rises in energy use), while some of Europe most mature countries performed worst (located in the upper left corner, implying above-average rises in energy use and below-average rises in gross output).

After performing index decomposition analysis for all countries, we used Figure 3 to identify four country groups. Our summary of the results will be brief – most graphs tell their own tale – but we will take a moment to address some country-specific peculiarities and refer the reader to the work of authors who delved into more detail. Our regional classification is as follows:

- Best Countries: Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Poland, Romania, Slovakia
- Medium I (Below Ø Output Growth, below Ø Energy Use Growth): France, Germany, Italy, Netherlands, Sweden, United Kingdom
- Medium II (Above Ø Output Growth, above Ø Energy Use Growth): Ireland, Lithuania, Luxembourg
- Worst Countries: Austria, Belgium, Denmark, Finland, Greece, Malta, Portugal, Slovenia, Spain

Best Countries

The 'best performing' block consists of Bulgaria, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Poland, Romania and Slovakia. All countries are characterized by an above-average rise in gross output and a below-average rise in energy use between 1995 and 2009. Astonishingly, all countries save Cyprus are Eastern European. What is interesting about these countries is that they experienced the largest structural change in our sample. Cornillie and Fankhauser (2004) identified a decoupling of energy use and economic activity in the Baltic States (Estonia, Latvia and Lithuania) between 1992 and 1998. We can confirm this trend for Latvia and Estonia, though not for Lithuania, which is part of the Medium II country group (above-average rises in gross output, above-average rises in Energy Use). But while Latvia's improved energy intensity owed itself to better technology, the improvement in Estonia was driven by less energy-intensive production. Our results are in line with Balezentisa et al. (2011), who offer a detailed discussion of the policy measures that affected the development in Lithuania, notably the investments in building modernization. Another example of improvement is Poland. As Gurgul and Lach (2012) note, in the past decade Poland's economic growth has been tied to changes in electricity utilization and to new, more energy-efficient technologies in the face of international environmental policy requirements. Romania and Bulgaria also experienced dramatically improved energy efficiency. As Popovici (2011) observed, "[t]he Romanian economy was in 1990 one of the most energy-intensive in the region – only Bulgaria's economy was more energy-intensive – due to the obsolete technologies [. . .] that were energy-intensive and had to import an increasing part of their raw materials. Due to the closure, technology upgrading and restructuring in the heavy industries, Romania is nowadays much less energy intensive" (Popovici, 2011, p. 1845).



(a) Bulgaria (b) Cyprus (c) Czech Republic

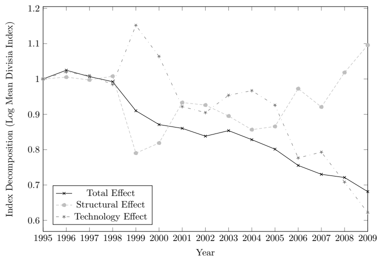
(d) Estonia (e) Hungary (f) Latvia

(g) Poland (h) Romania (i) Slovakia

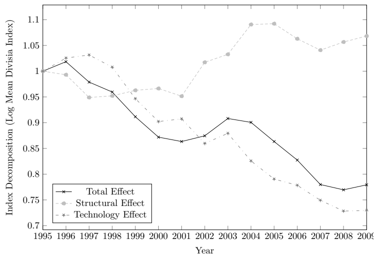
Figure 4: IDA for the best performing countries

Medium I

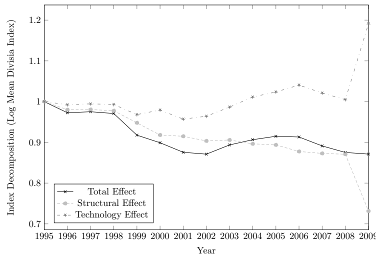
The second country group is characterized by above-average growth in gross output and an above-average growth in energy use. It consists of France, Germany, Italy, Netherlands, Sweden and the United Kingdom, all mature European economies. France and the Netherlands show a continuous decline in overall energy intensity, but while the economy in France shifted towards a more energy-intensive production, the economic composition in the Netherlands remained almost unaltered. The German economy moved towards more energy-intensive production, resulting in a 25.5% increase in the structural change index. Yet this effect is dominated by industrial improvement, as the nearly 40% decline in the technology index shows.



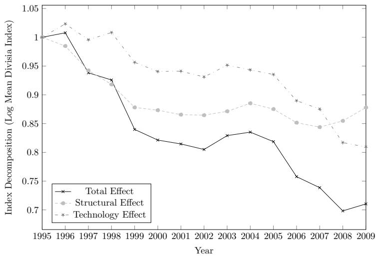
(a) France



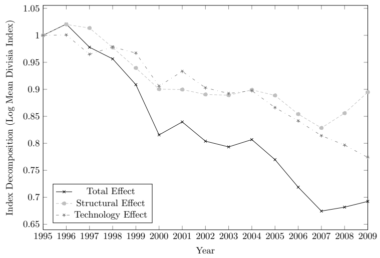
(b) Germany



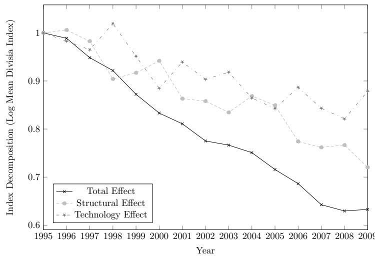
(c) Italy



(d) Netherlands



(e) Sweden

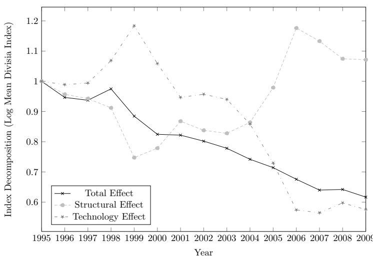


(f) United Kingdom

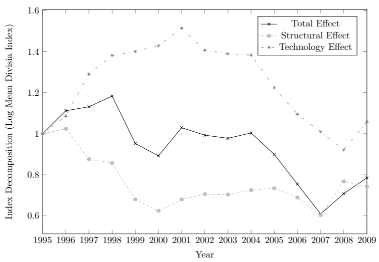
Figure 5: IDA for the Medium I Block

Medium II

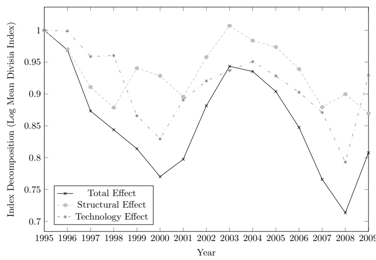
The third country group is characterized by a below-average growth in gross output and a below-average growth in energy use. It consists of Ireland, Lithuania and Luxembourg – all small countries. Lithuania is the only Eastern European country besides Slovenia that is not located in the best performing country group.



(a) Ireland



(b) Lithuania



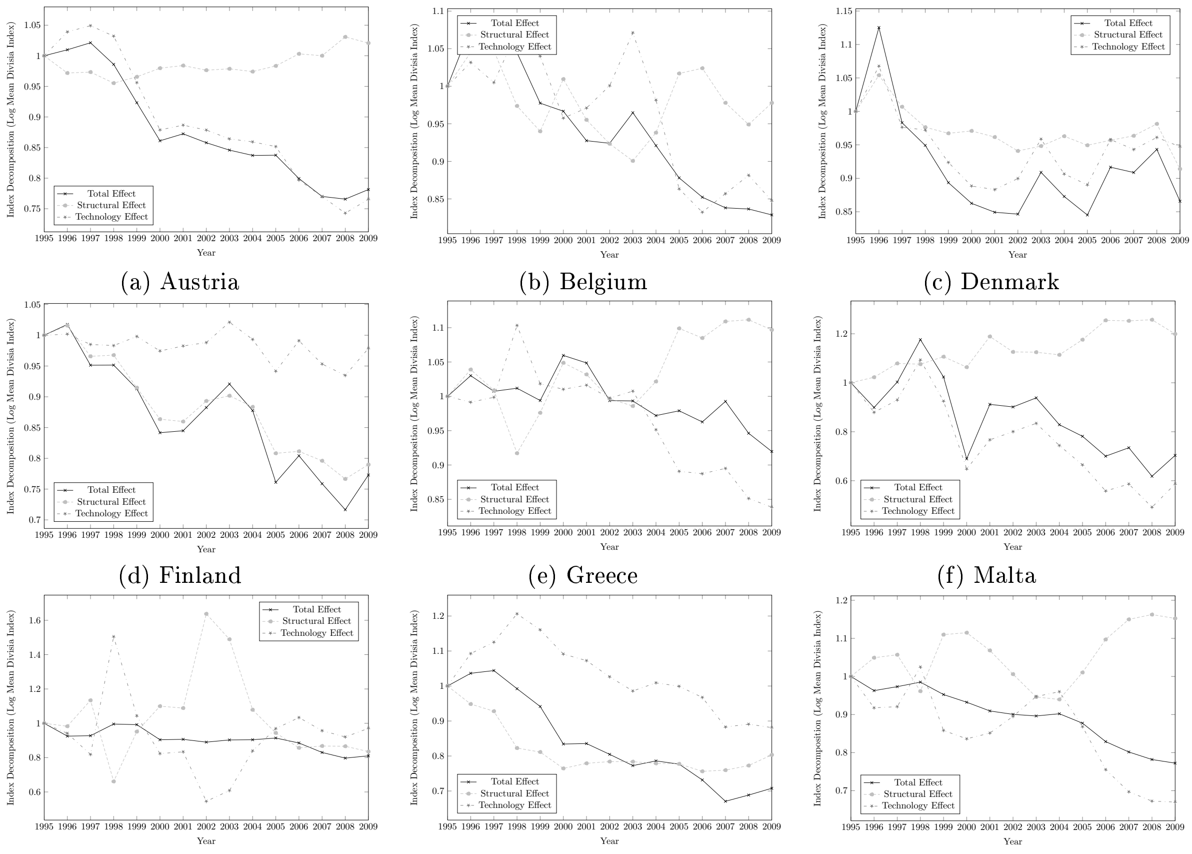
(c) Luxembourg

Figure 6: IDA for the Medium II Block

Worst Countries

Our final group consists of countries that performed below the European average in both categories: Austria, Belgium, Denmark, Finland, Greece, Malta, Portugal, Slovenia and Spain. Mendiluce et al. (2010) compared the evolution of energy intensity in Spain with 15 other European countries (including Portugal and Greece). Our analysis confirmed their finding that

Spain's energy intensity reached its highest level in 2004. Thereafter it declined, mainly due to the sharp decrease in the technology effect. We also confirmed the findings of Mendiluce et al. (2010) for other southern European countries: energy intensity remained almost unaltered – with the exception of Cyprus, which is located in our 'best performing' country group.



(a) Austria (b) Belgium (c) Denmark

(d) Finland (e) Greece (f) Malta

(g) Portugal (h) Slovenia (i) Spain

Figure 7: IDA for the "worst performing" Block

D. Summary

The first part of our study can be summarized as follows. First we employed the WIOD to depict the development of aggregate European energy intensity between 1995 and 2009. For this, we constructed an "artificial" EU27 aggregate. We then introduced sectoral details and performed an index decomposition analysis to quantify the contribution of structural change and technological improvements to the 27.4 % decline in European energy intensity. Finally, we disaggregated the "artificial" EU27 into countries and applied the index decomposition to 27 individual economies.

IV. Empirical Investigation

The second part of our paper takes a more descriptive approach. To analyze possible explanatory factors, we pursue the following empirical strategy. First we use the values obtained for the three indices and create a panel data set for 26 countries – Luxembourg is an outlier and has been excluded – and 12 years (1995 – 2006). We then apply our dataset to the work of Metcalf (2008), replicating his results and extending his model to cover other relevant factors. Our final exercise is a counterfactual experiment. We use the observed energy intensity levels in 1995 for each country and multiply them with the obtained index values for the total, the structural effect and the intensity effect. This brings out the level differences between energy intensities for three cases: the actual change (obtained by multiplying the energy intensity in 1995 by the total effect of the index value); the change when technology remains constant; the energy intensities that result when only the structure changes.

A. Model and Variables

We estimate three similar panel models j by index type for the dependent variables ($j \in (D_{Tot}, D_{Str}, D_{Int})$). Our indices control for influential factors – measuring the real decline in energy intensity, the fraction caused by structural change and the contribution of technology. Our estimation model is expressed by the following equation[12]:

$$\begin{aligned} \text{Index}_{jit} &= = \beta_0 + \beta\mathbf{X}_{it} + \delta\mathbf{Z}_{it} + \varepsilon_{it} \qquad \text{(IV.6)} \\ & \quad \text{with } j \in (D_{Tot}, D_{Str}, D_{Int}) \\ & \quad \beta\mathbf{X}_{it} \text{ as major covariates,} \\ & \quad \delta\mathbf{Z}_{it} \text{ as additional controls, and} \\ & \quad \varepsilon_{it} \text{ as an idiosyncratic error term.} \end{aligned}$$

We estimate the following equations:

$$\begin{aligned} \text{Index}_{jit} = \; & \beta_0 + \beta_1\text{INCOME}_{it} + \beta_2\text{INCOMESQR}_{it} + \beta_3\text{OPEN}_{it} + \qquad \text{(IV.7)} \\ & + \beta_4\text{K/L}_{it} + \beta_5\text{K/LSQR}_{it} + \beta_6\text{MANUFACSHARE}_{it} + \\ & + \beta_7\text{TFP}_{it} + \beta_8\text{ENERGYPRICE}_{it} + \beta_9\text{REGUL}_{it} + \\ & + \delta_1\text{VINTAGING}_{it} + \delta_2\text{AREA}_{it} + \delta_3\text{POPGROWTH}_{it} + \\ & + \delta_4\text{LATITUDE} + \delta_5\text{HDD}_{it} + \delta_6\text{COMMUNIST}_{it} + \\ & + \delta_7\text{RENEWABLESHARE}_{it} + \delta_8\text{TREND}_{it} + \delta_9\text{TRENDSQR}_{it} + \\ & + \varepsilon_{it} \\ & \text{with } j \in (D_{Tot}, D_{Str}, D_{Int}) \end{aligned}$$

The variables are:

[12] The model in Metcalf (2008) is a subset of our model. The only variable that we could not control for are cooling degree days.

- INCOME = Instrumented Income per Capita (logarithmic)
- INCOMESQR = Income per Capita squared (logarithmic)
- OPEN = Instrumented Trade Openness (logarithmic)
- K/L = Capital to Labor Ratio (logarithmic)
- K/LSQR = Capital to Labor Ratio squared (logartihmic)
- MANUFACSHARE = Share of Manufacturing (logarithmic)
- TFP = Estimated Total Factor Productivity (logarithmic and in differences)
- ENERGYPRICE = Price of Energy (logarithmic)
- REGUL = Index of Energy Efficiency Regulation
- VINTAGING = Capital Vintaging (logarithmic)
- AREA = Area of Country (logarithmic)
- POPGROWTH = Population Growth Rate
- LATITUDE = Latitude of the Country
- HDD = Heating Degree Days (logarithmic)
- COMMUNIST = Dummy = 1 for former communist countries
- RENEWABLESHARE = Share of “green” energy in total energy use (logarithmic)
- TREND = Control variable for time trend
- TRENDSQR = Control variable for time trend squared

Before presenting our results, we discuss and justify the variables. Our model consists of 15 variables (and a control for a time trend) attributable to various effects.

Income

The variables INCOME and INCOMESQR relate to technology and are based on Environmental Kuznets Curve (EKC) literature (see Copeland and Taylor (2004) for an excellent theoretical foundation and discussion). The EKC states that there is an inverted U-shaped relationship between income and pollution: a rising income is accompanied by higher levels of pollution up to a point, and then the relationship inverts and pollution begins to decline. The reasons for this trajectory are to be found on the supply side of the economy. Higher levels of income enable better and more efficient technologies on the supply side , as higher levels of income induce a shift in preferences for environmental protection. To avoid potential endogeneity issues, we rely on instrumental variables for income borrowed from the growth literature (Frankel and Rose, 2005).

The estimation equation for the instrument of income is based on Frankel and Rose (2005) and Managi et al. (2009); the estimation results can be found in appendix E:

$$\ln\left(\frac{Real\_GDP}{Pop}\right)_{it} = \alpha_0 + \alpha_1 \ln\left(\frac{Real\_GDP}{Pop}\right)_{it-1} + \alpha_2 \ln\left(\frac{Real\_I}{GDP}\right)_{it} + \alpha_3 \ln(n+g+\delta)_{it} + \alpha_4 \ln LABHS_{it} + \alpha_4 \ln K_{it}^{H_c} + \alpha_4 \ln\left(\frac{K}{L}\right) + \alpha_4 \ln RealOpenness_{it} + \varepsilon_{it} \tag{IV.8}$$

Equation IV.8 includes all influences causing income to grow from the level in $t-1$ to the level in t we want to condition (a standard from the economic growth literature). One such influence is the factor accumulation described by the Solow Model. Our approach models human capital in two ways. First we follow Hall and Jones (1999) and Alcalá and Ciccone (2004) and construct average human capital stocks $K_{it}^{H_c}$. Hall and Jones (1999) and Alcalá and Ciccone (2004) use old estimates of return to education and old data on average years of education. We rely on updated measures of return to education provided by Psacharopoulos and Patrinos (2004) and on the newest version of the Barro and Lee educational attainment data (Barro and Lee, 2010). Following Barro and Lee (2010), we interpolate the values between 5-year intervals. The average human capital stock $K_{it}^{H_c}$ in country i is defined as: $K_{it}^{H_c} = \exp(\phi(S_c))$, where S_c is average schooling and $\phi(\cdot)$ a piecewise linear function capturing estimated social Mincerian returns. (We rely on measures for Mincerian returns provided by Psacharopoulos and Patrinos (2004). The yearly rates of return to education cover 16 countries; the data for remaining 11 were obtained by reasoning). One problem that may arise from human capital measures is that high-skilled labor involves investment into human capital and new technologies. But the process of generating new technologies and innovations is inherently uncertain. To cope with this problem, we use the share of high-skilled worker compensation in total worker compensation ($LABHS$) provided in the WIOD socioeconomic accounts.

Obviously, investment expresses the change of capital stock over time from period t to $t+1$. Since the identity of savings and investment must be taken into account, we measure (net) investments (the change of capital stock over time) as the fraction of real GDP saved. (This data is provided by Penn World Tables 7.0.) Below we define all real investments as I/GDP. The growth of per capita income depends not only on investment in physical capital but also on its depreciation (δ) and the rate of labor productivity growth (g). As usual, we assume these values are 0.05. Another factor that negatively affects capital accumulation is the rate of population growth (n). We calculate n using the Penn World Tables 7.0. Together $(n+g+\delta)$ are expected to have a negative impact on income per capita. Following Managi et al. (2009) we also control for the (logarithmic) capital-to-labor ratio $\frac{K}{L}$ and (logarithmic) real openness $RealOpenness$.

We expect that the coefficient for INCOME will be positive and the coefficient for INCOMESQR will be negative in the case of D_{Tot} and D_{Int}. This implies higher index values for higher incomes until the peak of the EKC is reached and then a lower index value for higher rates of income.

Trade

The next variable is OPEN, defined as the sum of export and imports divided by real gross output in 1995 in US-$:

$$Openess_{ijt} = \frac{X_{ijt} + M_{ijt}}{GO_{it}REAL_{i,1995}}; \qquad i \neq j \tag{IV.9}$$

The gravity equation for the geography-based bilateral trade share of two countries i and j is borrowed from the work of Frankel and Romer (1999) and Frankel and Rose (2005):

$$\begin{aligned} \ln Openess_{ijt} \quad = \quad & \gamma_0 + \gamma_1 \ln Distance_{ijt} + \gamma_2 \ln Pop_{it} + \gamma_3 \ln Pop_{jt} \\ & + \gamma_4 \ln Area_{it} + \gamma_5 \ln Area_{jt} + \gamma_6 (LL_{it} + LL_{jt}) + \gamma_7 CB_{ijt} \\ & + \gamma_8 CB_{ijt} \ln Distance_{ijt} + \gamma_9 CB_{ijt} \ln Pop_{it} + \gamma_{10} CB_{ijt} \ln Pop_{jt} \\ & + \gamma_{11} CB_{ijt} \ln Area_{it} + \gamma_{12} CB_{ijt} \ln Area_{jt} + \gamma_{13} CB_{ijt}(LL_{it} + LL_{jt}) + \varepsilon_{ijt} \end{aligned} \tag{IV.10}$$

The regressor D_{ijt} represents the geographic distance between the capitals of the two trade partners i and j. Pop_{it} and Pop_{jt} are measures of population in countries i and j, respectively. (Here, in contrast to Frankel and Romer (1999), the measures do not cover the economically active population on account of missing 2009 data for some countries in the Penn World Tables.) ($Area_{it}$ and $Area_{jt}$) are controls for the size of two countries; LL_{it} and LL_{jt} are dummies measuring whether the countries are land locked. ($LL_{it}+LL_{jt}$ is the common landlocked dummy, which summarizes dummies representing landlocked status. The variable CB_{ijt} is a dummy that assumes the value of 1 when trade partners share a common border. The common border dummy is interconnected with other explanatory variables to capture trade between neighboring countries more accurately. The equation is estimated by means of least squares, using the bilateral trade data for all countries included in the WIOD. The geographical information was obtained from the CIA World Fact Book and from the CEEPI Gravity Data Set. After estimating the (first stage) regression to construct the instrument for trade openness, we aggregate the fitted values across all bilateral trade partners. The aggregation yields a given country's trade openness adjusted according to output-based PPPs. The aggregation method is presented in equation D16:

$$\hat{Openess}_{it} \quad = \quad \sum_{i \neq j} e^{\hat{\boldsymbol{\gamma}}' \boldsymbol{X}_{ijt}} \tag{IV.11}$$

The vector $\boldsymbol{\gamma}$ represents the coefficients in equation IV.10 whereas the vector $\boldsymbol{X}_{ijt}$ stands for the right-hand side variables in equation D15. From the first regression on, fitted values were used to predict trade openness. The results of the main regression are shown in Table 8 We had to run the regression for each year to get meaningful data because each geography variable is remains the same over time. Consequently, treating trade flows as a single observation would yield almost constant trade openness observations. The only way to solve the problem is to run the regression individually for each year. This procedure produces the correct predicted trade openness values with time variation – values we later need for our instruments.[13]

[13]Sascha Rexhäuser offers valuable insight about the procedure.

As Antweiler et al. (2001) demonstrate in their seminal paper, trade can have a significant and positive impact on the environment through its effects on income and economic composition. And when it does, we can expect that trade will also have a significant indirect effect on the economy's energy intensity. Accordingly, we expect the OPEN coefficient to be negative for all three indicators.

Capital-to-Labor Ratio and Manufacturing Share

The capital to labor ratio K/L is also relevant for the structure of the economy under investigation. We adopt the assumption of Antweiler et al. (2001) that greater capital intensity correlates with greater pollution and energy use (see also Cole and Elliott (2003) and Cole (2006) for further evidence). The WIOD has sectoral estimates for physical capital stocks for all countries and periods. These estimates allow us to test the hypothesis that an increasing capital-to-labor ratio (an indirect measure of structural change) results in increasing energy intensity. The correlation between total energy use and capital intensity (measured in physical capital stock per working hour) is 0.44 and statistically significant on the 1 % level for our 27-country sample. We expect a negative coefficient for the K/L variable for D_{Str}. Another important control variable as an indicator for structural change is the share of the secondary (manufacturing) block in an economy. We subtract the gross out of agriculture, mining and services from total gross output and use this as the share of manufacturing industries (MANUFACSHARE).

Total Factor Productivity

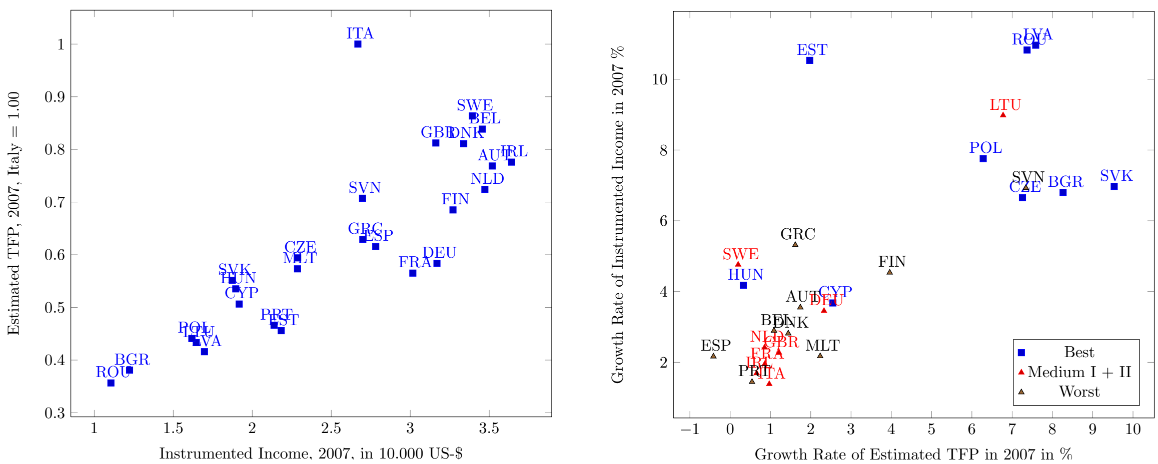
The next variable is the estimated *total factor productivity* (TFP). Syverson (2011) reports in his survey that even within U.S. four-digit SIC industries, the (average) difference in logarithmic multifactor productivity between an industry's 90^{th} and 10^{th} percentile plants is .651, resulting in a TFP ratio of $e^{.651} = 1.92$. That means, that even within a single four-digit SIC industry in a single country the 90^{th} percentile of the productivity distribution produces almost twice as much output with the same inputs as the 10^{th} percentile plant. **?** investigate direct measures of technology adoption for more than 75 different technologies and demonstrate that the cross-country differences in technology are roughly four times larger than cross-country differences in income per capita and that technology is positively correlated to income per capita. Thus, cross-country variation in TFP is almost solely determined by cross-country variation in physical technology. As the European Union is a much more heterogeneous economic environment than the United States, we argue that differences in total factor productivity growth are (a) substantial by themselves and (b) have a substantial impact on energy utilization. We rely on a standard measure for gross-output-based TFP as presented in Hsieh and Klenow (2010).[14] Level accounting can be interpreted as the cousin of the traditional growth accounting introduced by **?**. Comparison studies of labor productivity often define the United States as the technology leader and then measure the distance between other countries and this reference value. Because we are interested in changes in energy use technology, we use the country with the second-lowest aggregate energy intensity in 1995 as the reference country. (Austria and Luxembourg had very similar here. We made an arbitrary decision for Austria .) To estimate the total factor productivity we use the gross-output and capital-to-output ratios from the WIOD. We assume a share of capital

[14] Citing Hsieh and Klenow (2010) neglects many other important contributions dealing with multifactor productivity. For more here, see the surveys by Caselli (2005) and Syverson (2011).

of 0.3. To control for human capital, we combine these data with the updated Barro and Lee dataset on educational attainment and information on Mincerian returns to education provided by Psacharopoulos and Patrinos (2004).[15]. Our estimation equation for TFP builds on Hall and Jones (1999); Alcalá and Ciccone (2004) and Hsieh and Klenow (2010) and takes the form:

$$\mathrm{TFP}_{it} = \frac{\mathrm{rgdpwok}}{(\frac{\mathrm{K}}{\mathrm{GO}} \cdot \mathrm{rgdpwok})^{\alpha} \cdot \exp(\Theta \cdot \mathrm{SchoolingYears}))^{1-\alpha}} \tag{IV.12}$$

We combine multiple data sources to obtain our TFP estimate. We start with real gdp per worker from the Penn World Tables 7.0. K over GO describes the relationship of physical capital stock to gross output as recorded in the WIOD. α refers to the share of capital compensation and is taken to be 0.3, which is in line with common assumptions. Θ stands for Mincerian returns to education, again taken from Psacharopoulos and Patrinos (2004). We combine this information with our interpolated version of the Barro and Lee dataset, thus correcting the TFP measure for human capital formation. To see how our measure for total factor performs, we calculated the growth rates of TFP and instrumented income per capita and plotted them. The result is presented in Figures 8a and 8b:



(a) TFP vs. Income (b) TFP-Growth vs. Income-Growth

Figure 8: TFP vs. Instrumented Income and TFP-Growth vs. Income-Growth

We include the TFP variable expressed in logs . We expect that the coefficient will be negative in the case of D_{Tot} and D_{Int}, implying a lower index value for higher rates of total factor productivity. The effect on the economic structure is unknown ex ante.

Regulation and Prices

The next variables are prices (ENERGYPRICE) and regulatory measures (REGUL). We used the annual average energy prices as a measure for price induced changes to technology or economic structure. The data source is Eurostat.[16] We also collected data on environmental

[15]Psacharopoulos and Patrinos (2004) provides detailed information on Mincerian returns for 16 of our 27 countries. For the remaining 11 countries, we use values from countries with similar economic and political structures. For example, we apply the 6.4 % p.a. given for Belgium to the Netherlands.

[16]Of the 405 data points (spanning 27 countries and 15 years), 76 were missing, mostly from 1998. To create proxies for the absent data, we interpolated the values from 1997 and 1999.

regulation in the European Union for the time period under consideration. To account for various climate and environmental policies, we made use of the Policies and Measures Databases provided by the International Energy Agency (IEA, 2012). They consist of three different databases: Global Renewable Energy, Energy Efficiency, and Policy Measures Addressing Climate Change. Altogether, these databases contain data on more than 3,600 policies and on all types of policy measures going back to 1973 for some 50 countries. The information inherent in the databases encompasses indicators such as targeted sector (e.g. electricity, appliances, buildings, industry), technology (with particular emphasis on renewable technologies), jurisdiction (whether the policy is implemented on a subnational, national or international level) and policy type (e.g. R & D investments, standards, taxes, permits).

But before we could enlist this information in our research, we needed to prepare the data. First, we merged the databases, creating a common ground for the regulatory stringency index. Second, we broke down policies containing multiple indicators (e.g. solar PV/wind/bioenergy and R & D investments/standards) or policies assigned to multiple sectors into single policy measures. Sometimes this meant dropping observations when our manual search found no specific information or indicator for a database entry. We also dropped observations to avoid double counting, as some policies are reported in more than one of the original databases. This left us with approximately 3,200 policy measures for the analysis. Third, for the policy types and targeted technologies within the energy sector we constructed multi-level structures in which we assigned the types and technologies appearing in the original database to higher-level instances.[17]

We apply a weighting scheme for policy to construct our regulatory index. The various energy policies can be subdivided into three different groups, each characterizing a different level of stringency. First, there are technology-oriented measures such as voluntary approaches and the subsidization of R & D. These are the least stringent measures in the construction of our regulation index. The second group consists of command-and-control based policies such as standards and quotas. And finally, there are market-based instruments, which we classify as most stringent. Though we conducted sensitivity analysis with various weighting schemes, the results changed neither qualitatively nor quantitatively. Our index was constructed by the following formula:

$$\begin{aligned} REGUL_{i,t} \;=\; & \omega \sum TECH_{i,t} + \theta \sum COMMAND_{i,t} + \sum \phi MARKET_{i,t} \qquad \text{(IV.13)} \\ & \text{with } i \in 1, \ldots, 27, \\ & t \in 1995, \ldots, 2006, \\ & \omega,\ \theta \text{ and } \phi \text{ as weights} \\ & \text{and } TECHN,\ COMMAND \text{ and } MARKET \text{ as policy types.} \end{aligned}$$

For our main estimations we used 0.5 for ω, 0.8 for θ and 1.0 for ϕ.[18] Figure **??** illustrates the development of our reference energy efficiency regulation index for four countries: Germany,

[17] Again, we want to than Enrica De Cian, Elena Verdolini and Sebastian Voigt for providing us with their data.

[18] As mentioned, we used vastly different weighting schemes, ranging from equal weights to situations in which only command-and-control policies mattered (i.e. where ω and ϕ were 0). This approach did not affect the results, however.

Sweden, Poland and Slovenia. Two observations are remarkable. First, the index value is for all "mature" European countries whose energy efficiency is higher than that of Eastern European countries. And second, an energy efficiency trend can be found for Western countries but not for Eastern. These two observations hold true for the entire sample and will be important for the interpretation of the estimation results later in the paper.

Further Controls

We also included several other control variables in our regression model.[19] VINTAGING captures the national differences in capital stock vintaging (Source: WIOD). VINTAGING is included in the model as the ratio of investment to capital stock. The effect may be positive since fast growing countries may have newer capital stock, which uses less energy and is hence more efficient. AREA is the geographical area of a country in km^2 taken from the CIA World Fact Book. It captures the effects of potential economies of scale (Sala-i-Martin, 1997a,b). Larger countries may need larger, but also fewer, power plants. As a result, investment costs in new vintages occur less often and the countries profit. On the other hand, these countries may need larger power grids, which have lower efficiency. POPGROWTH is the population growth rate (see PWT 7.0). It captures the effect of a growing population on energy intensity, as "fast growing states may be adding infrastructure that is more energy efficient than slow growing states" (Metcalf, 2008, p. 9). Furthermore, as Kormendi and Meguire (1985) pointed out, a fast growing population may hamper economic growth and therefore lower income per capita and alter environmental preferences. The variable LATITUDE is the geographical latitude of a country (see CIA World Fact Book) and might be an important driver of energy intensity to be accounted for. The rationale behind the LATITUDE variable is twofold. First, southern European countries such as Italy and Spain have a larger demand for power plant cooling and air conditioning (in sectors outside the private sector) than central European countries. Conversely, northern European countries such as Finland and Sweden may have a larger demand for heating and electricity for light generation than the rest of Europe. By including the LATITUDE of a country we control for this effect. The second rationale behind the LATITUDE variable is this: the geographical latitude may be a determinant of long-run economic development and growth, as found by Rodrik et al. (2004). Accordingly, it can also affect the environmental preferences expressed by the POPGROWTH variable. In line with Metcalf (2008) we included heating demand days to control for climate factors.

The COMMUNIST variable is a dummy variable that equals 1 when a country was part of the former Soviet block. The reason for this variable is as follows. If the fall of the Iron Curtain brought with it a tremendous structural break, the old capital stock in these countries would be nearly worthless. In this case, the vintage capital structure would be different than that of the "old" European countries. Another consideration is the cheap abatement options and "low-hanging fruits" for energy efficiency in the former Soviet countries. Our COMMUNIST dummy captures these effects. We also introduced a control for the regulation index (REGUL). Because the regulation index measures current activities in energy efficiency policy, it might omit past efforts. Hence, we calculate the share of renewable energy sources in energy efficiency policy using

[19] Note that some of the variables are time-invariant and hence only used in cross-section or random-effects estimations.

information on 26 energy carriers from WIOD. The variable RENEWABLESHARE captures the efforts of past regulatory measures and accounts for "natural" endowments in renewable energy (such as those found in Sweden). Finally, we have included a time trend in our regressions to capture independent influential factors we did not account for.

B. Results and Interpretation

I. Empirical Approach

Our panel data sets afford two principle approaches for econometric modeling that can be applied to any of our models: fixed-effects estimators and random-effects estimators. The key advantage of using the fixed-effects estimator is that it typically includes dummy variables that capture the influence of time-invariant, unobservable factors – topography, other country-specific characteristics – that might be correlated with explanatory variables. The result: consistent estimates. By contrast, the random-effects estimator assumes that a correlation with the regressors is 0. When this assumption is met, the random-effects estimator is a feasible alternative, as it displays more efficiency than the fixed-effects estimator. If this assumption is violated, however, the estimates will be biased. We run both fixed- and random-effects estimators and apply the standard Hausman test to validate which type of estimator is more appropriate (Wooldridge, 2002).

II. Comparison of Our Results to Metcalf (2008)

In a first step we compare our results to the ones in Metcalf (2008). We reported fixed-effects panel estimations using the obtained index values as the dependent variables.

Study	Metcalf (2008)			Our Estimations		
Index	TOT.	STRUC.	TECH.	TOT.	STRUC.	TECH.
ENERGYPRICE (log)	-.110	.004	-.123	-0.068***	-0.112***	0.047
	(0.008)	(0.006)	(0.010)	(0.023)	(0.041)	(0.038)
INCOME (log)	2.276	-1.702	4.700	-0.207	3.485***	-2.348***
	(0.540)	(0.392)	(0.694)	(0.320)	(0.574)	(0.532)
INCOMESQR (log)	-.136	.098	-.273	0.010	-0.570***	0.357***
	(0.029)	(0.021)	(0.037)	(0.053)	(0.095)	(0.088)
HDD (log)	0.088	.021	.075	0.190***	-0.033	0.194***
	(0.013)	(0.009)	(0.017)	(0.044)	(0.080)	(0.074)
KL (log)	2.293	-2.600	4.211	-0.546*	-3.472***	1.763***
	(0.813)	(0.590)	(1.046)	(0.294)	(0.527)	(0.489)
KLSQR (log)	-.105	.113	-.188	0.083**	0.418***	-0.199***
	(0.037)	(0.027)	(0.047)	(0.035)	(0.063)	(0.058)
POPGROWTH	.286	.500	-.155	-0.032**	0.012	-0.036
	(0.138)	(0.100)	(0.177)	(0.015)	(0.026)	(0.024)
VINTAGING (log)	.001	.007	-.006	-0.043	-0.178***	0.116**
	(0.002)	(0.001)	(0.002)	(0.035)	(0.062)	(0.058)
TREND	-.01	-.006	-.003	-0.025***	-0.023***	0.004
	(0.001)	(0.0006)	(0.15)	(0.004)	(0.007)	(0.006)
TRENDSQR	.0001	.00002	.00008	0.000	0.001**	-0.001***
	(0.00002)	(0.00002)	(0.00003)	(0.000)	(0.000)	(0.000)
Observations				360	360	360
R^2 (within)				0.815	0.278	0.397
Root MSE						
F-Statistic				142.56	12.49	21.36

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

Table 1: Our results compared to Metcalf (2008)

Table 1 presents the results for the comparison with the study by Metcalf (2008) on U.S. energy intensity by state between 1970 and 2001. Our coefficient for energy prices indicates that a 10 % increase in energy prices results in a decline of energy intensity of 0.68 %. The effect is even stronger for the index value of the structural effect (-1.1 %). In both models the effect is statistically significant ($p < 0.01$). Surprisingly, the index value for the technology effect is not affected by the energy price. In contrast to Metcalf (2008), income (and its squared term) has no impact on the total effect. This is mainly due to the shorter time-period under investigation. Yet when we hold technology constant, the effect of INCOME and INCOMESQR supports an increasing, but inverted, u-shape relation between income and energy intensity. The calculated turning point – when an increase in INCOME leads to an increase in energy intensity – is $\approx$ 21,200 US-$ (1995). This is exactly the median of the INCOME in our sample. In other words, an increase in income leads to a decrease in energy intensity in half of the sample, provided technology holds constant. Countries with more heating degree days have, ceteris paribus, a higher index value for energy intensity. The magnitude is larger than in Metcalf's study. The most significant differences in our estimates are the coefficients for the capital-to-labor ratios. An increase in the capital-to-labor ratio leads to a decrease in the total effect and in the structural effect. The turning point for the total effect is a capital-to-labor ratio of 26.3, or around the 15 % percentile in the distribution of the sample's capital-to-labor ratios. The corresponding turning point for the structural effect – again, holding technology constant – is 63.8 (around the 30 % percentile). The estimate for POPGROWTH is negative and significant on the 5 %-level for the total effect index. Hence, fast growing countries have lower energy intensities. The capital vintaging effect is only observable in the regressions of the structural index. There, countries with higher investment-to-gross-output ratios tend to have lower energy intensity. The time trend variables are negative and significant in the models that explain the total effect and the structural effect.

III. Results of our Core Model: Index Values as Dependent Variables

In a second step, we use our extended model, which takes other potentially important determinants into account. We use a slightly different measure of the capital-to-labor ratio. First, we calculate the sample mean of the capital-to-labor ratio and then use relative capital-to-labor ratios. We believe that this concept is superior to Metcalf's , for it accounts not only for structural change but also for comparative advantages between countries. We also include the manufacturing share as an indicator of structural change. As technology is one main important driver, we use the total factor productivity measure to account for the heterogeneity with respect to productivity in Europe. Finally, we use our index for energy efficiency regulation. Table 2 summarizes our key findings.

	Fixed Effects Results		
Index	TOTAL	STRUCTURAL	TECHNOLOGY
INCOME (log)	-0.242	1.196***	-0.874**
	(0.227)	(0.410)	(0.398)
INCOMESQR (log)	0.080**	-0.138**	0.142**
	(0.039)	(0.070)	(0.068)
OPEN (log)	0.085**	0.128*	-0.100
	(0.039)	(0.071)	(0.069)
Relative KL (log)	0.206	0.255	-0.108
	(0.201)	(0.363)	(0.353)
Relative KLSQR (log)	-0.053	0.078	-0.076
	(0.071)	(0.128)	(0.125)
MANUFACSHARE (log)	-0.202***	-0.378***	0.366***
	(0.050)	(0.091)	(0.089)
TFP (log)	-0.478***	-0.879***	-0.056
	(0.111)	(0.201)	(0.195)
ENERGYPRICE (log)	-0.018	-0.107**	0.107**
	(0.026)	(0.047)	(0.045)
REGULATION (log)	-0.001	-0.007	0.005
	(0.005)	(0.009)	(0.009)
VINTAGING (log)	0.020	0.124*	-0.001
	(0.036)	(0.065)	(0.063)
POPGROWTH	-0.069***	-0.054*	-0.034
	(0.016)	(0.029)	(0.028)
HDD (log)	0.204***	0.010	0.156**
	(0.045)	(0.081)	(0.079)
RENEWABLESHARE	-0.199	0.174	-0.490
	(0.273)	(0.495)	(0.480)
Time Fixed Effects	Yes	Yes	Yes
Observations	338	338	338
R^2 (within)	0.819	0.345	0.349
F-Statistic	89.507	10.417	10.637
Hausman-Test	30.22***	29.98***	25.23**
* p<0.1, ** p<0.05, *** p<0.01, Std.Err. in Pars			

Table 2: Fixed Effects results: Indexes as Dependent Variables

Once again, the dependent variables cover the indices for total effects, structural effects and technology effects. Our sample consist of 338 observations spanning 26 countries (Luxembourg is again excluded) and the years 1995 to 2007. (We have omitted the years 2008 and 2009.)

The total effect increases with INCOME, but again the relationship follows an inverted u-shape course. The estimated turning point appears at an INCOME of 9.236 US-$, a value in the 10 % percentile. The corresponding turning point of the structural effect is an INCOME of 46,746 US-$. Because the coefficient on INCOME is negative for the technology effect, the decrease in energy intensity happens via the efficiency channel. We conclude that scale effects are dominated by technology effects, as a rising INCOME lowers aggregate energy intensities. This could be due to an increase in environmental regulation (preference shifts) or the usage of more advanced technologies. An increasing OPENNESS variable – i.e. an increasing participation in international trade – lowers, ceteris paribus, the total energy intensity index. Because the coefficient for the structural effect is positive (implying higher values for the structural effect), the decrease in the total effect is once again explained by the efficiency channel. The corresponding coefficient is even higher and statistically significant on the 1 %-level. We expect that this could be due to an outsourcing of energy-intensive industries or imports of improved technology from abroad. The total effect increases as the relative capital to labor increases. The calculated turning point is a relative capital-to-labor ratio of 3.79, a value above the maximum level of

3.59 for the relative capital-to-labor ratio in the sample. (Note that the squared term is not significant). The effect of an increasing capital-to-labor ratio is not significant in the regressions for the other two index values. Hence, we can confirm that capital and energy complement each other in the short run (?). This finding is also supported by the coefficient of VINTAGING. Countries with higher investment rates tend to have higher energy intensity. Most important is the TFP variable, which represents advantages in technology. Countries with higher growth rates in total factor productivity have, ceteris paribus, lower energy intensities. Surprisingly, this occurs via the structural channel. Our control variable for energy efficiency regulation is not significant in any model. To summarize, the variables we declared important for technological change (INCOME, INCOMESQR and TFP) play the most crucial role in driving the decline in energy intensity, though structural change factors (as e.g. OPEN, KL and KLSQR) are also relevant.

IV. Results of our Core Model: Real Values as Dependent Variables

Our final empirical exercise is a counterfactual experiment. We combine the energy intensity in 1995 with the obtained index values for the three effects. By doing this, we take the level differences between energy intensities into account. Hence, our dependent variables are no longer index values, but the three logarithmic energy intensities. Table 3 summarizes the results of running our core model on the three energy intensity levels:

	Fixed Effects Results		
Index	TOTAL	STRUCTURAL	TECHNOLOGY
INCOME (log)	-0.476*	1.185***	-1.718***
	(0.282)	(0.436)	(0.455)
INCOMESQR (log)	0.118**	-0.144*	0.275***
	(0.048)	(0.074)	(0.078)
OPEN (log)	0.096**	0.293***	-0.203**
	(0.049)	(0.075)	(0.078)
Relative KL (log)	0.293	0.262	0.047
	(0.249)	(0.386)	(0.403)
Relative KLSQR (log)	-0.085	0.113	-0.206
	(0.088)	(0.136)	(0.142)
MANUFACSHARE (log)	-0.282***	-0.727***	0.446***
	(0.063)	(0.097)	(0.101)
TFP (log)	-0.661***	-0.908***	0.239
	(0.138)	(0.213)	(0.223)
ENERGYPRICE (log)	-0.041	-0.151***	0.114**
	(0.032)	(0.050)	(0.052)
REGULATION (log)	-0.001	-0.006	0.005
	(0.006)	(0.010)	(0.010)
VINTAGING (log)	0.023	0.107	-0.083
	(0.045)	(0.069)	(0.072)
POPGROWTH	-0.090***	-0.062**	-0.028
	(0.020)	(0.030)	(0.032)
HDD (log)	0.230***	0.031	0.194**
	(0.056)	(0.086)	(0.090)
RENEWABLESHARE	-0.444	0.061	-0.517
	(0.339)	(0.525)	(0.549)
Time Fixed Effects	Yes	Yes	Yes
Observations	338	338	338
R^2 (within)	0.834	0.485	0.421
F-Statistic	99.307	18.662	14.389
* p<0.1, ** p<0.05, *** p<0.01, Std.Err. in Pars			

Table 3: Fixed Effects results: Levels as Dependent Variables

V. Conclusion

The purpose of this study is to explain the forces driving improvements in energy intensity in the European Union between 1995 and 2009, in times with and without climate policy and economic turbulence. It contributes to the large literature on energy decomposition analysis in three ways. First, it is the only analysis of energy intensity at country and sectoral levels for the entire European Union using a perfect decomposition methodology. Second, this study uses econometric methods to identify the drivers of change in efficiency and economic activity indexes. And finally, it demonstrates the scientific usefulness of the new WIOD. We find that technological advances are a main explanatory factor for energy intensity improvement. Although structural change is nearly as important – no surprise after the fall of the Iron Curtain – technological progress is the key driving force. This is an optimistic conclusion, as it means that the development is replicable in less developed regions such as India or China.

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A Countries and Sectors in the WIOD-Database

Countrycode	**Country**	**Countrycode**	**Country**
AUS	Australia	JPN	Japan
AUT	Austria	KOR	Korea
BEL	Belgium	LVA	Latvia
BRA	Brazil	LTU	Lithuania
BGR	Bulgaria	LUX	Luxembourg
CAN	Canada	MLT	Malta
CHN	China	MEX	Mexico
CYP	Cyprus	NLD	Netherlands
CZE	Czech Republic	POL	Poland
DNK	Denmark	PRT	Portugal
EST	Estonia	ROM	Romania
FIN	Finland	RUS	Russia
FRA	France	SVK	Slovakia
GER	Germany	SVN	Slovenia
GRC	Greece	ESP	Spain
HUN	Hungary	SWE	Sweden
IND	India	TWN	Taiwan
IDN	Indonesia	TUR	Turkey
IRL	Ireland	GBR	United Kingdom
ITA	Italy	USA	United States

Table 4: Country coverage of the WIOD database

WIOD industries	**NACE**
AGRICULTURE, HUNTING, FORESTRY AND FISHING	AtB
MINING AND QUARRYING	C
FOOD , BEVERAGES AND TOBACCO	15t16
Textiles and textile	17t18
Leather, leather and footwear	19
WOOD AND OF WOOD AND CORK	20
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	21t22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical products	24
Rubber and plastics	25
OTHER NON-METALLIC MINERAL	26
BASIC METALS AND FABRICATED METAL	27t28
MACHINERY, NEC	29
ELECTRICAL AND OPTICAL EQUIPMENT	30t33
TRANSPORT EQUIPMENT	34t35
"MANUFACTURING NEC; RECYCLING"	36t37
ELECTRICITY, GAS AND WATER SUPPLY	E
CONSTRUCTION	F
"Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel"	50
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
"Retail trade, except of motor vehicles and motorcycles; repair of household goods"	52
HOTELS AND RESTAURANTS	H
Inland transport	60
Water transport	61
Air transport	62
"Supporting and auxiliary transport activities; activities of travel agencies"	63
POST AND TELECOMMUNICATIONS	64
FINANCIAL INTERMEDIATION	J
Real estate activities	70
Renting of m & eq and other business activities	71t74
"PUBLIC ADMIN AND DEFENCE; COMPULSORY SOCIAL SECURITY"	L
EDUCATION	M
HEALTH AND SOCIAL WORK	N
OTHER COMMUNITY, SOCIAL AND PERSONAL SERVICES	O

Table 5: WIOD industries and definition by NACE

B Descriptive Statistics

Variable	Mean	SD	Min	Max
Instrumented Per Capita Income (logarithmic)	2.975	0.455	1.781	3.592
Instrumented Per Capita Income Squared (logarithmic)	9.054	2.554	3.172	12.906
Instrumented Trade Openness (logarithmic)	4.32	0.254	3.708	4.964
Share of Manufacturing Sector in the Economy (logarithmic)	3.766	0.219	3.256	4.459
Capital to Labor Ratio (logarithmic)	4.492	0.914	2.581	5.798
Capital to Labor Ratio Squared (logarithmic)	21.009	7.898	6.662	33.614
Estimated Total Factor Productivity (logarithmic)	-0.603	0.376	-1.523	0.053
Capital Vintaging (logarithmic)	2.008	0.29	0.76	2.686
Energy Price (logarithmic)	-2.832	0.381	-4.006	-1.893
Regulation Index (logarithmic)	0.805	0.988	-0.693	3.239
Area in km2 (logarithmic)	11.354	1.523	5.756	13.212
Population Growth in %	0.207	0.666	-1.433	2.64
Geographical Latitude	48.971	7.541	35	64
Heating Degree Days (logarithmic)	7.854	0.562	5.726	8.699
Fromer Socialist Country	0.385	0.487	0	1
Share of Green Energy	0.119	0.104	0	0.401

Table 6: Descriptive Statistics of used Variables

Year	Mean	Std. Dev.	Min	Max
Total Effect				
1995	1	0	1	1
1996	1	0.06	0.9	1.13
1997	0.96	0.07	0.87	1.13
1998	0.95	0.1	0.74	1.18
1999	0.88	0.1	0.72	1.11
2000	0.83	0.11	0.62	1.06
2001	0.83	0.12	0.59	1.05
2002	0.81	0.12	0.54	0.99
2003	0.81	0.13	0.57	0.99
2004	0.79	0.14	0.53	1
2005	0.75	0.14	0.48	0.98
2006	0.71	0.15	0.42	0.96
2007	0.68	0.15	0.45	0.99
2008	0.66	0.16	0.43	0.95
2009	0.67	0.15	0.39	0.92
Structural Effect				
1995	1	0	1	1
1996	1.01	0.06	0.94	1.16
1997	0.98	0.09	0.81	1.2
1998	0.93	0.11	0.65	1.23
1999	0.91	0.14	0.64	1.22
2000	0.92	0.2	0.57	1.48
2001	0.91	0.2	0.49	1.37
2002	0.92	0.23	0.45	1.63
2003	0.9	0.21	0.45	1.48
2004	0.88	0.18	0.44	1.22
2005	0.88	0.2	0.43	1.26
2006	0.88	0.22	0.43	1.36
2007	0.87	0.25	0.42	1.51
2008	0.88	0.24	0.44	1.52
2009	0.88	0.24	0.43	1.53
Technology Effect				
1995	1	0	1	1
1996	0.99	0.07	0.79	1.12
1997	0.99	0.09	0.76	1.29
1998	1.04	0.15	0.70	1.5
1999	0.99	0.14	0.66	1.4
2000	0.93	0.18	0.56	1.43
2001	0.94	0.19	0.55	1.51
2002	0.92	0.19	0.55	1.41
2003	0.93	0.18	0.54	1.39
2004	0.92	0.18	0.51	1.38
2005	0.89	0.2	0.48	1.3
2006	0.84	0.19	0.43	1.17
2007	0.82	0.19	0.35	1.16
2008	0.78	0.18	0.31	1.09
2009	0.81	0.22	0.27	1.21

Table 7: Summary Statistics for the Country-Specific IDA (1995 = 1.00)

C Sectoral Development of EU27 Energy Intensity between 1995 and 2009

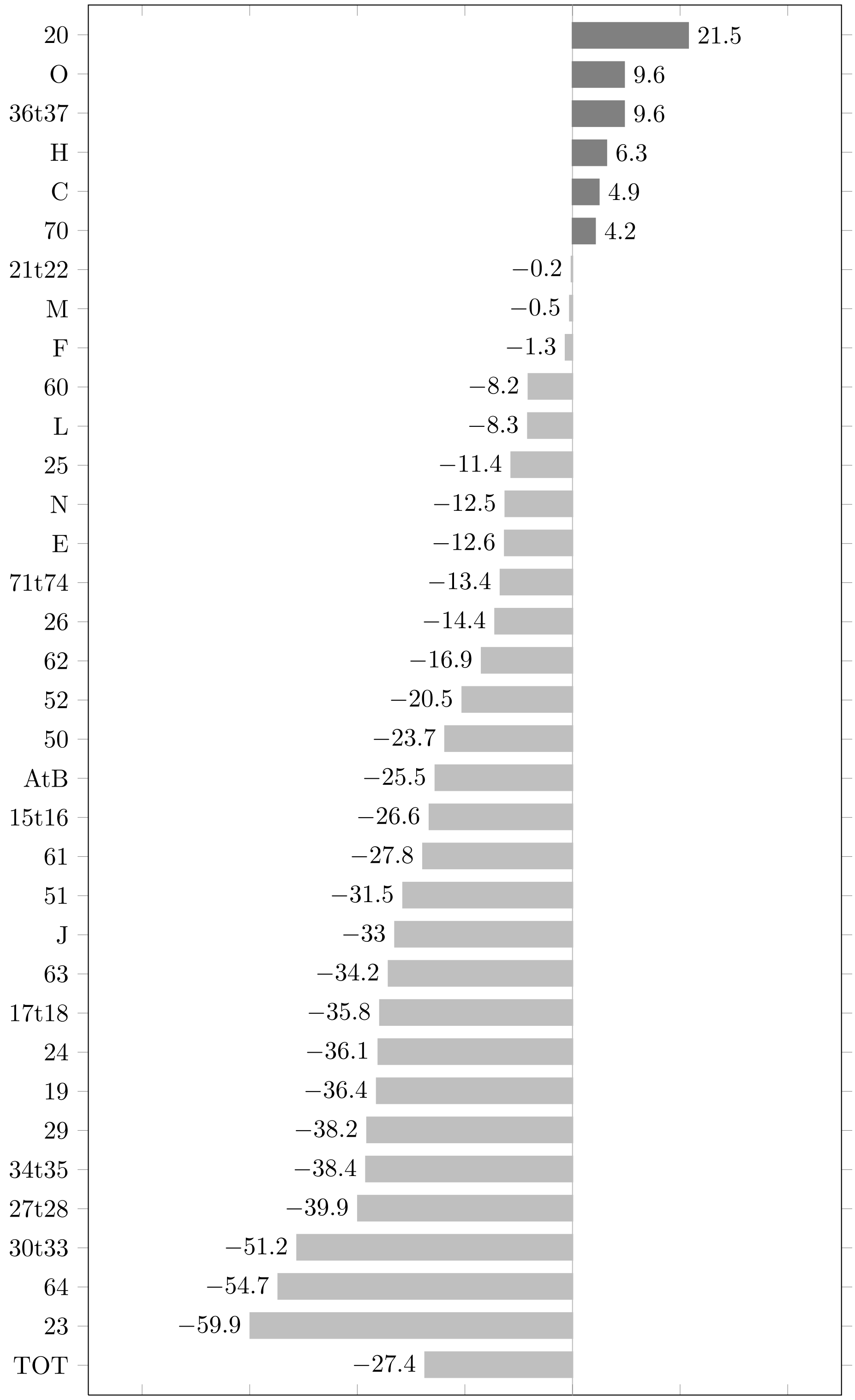

Figure 10: Sectoral Development of the EU27 Energy Intensity

D The Trade Instrument

We define real openness between country i and country j as:

$$Openess_{ijt} = \frac{X_{ijt} + M_{ijt}}{GO_{it} REAL_{i,1995}}; \qquad i \neq j \tag{D14}$$

The gravity equation estimated to obtain the geography-based bilateral trade share of two countries i and j is (**?**):

$$\begin{aligned} \ln Openess_{ijt} \quad = \quad & \gamma_0 + \gamma_1 \ln Distance_{ijt} + \gamma_2 \ln Pop_{it} + \gamma_3 \ln Pop_{jt} \\ & + \gamma_4 \ln Area_{it} + \gamma_5 \ln Area_{jt} + \gamma_6 (LL_{it} + LL_{jt}) + \gamma_7 CB_{ijt} \\ & + \gamma_8 CB_{ijt} \ln Distance_{ijt} + \gamma_9 CB_{ijt} \ln Pop_{it} + \gamma_{10} CB_{ijt} \ln Pop_{jt} \\ & + \gamma_{11} CB_{ijt} \ln Area_{it} + \gamma_{12} CB_{ijt} \ln Area_{jt} + \gamma_{13} CB_{ijt} (LL_{it} + LL_{jt}) + \varepsilon_{ijt} \end{aligned} \tag{D15}$$

Our constructed trade share is then defined as:

$$\hat{Openess_{it}} \quad = \quad \sum_{i \neq j} e^{\hat{\gamma}' \boldsymbol{X}_{ijt}} \tag{D16}$$

The vector $\boldsymbol{\gamma}$ represents the coefficients in equation D15 whereas the vector $\boldsymbol{X}_{ijt}$ stands for the right-hand side variables in equation D15. From the first stage regression, fitted values where used to predict trade openness.

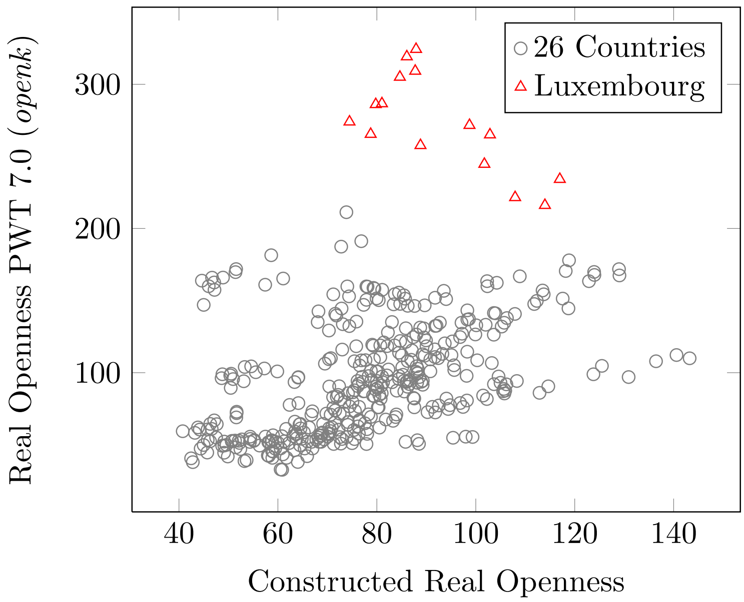

Figure 11: Constructed vs. Actual Trade Share

Dependent Variable:	OLS Estimates	
log Openness	Coefficients	t-Statistic
log_ Distance	-0.943***	-58.10
	(0.016)	
log_ Pop_ i	-0.069***	-5.30
	(0.013)	
log_Area_ i	0.043***	0.04
	(0.011)	
log_ Pop_ j	0.531***	40.25
	(0.013)	
log_Area_ j	-0.003	-0.34
	(0.010)	
CommonLandlocked	-0.158***	-5.69
	(0.028)	
CB	0.573	1.42
	(0.403)	
CB_ Dist	-0.359***	-3.06
	(0.117)	
CB_ Pop_ i	-0.472***	-8.94
	(0.053)	
CB_ Area_ i	0.612***	11.49
	(0.053)	
CB_ Pop_ j	0.194***	4.14
	(0.047)	
CB_ Area_ j	-0.223***	-4.45
	(0.050)	
CB_ LL	0.273***	4.6
	(0.067)	
constant	-2.196***	-16.654
	(0.132)	
Model Summary:		
Observations	22224	
F-Statistic	839.59	
Adj. R^2	0.266	
Root-MSE	1.973	

* p<0.10, ** p<0.05, *** p<0.01, robust standard errors appear in parentheses

Table 8: Estimation Results for Gravity Model

E The Income Instrument

The estimation equation for the instrument of income is:

$$\ln\left(\frac{Real\_GDP}{Pop}\right)_{it} = \alpha_0 + \alpha_1 \ln\left(\frac{Real\_GDP}{Pop}\right)_{it-1} + \alpha_2 \ln\left(\frac{Real\_I}{GDP}\right)_{it} + \alpha_3 \ln(n+g+\delta)_{it} + \alpha_4 \ln LABHS_{it} + \alpha_4 \ln K_{it}^{H_c} + \alpha_4 \ln\left(\frac{K}{L}\right) + \alpha_4 \ln RealOpenness_{it} + \varepsilon_{it} \tag{E17}$$

Dependent Variable: log Real GDP per Capita	Fixed Effects Estimates: Coefficients	t-Statistic
$\ln\left(\frac{Real\_GDP}{Pop}\right)_{it-1}$	0.881*** (0.02)	45.67
$\ln\left(\frac{Real\_I}{GDP}\right)_{it}$	0.140*** (0.02)	7.15
$\ln(n+g+\delta)_{it}$	-0.137*** (0.03)	-4.57
$\ln LABHS_{it}$	0.030* (0.02)	1.96
$\ln K_{it}^{H_c}$	0.186 (0.11)	1.68
$\ln\left(\frac{K}{L}\right)$	-0.018 (0.03)	-0.63
$\ln RealOpenness_{it}$	0.011 (0.03)	0.42
constant	0.323* (0.18)	1.76
Model Summary:		
Observations	375	
F-Statistic	1332.95	
Adj. R^2	0.9797	

* p<0.10, ** p<0.05, *** p<0.01, robust standard errors appear in parentheses

Table 9: Estimation Results for Income Instrument

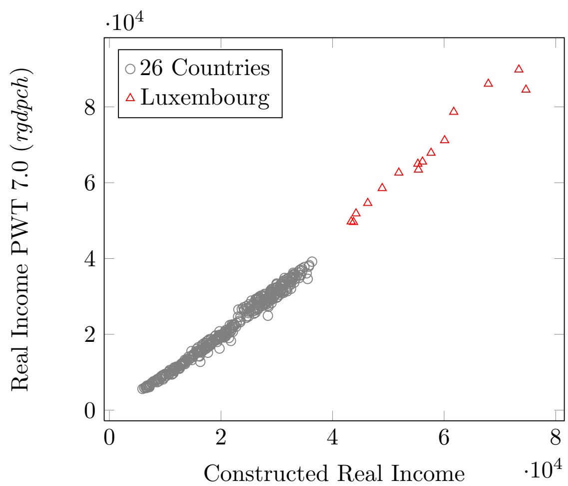

Figure 12: Constructed vs. Actual Real Income per Capita

F Evidence from the Cross-Section

	Cross Section Results		
Index	TOTAL	STRUC.	TECHN.
INCOME (log)	-0.055	-0.806	0.858
	(0.258)	(0.603)	(0.555)
INCOMESQR (log)	0.017	0.129	-0.139
	(0.052)	(0.106)	(0.099)
OPEN (log)	-0.030	0.060	-0.112
	(0.063)	(0.125)	(0.112)
Relative KL (log)	0.060	0.013	0.000
	(0.174)	(0.208)	(0.264)
Relative KLSQR (log)	-0.027	0.001	-0.014
	(0.050)	(0.065)	(0.075)
MANUFACSHARE (log)	-0.102	-0.104	0.081
	(0.079)	(0.094)	(0.119)
TFP (log)	-0.053	-0.001	-0.070
	(0.089)	(0.125)	(0.140)
ENERGYPRICE (log)	-0.006	-0.146**	0.168
	(0.067)	(0.065)	(0.115)
REGULATION (log)	0.002	-0.025*	0.032**
	(0.009)	(0.013)	(0.015)
VINTAGING (log)	-0.013	0.041	-0.071
	(0.055)	(0.072)	(0.090)
AREA in km2 (log)	-0.023*	0.001	-0.035
	(0.012)	(0.023)	(0.024)
POPGROWTH in %	-0.002	-0.027	0.014
	(0.028)	(0.044)	(0.039)
LATITUTDE	-0.010**	-0.011*	-0.000
	(0.004)	(0.006)	(0.007)
HDD (log)	0.146**	0.005	0.174*
	(0.069)	(0.108)	(0.094)
SOCIALIST	-0.145**	-0.265**	0.059
	(0.068)	(0.109)	(0.103)
RENEWABLESHARE	0.178	0.047	0.204
	(0.144)	(0.197)	(0.248)
TREND	-0.030***	-0.012	-0.010
	(0.008)	(0.014)	(0.015)
TRENDSQR	0.000	0.001	-0.001
	(0.001)	(0.001)	(0.001)
CONSTANT	1.137*	2.400**	-0.468
	(0.618)	(1.083)	(1.140)
Observations	338	338	338
R^2	0.689	0.478	0.328
F-Statistic	38.167	14.919	18.449
Root-MSE	0.088	0.135	0.145
* p<0.1, ** p<0.05, *** p<0.01; Clustered Std.Err. in pars			

Table 10: Cross Section Results: Index as Dependent Variables