LUND UNIVERSITY
School of Economics and Management

One slope does not fit all

Investigating Heterogeneity in Cointegration and Panel Methods in the Energy Intensity Literature

by

Sara Svensson

May 2022
Master Thesis II: Economics
Supervisor: Joakim Westerlund
Lund University School of Economics and Management

Abstract

This thesis aims to analyze the methods of existing studies on the relationship between energy intensity and economic variables. I study panel data from 42 countries to examine the cointegration between energy intensity and GDP, capital stock, population, and CO2 emissions as well as estimate their relationship with a pooled common correlated effects (CCEP) estimator. Then I investigate the heterogeneity by testing for cointegration and estimating coefficients for each country separately. The heterogeneity analysis shows that the results for cointegration and regression estimates on a panel data level do not cohere with the test results and coefficient estimates for the countries separately. The results imply that previous studies which have not accounted for the cointegration vector and slope coefficient heterogeneity may not have robust results and could explain why the earlier literature presents such conflicting results.

Contents

1 Introduction

Precisely how economic factors influence energy consumption is still under debate. If economic growth and new investments cannot occur without increasing energy consumption, continued growth could endanger our planet. If, on the other hand, growth and investments reduce energy consumption, the prospects are more optimistic. Either way, the unclarity of previous empirical research provides little or potentially misleading guidance for the political debate surrounding climate change.

In this thesis I study the unclarity of the energy-economy debate by providing an empirical analysis of energy intensity and capital stock, population, carbon dioxide emissions (CO2) and, gross domestic product (GDP) in 42 countries. By dissecting the analysis on a country level, the question I answer is if the differences between countries in the study can lead to misleading empirical results. The dissection provides evidence that economic factors influence various countries' energy consumption in different ways. Not accounting for the country differences or heterogeneity could skew results from the standard empirical methods in the energy-economy literature.

As the literature on energy economics has grown, so has the amount of studies that question their results through meta-analysis. Several authors have meta-analyzed the causality energy-growth literature and found the presence of both publication bias and p-hacking, meaning the literature's results are not only sometimes unclear but also sometimes false (Bruns & Stern 2019, Hajko 2017).

The causality literature is one part of the energy-economy debate, but there is also a whole field of studies that takes the causal direction between energy and economic variables for granted. These studies often use panel methods based on cointegrating relationships between the variables (Pfeiffer, Millar, Hepburn & Beinhocker 2016, Santiago, Fuinhas & Marques 2020, Samargandi 2019). Although several econometric issues can accompany these methods, no one has examined how these issues can influence the results. I provide a closer look at how one of the econometric issues - heterogeneity - can influence the results from these methods.

Based on the above, this thesis seeks to expand the literature on energy intensity using panel methods. Therefore, the study adds to the existing literature in the sense that: (a) it investigates the relationship between energy, growth, and capital in a dataset of 42 countries using the standard approach from the literature; and (b) investigates the heterogeneity to shed light on possible pitfalls of using cointegration in the standard approach. Two research questions are considered:

• When using the standard approach, what is the relation between energy intensity and capital stock, GDP, population, and CO2?

• How heterogeneous are the country estimates and how does this compare to the results from the standard approach?

To empirically investigate the two posed questions, I begin by using the standard methods used in earlier research to examine the presence of cointegration and proceed to use the pooled common correlated effects estimator (CCEP) to study the estimates. Further, I dissect the cointegration tests and regression coefficients on a country level to control for the effects of heterogeneity.

The remainder of the thesis is organized as follows. Section 2 summarizes current debates on the determinants of energy intensity and presents studies questioning the validity of these results. Section 3 describes the data definitions and sources, while section 4 presents the model specification and discusses econometric issues. Section 5 reports the results from the different empirical specifications, synthesizes the empirical findings, and discusses the results. Section 6 contains the conclusions and suggestions for further research.

2 Energy Intensity in the Literature

In this section, the literature on the determinants of energy intensity and its contradictions will be discussed. Additionally, studies on the validity of the energy growth literature are presented.

2.1 Divisions in the Energy Intensity Literature

Energy use stands for over 73 percent of global greenhouse gas emissions (Hannah Ritchie & Rosado 2020). If we reduce energy intensity at the same pace or a faster pace than economic growth, we could sustain economic growth without harming the environment. The interconnection between emissions and energy consumption makes the relationship between energy intensity and economic variables of great importance to the debate of if it is possible to combine economic growth with climate change mitigation.

Increasing energy efficiency could help reduce 40 percent of the emissions that the world needs to abate to align with the Paris Agreement (IEA 2019). Since the concept of energy intensity is used interchangeably with energy efficiency, it is no surprise that many studies are attempting to investigate the determinants of energy intensity. And still, all these attempts have led to few unanimous conclusions.

There is no clear consensus in the empirical literature studying the relationship between energy intensity and growth (Menegaki 2014). On the one hand, empirical studies covering both high, middle, and low-income countries have found a negative relationship between GDP and energy intensity, meaning countries with growth use less energy per unit of GDP (Belke, Dobnik & Dreger 2011, Filipović, Verbič & Radovanović 2015, Jimenez & Mercado 2014, Mahmood & Ahmad 2018). On the other hand, some argue that the empirical relationships depend too much on the country or method to be interpreted as a significant causal relationship (Menegaki 2014, Hajko 2017).

The studies that find relationships between energy and growth are often based on panel data methods derived from a cointegrating relationship. They argue that energy intensity reduction is due to growth economies making necessary investments and implementing policies to improve energy efficiency. On the contrary, others choose a more in-depth country study to argue that the decrease in energy intensity is a long-term trend in technological development and not related to the growth of any individual economy (Gales, Kander, Malanima & Rubio 2007).

Another relationship investigated in the literature is between capital stock and energy intensity. Capital stock and energy consumption are closely linked since capital (buildings, vehicles, machines, tools, infrastructure) requires energy to be built and to function (Martinez et al. 2019, Santiago et al. 2020). Large amounts of the end-use of primary energy (transport, households, and industry) are also part of the capital stock, meaning their degree of energy efficiency is one of the determinants of energy intensity (Martinez et al. 2019). The relation between capital stock and energy can be twofold. Investments in new energy-efficient technologies or infrastructure could reduce energy intensity, while a large capital stock of energy-intensive infrastructure could increase energy intensity.

There are also divisions among the studies of capital stock and energy intensity, even though it is a somewhat newer field. Studies in Latin America and the Caribbean show evidence for both a long-run positive relationship and no long-run relationship between energy intensity and capital stock (Koengkan et al. 2019, Santiago et al. 2020). Santiago et al. (2020) who do find the long-run relationship, explained it by an infrastructure gap, indicating higher GDP has not been accompanied by investments in more energy-efficient capital stock. Lee & Chien (2010) who look at the relationship from a causality perspective, do not find any clear relationship between capital and energy since it differs between countries.

Other variables have also been found to have significant impacts on energy intensity. Energy prices are found to have a significant impact both across and within countries to decrease energy efficiency or intensity (Filipović et al. 2015, Gamtessa & Olani 2018). However, other studies have found prices increase energy intensity which is especially true if they are energy producers and earn more when prices rise (Samargandi 2019, Santiago et al. 2020). Recent literature has also found that energy intensity can depend on the physical preconditions in different countries and how heat and electricity consumption effects energy intensity (Jin 2022). Trade openness is also found to reduce energy intensity (Samargandi 2019).

In Asia, urbanization has been found to reduce energy intensity (Bilgili et al. 2017). Although it is hard to get hold of a proxy for urbanization comparable between different countries, many studies include population growth in some manner, either by including it as a control variable or by dividing other variables by population (Mahmood & Ahmad 2018, Santiago et al. 2020).

C02 emissions have been shown to have a mixed relationship with energy intensity. On the one hand, significant emissions contribute to environmental pressure and create incentives for governments to develop policies to decrease emissions. If the electricity generation in the country is dependent on fossil fuels, decreasing emissions can include investing in more energy-efficient technology (Santiago et al. 2019). On the other hand, this relationship depends mainly on the country's energy mix.

In conclusion, the earlier literature on the determinants of energy intensity has found relationships with many different variables in many different ways. Even though many of the studies include different countries and variables, it is worrying that the results are divided. The heterogeneity of these results is one of the reasons I proceed to control for the heterogeneity between countries using some of the most common variables from earlier literature.

2.2 Questioning the Validity of Energy Economics

Econometric studies of growth data often get criticized for working with sparse annual data and many bidirectional variables. Recently there has been an increasing amount of meta-analyses investigating the replicability of earlier studies and the presence of p-hacking in the energy economics literature. P-hacking is when researchers select estimators, data, and statistics with statistically significant p-values for publication in favor of the estimators which do not show any significance (Bruns & Stern 2019).

Menegaki (2014) constructs a meta-analysis of 51 studies showing that the results of the relationship between energy and growth depend on the method employed for cointegration, the data type, and the inclusion of different variables such as price or capital. The number of countries and which countries were included also seemed to have a large impact on the result.

Bruns & Stern (2019) construct another meta-analysis and find the presence of p-hacking in the energy economics literature. They argue that if they account for the p-hacking, there is no genuine evidence of the relationship between economic growth and energy consumption. More specifically, the authors find evidence that adding control variables to VAR models is used to decrease the degrees of freedom, which can, in turn, increase the possibility of receiving false-positive findings of Granger causality due to overfitted lags, even though there may be no real evidence for causal relationships.

Hajko (2017) analyses over 100 articles from the energy growth literature and finds that the Energy-Economy Nexus has produced several studies with incongruent or even contradictory empirical results. The majority of the literature results are likely subject to significant methodological omissions, biases, and reporting of false positives, with limited energy data coverage likely being the primary cause of the problems.

While the literature on energy intensity is expanding, one should be cautious not to apply the same mistakes in energy growth causality literature. This study will look at the effect of different countries in the data on cointegrating relationships and fixed effects estimators. Except for the meta-analysis by Menegaki (2014), which showed that the number of countries included in the study had a significant effect on the outcome of cointegration, there has been no closer look at how including heterogeneous countries in the same panel data methods within energy intensity can skew results.

In the following sections, I will dissect the cointegrating relation between two variables commonly investigated in relation to energy intensity, growth, and capital stock, testing the validity of using the area's cointegration and panel data methods. The goal is that this can help us proceed further within this important and influential area of research with caution.

3 Data

Using panel data enables the inclusion of a large number of observations which is one of the reasons it is a common setup in the energy literature. I chose the data used in this study by matching countries and years that have data on capital stock and energy intensity for the same years. The merge leaves 1050 observations between 1990-2015, covering 42 countries.

The complete list of the countries included can be found in the appendix. However, it is noteworthy that the countries included are all located in Europe, South Caucasus, or Central Asia due to the data availability. To compare to earlier studies and increase the number of observations, I keep all the years and the countries with available data in the analysis.

3.1 Dependent Variable: Energy Intensity

Energy intensity measures the relationship between energy usage and a country's monetary output and the dependent variable in this study. The energy growth literature uses the measure as a proxy of energy efficiency (Martinez et al. 2019). Energy intensity is calculated by dividing energy consumption by GDP, as illustrated in equation (1).

$$EI = \frac{PrimaryEnergyConsumption}{GDP} \tag{1}$$

The version of energy intensity used here is the energy intensity level of primary energy consumption, which is available for the years 1990-2015 through World Development Indicators (WDI 2021*b*). Primary energy covers consumption of the energy sector itself, losses during transformation and distribution, and the final consumption by end-users. Low energy intensity means the country requires low amounts of energy to transfer into other resources (such as goods or services). In contrast, high energy intensity indicates that a country needs large amounts of energy for one unit of monetary output (Martinez et al. 2019).

In the late 1900s, energy intensity has trended downwards in most countries (Martinez et al. 2019). Figure 1 confirms that this is also the case between 1990 and 2015. The mean of the 42 countries' energy intensity, represented by the red dotted line, has decreased from approximately 12 to 7 megajoule (MJ) per dollar of GDP. The major end-use areas of primary energy-use are transport, households, and industry (Hannah Ritchie & Rosado 2020).

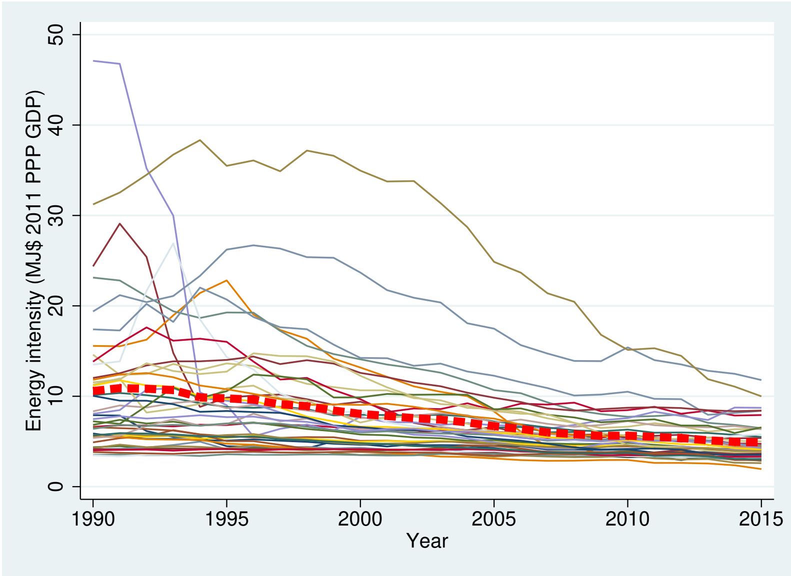

Figure 1: Energy Intensity

Using energy intensity as a proxy for energy efficiency comes with some challenges. Energy intensity can be affected by many different things such as new extraction and conversion technology, more efficient material use, or other nations producing the products another country purchases (Bilgili et al. 2017, Jin 2022, Samargandi 2019). All these factors could lead to an increase in GDP with lower or the same energy usage levels, which will decrease energy intensity without investments in more energy-efficient infrastructure and machinery. It is, however, the most common proxy for energy efficiency used in the literature since energy efficiency is hard to measure and compare between countries (Menegaki 2020).

Table 1: Data Definitions and Sources

Variables	Name	Unit	Source
ln Energy Intensity	EI	Energy intensity level of primary energy (MJ/$ 2011 PPP GDP)	WDI (2021*b*)
ln Capital Stock	CAP	Private and government capital stock in billions of constant international 2011 $.	IMF (2021)
ln Gross Domestic Product	GDP	Gross Domestic Product in 2011$	WDI (2021*c*)
ln Carbon Dioxide Emissions	CO2	CO2 emissions (kt)	WDI (2021*a*)
ln Population	POP	Total Population	WDI (2021*d*)

3.2 Independent Variables

Energy intensity could be influenced by a many different variables. I have limited the independent variables to the ones used by earlier literature and according to data availability. The variables included are presented in Table 1.

Capital stock data is retrieved from the International Monetary Fund (IMF 2021) which measures it through private and public capital stock and GDP through the WDI. The control variables are C02 emissions and population since they have a shown effect on energy intensity and are similar to what other studies use as control variables (Koengkan et al. 2019, Santiago et al. 2019, Lee & Chien 2010). Unfortunately, data availability prevented the collection of more control variables that could also influence energy intensity, such as energy prices, investments in the energy sector, policies, temperatures (high reliance on airconditioning or heating), and transition to a service economy (Jin 2022, Gamtessa & Olani 2018).

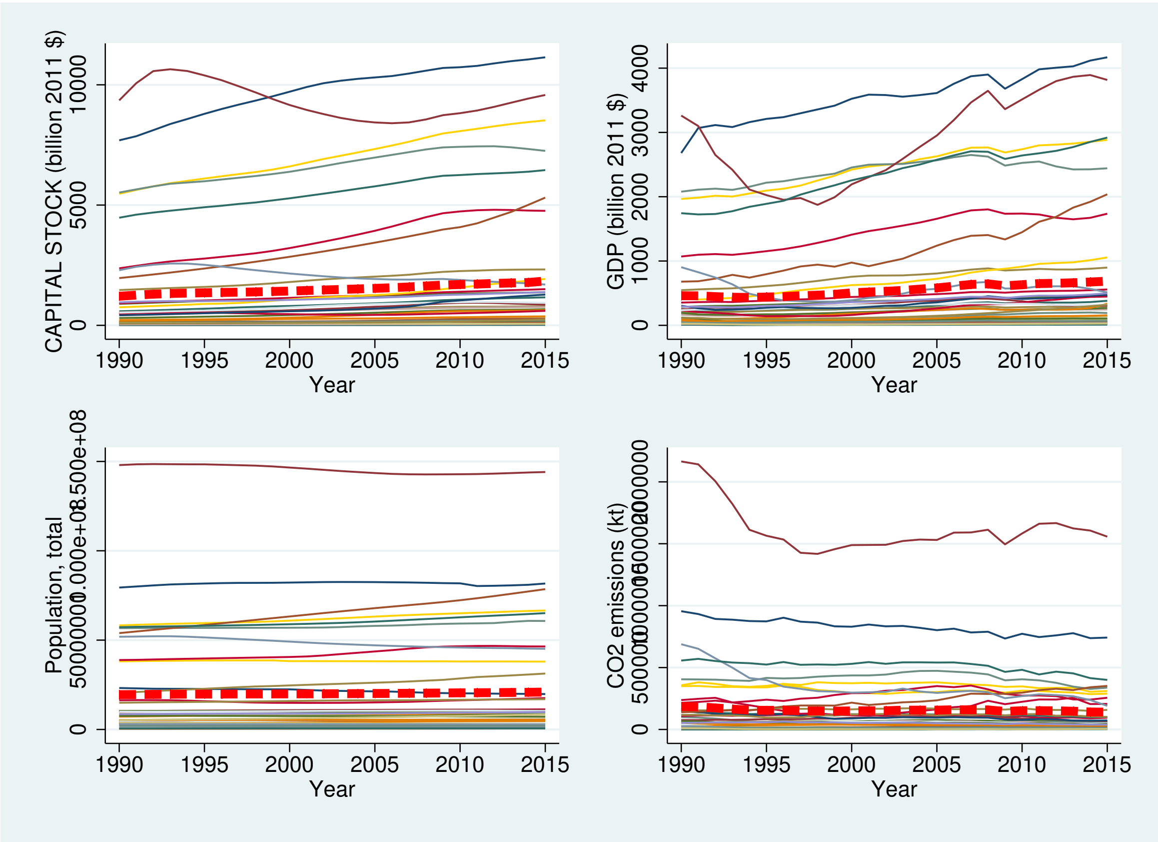

Figure 2: Capital Stock, GDP, Population and GDP

Figure 2 illustrates that both capital stock and GDP have increased slightly on average in the period of interest in the countries. However, there is quite a big spread of the levels of the variables for different countries. Since the data covers a large range of values, the natural logarithms will be used in the rest of the study to reduce the wide range to a more manageable size. Population and CO2 emissions have also increased slightly.

Table 2: Summary Table

	Mean	SD	Min	Max
EI	1.893	0.577	0.667	3.852
CAP	5.967	1.767	2.230	9.319
GDP	4.900	1.728	0.328	8.335
POP	15.73	1.557	10.09	18.82
CO2	33.12	1.004	24.83	34.54
Observations	1050			

In Table 2, the means, standard deviations, and minimum and maximum values for the natural logarithm of each variable are presented. The mean and standard deviation of energy intensity is much lower than the other variables as it is a quota. The spread in population and emissions is the largest.

Table 3: Cross-Section Dependence Test

Name	CD-test	Corr
EI	111.97***	0.715
CAP	87.61***	0.601
GDP	131.13***	0.844
CO2	7.85***	0.049
POP	5.96***	0.034

The results of the cross-section dependence test in Table 3 indicate the presence of cross dependence among all variables with Pesaran's cross-sectional dependence test. Pesaran's test suits the data well since the period (T) is small in comparison to the number of countries (Pesaran 2021). The results are in line with findings in the literature on energy consumption and growth (Menegaki 2020). It is reasonable to believe this cross dependence remains when looking at energy intensity, especially when only including countries from specific regions. For example, in the countries in the European Union (EU), the coalition can influence conditions and regulations on the energy market, which may influence different countries at the same time (Menegaki 2020).

4 Methodology

It is common in the energy economics literature to use panel data methods. Within panel data methods, many different estimators are used to overcome different constraints that appear when using panel data, such as non-stationarity, cointegration, cross-sectional dependence, and heterogeneity. This section introduces the method within the standard approach that best suits the data's properties.

There are many ways of going about model selection even within the energy economics literature, some better than others. For consistency, I derive the standard approach from Menegaki (2020)'s guide together with earlier literature with similar variables cited in section 2. Therefore, I use two criteria for the model selection; it has to suit the issues in the data, but it also has to be present in earlier literature for the study of heterogeneity and comparison to make sense.

4.1 Order of Integration

Many econometric tools rely on stationarity, meaning the properties of a time series, such as mean and variance, do not change over time. If the data is not stationary as level data, the first difference of the variables can be used to achieve stationarity in the first differences instead. If the series is stationary as level data, it is integrated at the level zero I(0), while if it is stationary as a first difference, it is integrated at the order one I(1). There is a consensus in the literature that none of the variables included in this study are stationary as level data. Therefore, it is important to test the data in both orders to investigate which statistical tools the analysis can use.

There are two issues to consider when determining which stationarity test to use for panel data, cross dependence and the relation between N and T (Menegaki 2021*a*). Since the Pesaran cross-dependence test in Table 3 presented evidence for cross-sectional dependence, I will use with Pesarans panel unit root test which allows cross-dependence (Pesaran 2007).

4.2 Panel Cointegration

Two sets of variables are cointegrated if a linear combination of the variables has a lower order of integration than they do separately. If the energy intensity and capital stock series have a lower order of integration together than they do on their own, the two variables are cointegrated. If a cointegrating relationship is present, it allows working with non-stationary variables.

The test I use to study cointegration is Pedroni's (Pedroni 2004). Pedroni's test has performed the best when assuming heterogeneous panel data within energy growth literature according to Tugcu (2018). As there is reason to believe that there exists heterogeneity in the countries of Europe and the other countries in the data, I use this test. It is also possible to include multiple regressors in this test which allows the inclusion of all variables integrated at order one in the test.

4.3 Model Selection

In earlier studies covering the effect of different variables on energy intensity, it is common to use panel data models which exploit the cointegration relationship. Several types of panel estimators can do this, and one can choose between them depending on if there is cross-dependence in the data, the size of N and T, and whether or not one wants to impose restrictions on homogeneity (Menegaki 2021*b*).

In an attempt to examine the relationship between energy intensity and capital stock, GDP, population, and CO2 emissions, I specify the following model:

$$EI_{it} = \alpha + \beta_1 CAP_{it} + \beta_2 GDP_{it} + \beta_3 POP_{it} + \beta_4 CO2_{it} + \epsilon_{it} \qquad (2)$$

In equation (2), energy intensity is the dependent variable energy intensity, while CAP, GDP, POP, and CO2 are the independent variables, and ϵ_{it} is the error term. The partial slope coefficients are represented by the β's, and α represents the intercept.

There are several ways to move forward when there is evidence for cointegration in the panel data. Mean group (MG), pooled mean group (PMG), and dynamic fixed effect (DFE) estimators are used in previous literature (Samargandi 2019). However, these estimators are not optimal for small samples and cannot deal appropriately with cross dependence (Pesaran et al. 1999).

An estimator which has gained more traction during the last couple of years is the common correlated effects (CCE) estimator. The CCE estimators use cross-sectional averages of the dependent and explanatory variables to approximate a linear combination of unobserved factors. It uses a standard panel regression augmented with the averages from the approximation, making the estimator robust to different typed of error cross-section dependence, possible unit roots in factors, and slope heterogeneity. This means it can deal with cross-dependence (Menegaki 2021*b*).

The common correlated effects pooled estimator (CCEP) can allow cross-sectional dependence, endogeneity, and serial correlation while also accounting for heterogeneity. Throughout the rest of the analysis, I will use the CCEP since it is supposed to deal with most of the issues found in the data out of all the panel data estimators while being able to exploit the cointegration. It is also used in several other studies and recommended by Menegaki (2020) which implies it is one of the methods within the standard approach.

5 Results

In this section, I begin by presenting the results on the order of integration, cointegration, and panel estimators in this section according to the standard approach selected in Section 4. Then I examine the heterogeneity among countries in the relationships between the variables by testing for cointegration and estimating coefficients with time series methods instead of panel methods on a country level.

5.1 Results Based on the Standard Approach

I test which variables are stationary by using Pesaran's unit root test, which controls for cross-dependence (Pesaran 2007). After a visual inspection of the variables, a trend is included in the test. The results are presented in Table 4 and show that the variables energy intensity, capital stock, GDP, and population are non-stationary as level data but stationary as first differences meaning they are integrated at level one, I(1). CO2 emissions is the only stationary variable, meaning it will not be included in the cointegration analysis.

Table 4: Panel Unit Root Tests

Variable	Level	1st Diff
EI	-0.421	-11.925***
CAP	7.779	-1.574**
GDP	-0.821	-5.767***
POP	1.071	-7.043***
CO2	-5.064 ***	-17.371***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Lag length is set to 1 according to AIC and BIC criteria. CIPS zt-bar statistics presented.

Since four of the five variables included in the analysis are I(1), I proceed to test if the non-stationary explanatory variables are cointegrated with the dependent variable. Cointegration between energy intensity and the I(1) variables is tested with the panel cointegration test by Pedroni. I test each I(1) variable separately and then all together. A trend is included in this test to account for the panel-specific time trends in each country.

Table 5: Testing for Cointegration with Energy Intensity (Pedroni)

Statistic	CAP	GDP	POP	ALL I(1)
Modified Phillips-Perron t	0.2804	0.4031	0.3487	1.0609
Phillips-Perron t	-5.1020***	-3.9107***	-4.8740***	-6.8472***
Augmented Dickey-Fuller t	-4.0426***	-3.6826***	-3.8842***	-6.8356***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Panel and time trends included.

Results from the tests for cointegration between energy intensity and I(1) explanatory variables are presented in Table 5. The results provide evidence for cointegration for all I(1) variables. The test's null hypothesis is no cointegration, while the alternative hypothesis is that the variables are cointegrated in all panels. Two of the three test statistics in each cointegration test reject the null hypothesis and confirm the alternative hypothesis that there is cointegration in all panels. The Augmented Dickey-Fuller test statistic is the recommended statistic to use for samples with below 100 time periods (Pedroni 2004). So, although the evidence is somewhat weak or insecure, it is standard to proceed with cointegration if there is evidence to support it in the most suitable test statistic.

Since there is evidence for cointegration when using the standard approach, I proceed with the methods that use the cointegrated level data to provide estimates. Depending on the properties of the data, there are multiple estimators used within the standard approach when there is cointegration. As stated in the model selection section, the CCEP estimator is the most suitable for the energy intensity data sample used in this thesis since it accounts for cross-dependence.

In Table 6, the results from the pooled CCEP estimator are presented. The coefficients are reported for each variable that showed a cointegrating relationship with energy intensity. The coefficient for capital stock is approximately 0.3, significant at the one percent level, indicating that an increase in capital stock is associated with an increase in energy intensity. Since energy intensity is a quota, higher capital stock is associated with less GDP per MJ of primary energy use. The result is similar to the relation between energy intensity and capital stock found in Santiago et al. (2020).

The GDP coefficient in Table 6 is significantly negative, approximately 0.49, with a standard error of 0.03. The positive relationship is similar to results found in earlier literature using similar methods to estimate the relationship between GDP and energy intensity (Belke et al. 2011, Menegaki 2014). Population has the largest coefficient of the three explanatory variables at approximately 2.8 and a standard error of 0.27. The coefficient implies that an increase in population is associated with an increase in the amount of MJ used per unit of GDP.

Table 6: Common Correlated Effects Regression on Energy Intensity

	EI
CAP	0.295***
	(0.0747)
GDP	-0.488***
	(0.0372)
POP	2.794***
	(0.256)
Observations	1050

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, the results from the standard approach are similar to the results from earlier literature. The tests confirmed cointegrating relationships between energy intensity and GDP, capital stock, and population. The coefficients from the CCEP estimator indicated that increases in GDP are associated with lower energy intensity. In contrast, increases in population and capital stock are associated with increases in energy intensity, confirming some of the relationships between the variables from earlier literature. Using the standard approach on the data and receiving similar results to some of the earlier literature indicates it is possible to inspect the heterogeneity closer. Earlier literature using the standard approach may, to some degree, be subject to similar issues as the ones found in the following subsection.

5.2 Results under Heterogeneity

Heterogeneity is one of the limitations of working with panel data. Even if the methods which best solve issues such as cross-section dependence and cointegration, heterogeneity remains a problem worth further investigating. Suppose the heterogeneity only implies that each country is at a different starting level. In that case, one country may have consistently lower energy intensity or higher GDP than other countries, and it is possible to account for this via particular estimators such as fixed effects estimators. However, it is harder to find an estimator which can deal with the relationship between the variables behaving differently, so-called heterogeneous slopes.

To closer investigate the presence of heterogeneity, I run the Pesaran & Yamagata (2008) test for heterogeneous slopes. The test allows N to be larger than T, which is the case in the dataset. The test rejects the null hypothesis of homogeneous slopes meaning there are differences between the slopes of countries. I also test the robustness of this test with cross-sectional dependence according to Pesaran (2006). These results still reject the null of slope homogeneity, meaning there are differences in the relationship between the I(1) variables and energy intensity in various countries. I look further into how different the relationships are in this section.

Cointegration is a good concept in theory. It solves many of our problems and leads to super consistency when it works. In practice, it is unlikely that all countries cointegrate with the same cointegrating vector. Since it is plausible that energy intensity, capital stock, and GDP interact differently in different countries, I investigate the cointegrating relationships separately for each country. I use the Engle-Granger test to examine how many countries show evidence of cointegrating relationships when testing on an individual level.

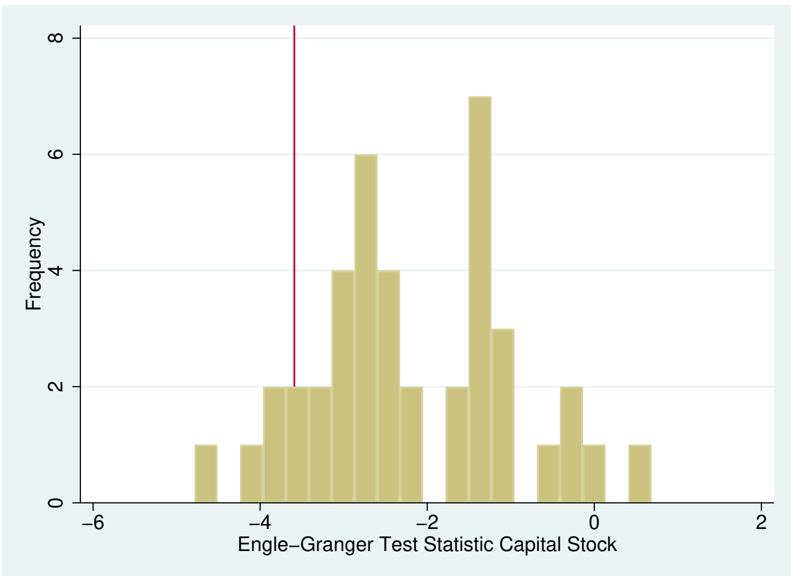

Figure 3: Cointegration Statistics: Energy Intensity and Capital Stock

Figure 3 reports the result of the Engle-Granger cointegration test between energy intensity and capital stock. The red lines are the critical values for the test at the five percent level, meaning that only countries on the left-hand side of the critical value (7 countries) show any significant sign of cointegration. Most countries are on the right-hand side of the red lines meaning most countries show no evidence of a cointegrating relationship between energy intensity and capital stock.

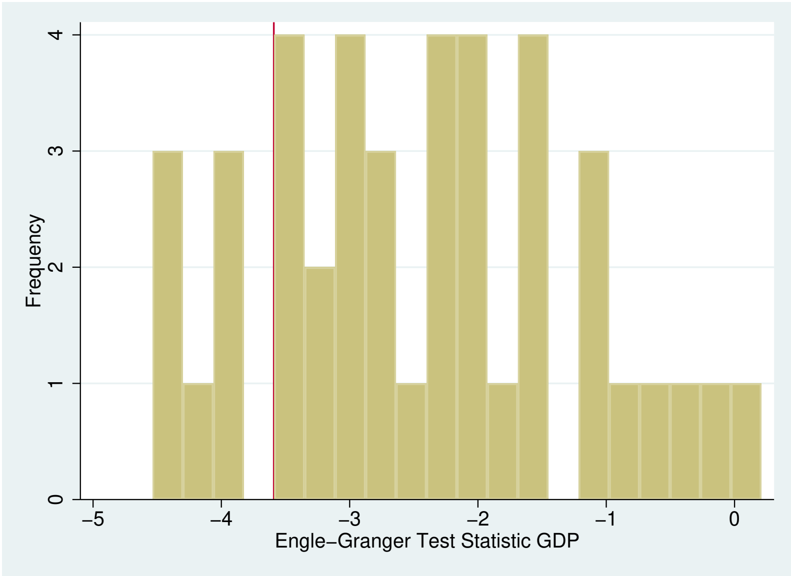

Figure 4: Cointegration Statistics: Energy Intensity and GDP

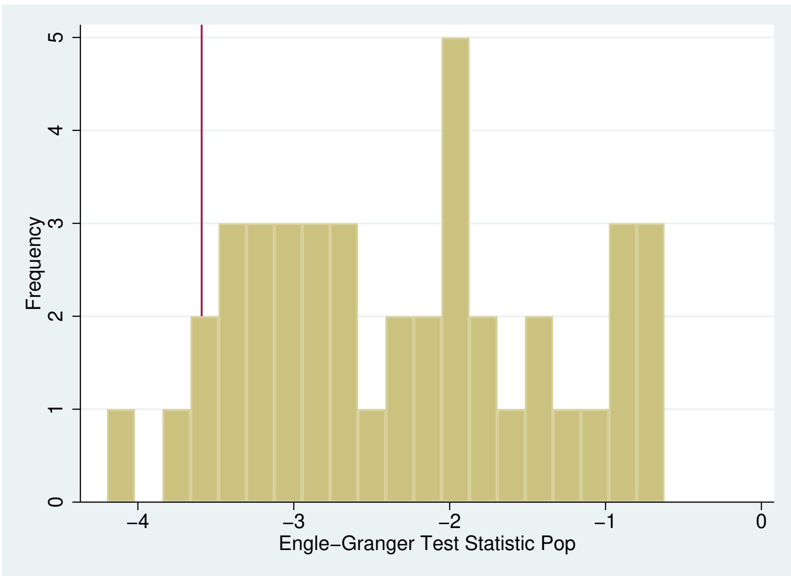

Figure 5: Cointegration Statistics: Energy Intensity and Population

Figure 4 illustrates a similar result for the cointegrating relationships between energy intensity and GDP. Few countries are on the left-hand side of the red lines and show evidence of cointegration between energy intensity and GDP. Figure 5 shows similar results for the relationship between energy intensity and population since only a couple of countries are on the left-hand side of the five percent critical value.

The histograms over countrywise cointegration tests with each I(1) variable and energy intensity indicate that there is not as much evidence for cointegration as initially found in Table 5 using Pedroni's cointegration test for panel data. If there is only cointegration in some countries, it questions if it is possible to use level data to estimate relationships. Pedroni's test does not assume the cointegrating vector is completely homogeneous but allows for some heterogeneity in the cointegrating relationship. However, only "enough" of the individual cross-sections have to have statistics far away to reject the null, implying there is still possibilities for countries not to have cointegrating relationships.

Figures 6, 7, and 8 show the coefficient results from a time series regression for each country separately. The figures show how much the coefficients and their significance levels can vary between countries. The dot in each figure is the coefficient value, and the lines are the confidence intervals. All three explanatory variables are included in the regression, and the figures illustrate the values of one coefficient each. Figure 6 illustrates the relationship between capital stock and energy intensity in the

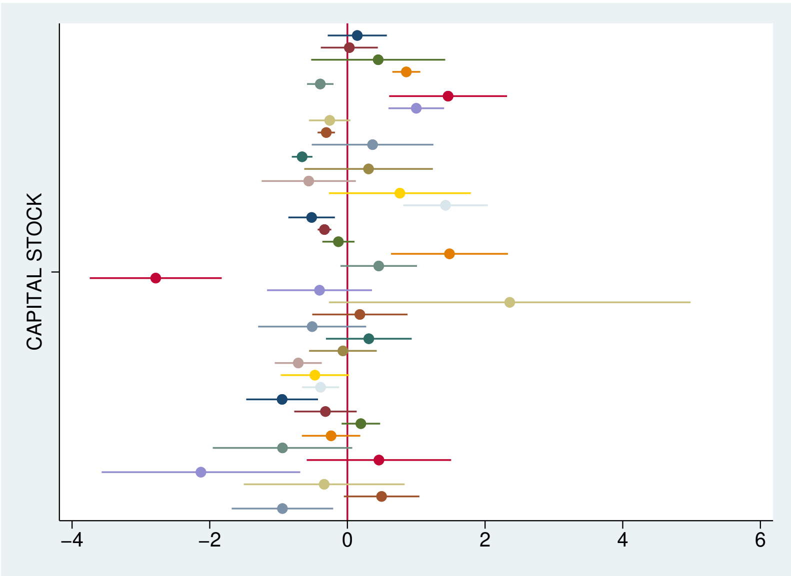

Figure 6: Capital Stock on Energy Intensity Regression Coefficients

model by plotting all the coefficients for each country separately. The coefficients span between approximately negative two and two, indicating that the variables are associated in different directions in different countries. Many of the confidence intervals are large and on both the positive and negative sides of the x-axis, meaning it is hard to conclude a general direction in which the relationship is going. The results from the graph confirm the suspicion that the relation between the variables is heterogeneous and varies between countries. This implies that while increases in capital stock can be associated with an increase in energy intensity in some countries, it be associated with a decrease in others.

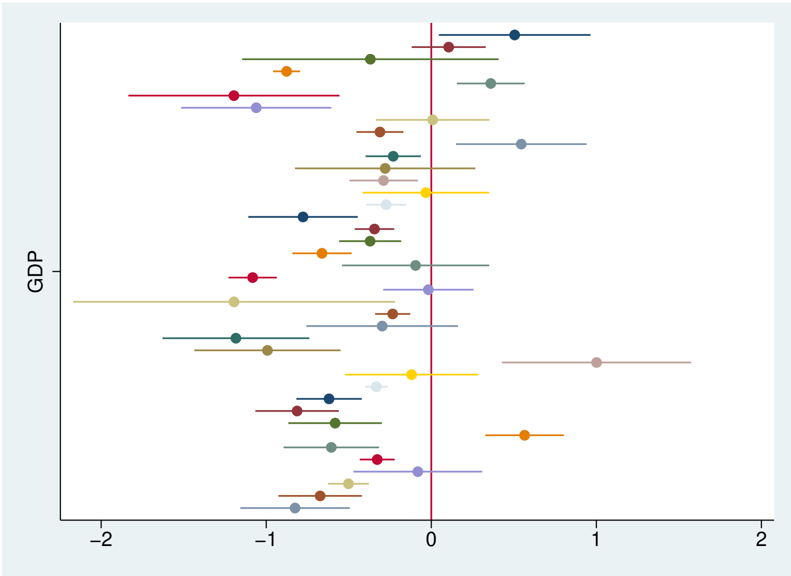

Figure 7: GDP on Energy Intensity Regression Coefficients

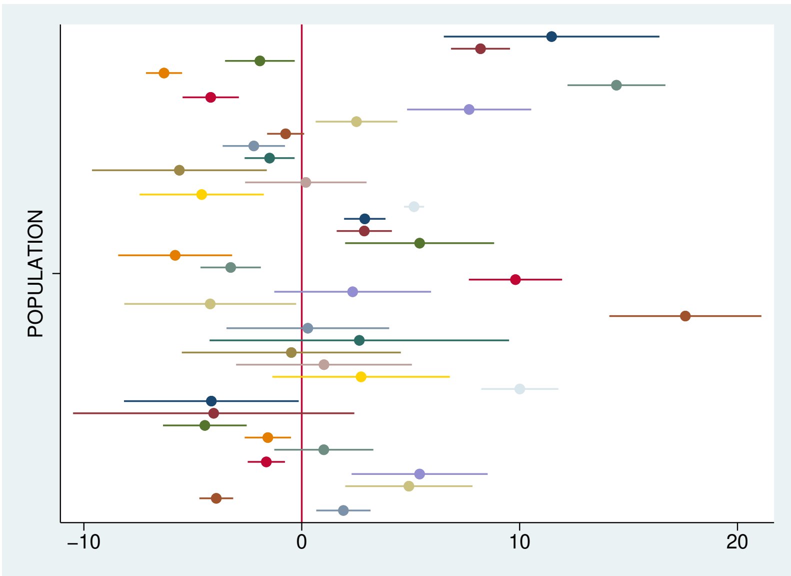

Figure 8: Population on Energy Intensity Regression Coefficients

Figure 7 presents the coefficient results from the relationship between GDP and energy intensity, spanning between -1 and 1. Although more countries are significantly on the left-hand side than for the coefficients in Figure 6, about a fourth of the confidence intervals still cross the zero, and four are on the positive side. The result indicates that GDP is associated with decreased energy intensity in some countries but not in all countries. These results can be interpreted as an increase in GDP more often being associated with a decrease in energy intensity than capital stock, but the result is still somewhat unclear.

In Figure 8, the relationship between population and energy intensity is illustrated. The coefficients span between approximately -5 and 18, including relatively large confidence intervals. Like in the capital stock coefficients, the coefficients are on both the negative and positive side meaning it is hard to conclude the direction of the relationship.

5.3 Comparing the Standard Approach to Results under Heterogeneity

Different factors likely influence energy intensity in different ways in various countries. In some countries, a sharp increase in GDP may drive an increase in energy intensity. In contrast, other countries may have shifted from an industry-intensive economy to a service-intensive one. Controlling for all factors in panel models is not possible. This heterogeneity is essential for model selection as it biases many estimators used when investigating panel data (Juhl & Lugovskyy 2014).

While the cointegration tests showed evidence for cointegration between all the I(1) variables and energy intensity in the panel cointegration test, the country-level results contradicted this. When looking at cointegration for the countries separately, there was no cointegrating relationship for the majority of the countries between any of the variables. The inconclusive results indicated that looking at cointegration on a panel level may give misleading results.

The null hypothesis of many cointegration tests is that no countries should have cointegrating relationships. This means the null hypothesis can be rejected if just one country does show evidence of cointegration. As observed in the cointegration histograms, there is evidence for cointegration in some countries while the clear majority do not show any evidence for cointegration. It may not be suitable to go on and investigate the data with cointegration as a precondition if only 7 of the 42 countries show country-level evidence of a cointegrating relationship.

There are also significant differences when comparing the coefficients from the CCEP estimator in Table 6 and the results from the time series regressions in Figures 6, 7, and 8. The CCEP estimator is supposed to perform well even under samples as small as T=20 and N=30, which is the case in this thesis (Pesaran 2006). However, although it is supposed to deal with heterogeneity better than other estimators, it still has to report a final coefficient (Pesaran 2006).

The panel coefficient for capital stock was 0.3 significant at a one percent level, while most of the individual country coefficients in Figure 6 are insignificant and both positive and negative. These results indicated that the relationship between capital stock and energy intensity might be too heterogeneous to fit into a panel model.

The difference between the panel and country-specific GDP and energy intensity coefficients is not as big as for capital stock and energy intensity. The panel CCEP coefficient is approximately -0.4 and significant, and in Figure 7, most of the countries' coefficients are between zero and negative one. However, the confidence intervals indicate that there is still uncertainty regarding which direction the relationship goes in many countries.

The relationship between population and energy intensity is perhaps the most diverse and most different from the CCEP results. While the CCEP coefficient was 2.7, many of the countries' coefficients were below zero or insignificantly around zero. Some countries had higher coefficients which could be what skewed the results.

It is hard to make classical divisions into low, middle, and high-income countries in the energy intensity literature to solve heterogeneity. Although countries have the same economic status, their energy intensity can be significantly affected by local geographical conditions, such as their access to natural resources that can provide cheap energy or their use of heat or air conditioning. This makes studying country-level energy intensity factors even harder, even if trying to account for heterogeneity by dividing countries into different groups. In this case, so few countries showed evidence of country-level cointegration that further analysis of country groups was not possible.

In conclusion, this section has provided further evidence that the relationships of energy intensity, GDP, and capital stock may be too diverse to mold into a regular panel data analysis without having access to data on all the factors that may influence energy intensity.

6 Conclusion

This study aims to provide a closer look at the methods used to study cointegrating relationships between energy intensity, capital stock, population, and GDP. Earlier literature has not found any consensus regarding the relationships between energy intensity, GDP, and capital. While several studies have found p-hacking and publication bias in the causality literature on energy and economic variables, no one has controlled the studies that use cointegration and panel methods to investigate energy intensity.

The standard approach's empirical findings suggested enough evidence of cointegrating relationships between energy intensity and capital stock, GDP and population to proceed with cointegration methods. A closer look at the coefficients through a CCEP estimator showed that increased GDP is associated with decreased energy intensity. In contrast, an increase in population and capital stock is associated with increased energy intensity. Hence, this answers the first research question.

Since the standard approach does not account for heterogeneity and there is reason to believe a presence of heterogeneity in the sample, I dissected the methods at a country level. A closer look at the coefficients showed that the evidence for cointegration was weak and only existed in some countries. Furthermore, the time series regression coefficients pointed in different directions, and many were insignificant. The inconclusive results from the country-level observations undermine the initially significant results from the standard approach, which answers the second research question.

Although this study does not contribute to any new conclusions regarding how capital stock, population, and GDP relate to energy intensity, it provides further insight into the structure of the panel data methods studying these relationships. It is inevitably an essential question for those working with energy transitions and policy-making, which makes relying on methods that assume homogeneity potentially misleading. Replicating the whole literature would have been a much too big subject for this relatively small thesis. Nevertheless, the findings of the heterogeneous relationships between capital stock, GDP, population, and energy intensity provide some evidence that we should continue investigating the topic with caution.

6.1 Limitations

The analysis of the differences at the country level shows how results can be affected by which countries the sample includes. Heterogeneity could maybe explain some of the divisions in the literature. However, this study has not been able to replicate the exact method and data of earlier literature due to data access. There are several ways to improve the analysis if newer data could be obtained on the energy intensity of more countries and more control variables such as energy prices, heat demand, and changes within sectors or industries.

6.2 Further Research

Considering the heterogeneity found using the standard approach within this area of literature, future research could attempt to find less heterogeneous places to study the same relationships. One possibility is to study relationships within countries in different sectors or regions to avoid some of the heterogeneity which has become a problem for the field.

As there is evidence for heterogeneity, it would also be interesting to construct a meta-analysis of the cointegration studies. Many of the tests for cointegration quickly reject the null of no cointegration since only one, or a few, of the countries, need to show evidence. Proceeding with meta-analysis methods, it would be interesting to see how many of the methods within the studies show robust significant studies if it were harder to reject the null hypothesis.

References

Belke, A., Dobnik, F. & Dreger, C. (2011), 'Energy consumption and economic growth: New insights into the cointegration relationship', *Energy Economics* **33**(5), 782–789.

Bilgili, F., Koçak, E., Bulut, Ü. & Kuloğlu, A. (2017), 'The impact of urbanization on energy intensity: Panel data evidence considering cross-sectional dependence and heterogeneity', *Energy* **133**, 242–256.

Bruns, S. B. & Stern, D. I. (2019), 'Lag length selection and p-hacking in granger causality testing: prevalence and performance of meta-regression models', *Empirical Economics* **56**(3), 797–830.

Filipović, S., Verbič, M. & Radovanović, M. (2015), 'Determinants of energy intensity in the european union: A panel data analysis', *Energy* **92**, 547–555. Sustainable Development of Energy, Water and Environment Systems.
URL: *https://www.sciencedirect.com/science/article/pii/S0360544215009056*

Gales, B., Kander, A., Malanima, P. & Rubio, M. (2007), 'North versus south: Energy transition and energy intensity in europe over 200 years', *European Review of Economic History* **11**(2), 219–253.

Gamtessa, S. & Olani, A. B. (2018), 'Energy price, energy efficiency, and capital productivity: Empirical investigations and policy implications', *Energy Economics* **72**, 650–666.
URL: *https://www.sciencedirect.com/science/article/pii/S0140988318301452*

Hajko, V. (2017), 'The failure of energy-economy nexus: A meta-analysis of 104 studies', *Energy* **125**, 771–787.

Hannah Ritchie, M. R. & Rosado, P. (2020), 'Co and greenhouse gas emissions', *Our World in Data* . https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

IEA (2019), *Multiple Benefits of Energy Efficiency*, IEA, Paris.
URL: *https://www.iea.org/reports/multiple-benefits-of-energy-efficiency*

IMF (2021), *IMF Investment and Capital Stock Dataset, 1960-2019.*
URL: *https://infrastructuregovern.imf.org/content/dam/PIMA/Knowledge-Hub/dataset/InvestmentandCapitalStockDatabaseUserManualandFAQ$_{M}$ay2021.pdf*

Jimenez, R. & Mercado, J. (2014), 'Energy intensity: A decomposition and coun-

terfactual exercise for latin american countries', *Energy Economics* **42**, 161–171.
URL: *https://www.sciencedirect.com/science/article/pii/S0140988313002983*

Jin, T. (2022), 'Impact of heat and electricity consumption on energy intensity: A panel data analysis', *Energy* **239**, 121903.

Juhl, T. & Lugovskyy, O. (2014), 'A test for slope heterogeneity in fixed effects models', *Econometric Reviews* **33**(8), 906–935.

Koengkan, M., Santiago, R. & Fuinhas, J. A. (2019), 'The impact of public capital stock on energy consumption: Empirical evidence from latin america and the caribbean region', *International Economics* **160**, 43–55.
URL: *https://www.sciencedirect.com/science/article/pii/S2110701719301003*

Lee, C.-C. & Chien, M.-S. (2010), 'Dynamic modelling of energy consumption, capital stock, and real income in g-7 countries', *Energy Economics* **32**(3), 564–581.
URL: *https://www.sciencedirect.com/science/article/pii/S0140988309001558*

Mahmood, T. & Ahmad, E. (2018), 'The relationship of energy intensity with economic growth: Evidence for european economies', *Energy strategy reviews* **20**, 90–98.

Martinez, D., Ebenhack, B. W. & Wagner, T. (2019), *Energy efficiency: Concepts and calculations*, Elsevier.

Menegaki, A. (2020), *A Guide to Econometric Methods for the Energy-Growth Nexus*, Academic Press.

Menegaki, A. (2021*a*), Chapter 2 - stationarity and an alphabetical directory of unit roots often used in the energy-growth nexus, *in* A. Menegaki, ed., 'A Guide to Econometrics Methods for the Energy-Growth Nexus', Academic Press, pp. 31–61.
URL: *https://www.sciencedirect.com/science/article/pii/B9780128190395000021*

Menegaki, A. (2021*b*), Chapter 3 - an a–z guide for complete research when using the autoregressive distributed lag (ardl) bounds test approach in the broader energy-growth nexus, *in* A. Menegaki, ed., 'A Guide to Econometrics Methods for the Energy-Growth Nexus', Academic Press, pp. 63–101.
URL: *https://www.sciencedirect.com/science/article/pii/B9780128190395000070*

Menegaki, A. N. (2014), 'On energy consumption and gdp studies; a meta-analysis of the last two decades', *Renewable and Sustainable Energy Reviews* **29**, 31–36.
URL: *https://www.sciencedirect.com/science/article/pii/S1364032113006217*

Pedroni, P. (2004), 'Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the ppp hypothesis', *Econometric theory* **20**(3), 597–625.

Pesaran, M. H. (2006), 'Estimation and inference in large heterogeneous panels with a multifactor error structure', *Econometrica* **74**(4), 967–1012.

Pesaran, M. H. (2007), 'A simple panel unit root test in the presence of cross-section dependence', *Journal of applied econometrics* **22**(2), 265–312.

Pesaran, M. H. (2021), 'General diagnostic tests for cross-sectional dependence in panels', *Empirical Economics* **60**(1), 13–50.

Pesaran, M. H., Shin, Y. & Smith, R. P. (1999), 'Pooled mean group estimation of dynamic heterogeneous panels', *Journal of the American statistical Association* **94**(446), 621–634.

Pesaran, M. H. & Yamagata, T. (2008), 'Testing slope homogeneity in large panels', *Journal of econometrics* **142**(1), 50–93.

Pfeiffer, A., Millar, R., Hepburn, C. & Beinhocker, E. (2016), 'The '2 c capital stock'for electricity generation: Committed cumulative carbon emissions from the electricity generation sector and the transition to a green economy', *Applied Energy* **179**, 1395–1408.

Samargandi, N. (2019), 'Energy intensity and its determinants in opec countries', *Energy* **186**, 115803.

Santiago, R., Fuinhas, J. A. & Marques, A. C. (2019), Income inequality, globalization, and economic growth: a panel vector autoregressive approach for latin american countries, *in* 'The Extended Energy-Growth Nexus', Elsevier, pp. 57–96.

Santiago, R., Fuinhas, J. A. & Marques, A. C. (2020), 'An analysis of the energy intensity of latin american and caribbean countries: Empirical evidence on the role of public and private capital stock', *Energy* **211**, 118925.

Tugcu, C. T. (2018), Panel data analysis in the energy-growth nexus (egn), *in* 'The economics and econometrics of the energy-growth nexus', Elsevier, pp. 255–271.

WDI (2021*a*), 'Co2 emissions (kt)(en.atm.co2e.kt)'. data retrieved from World Development Indicators, `https://databank.worldbank.org/source/world-development-indicators#`.

WDI (2021*b*), 'Energy intensity level of primary energy (mj/$2017 ppp gdp)'. data retrieved from World Development Indicators, https://databank.worldbank.org/source/world-development-indicators#.

WDI (2021*c*), 'Gdp, ppp (constant 2017 international $)'. data retrieved from World Development Indicators, https://databank.worldbank.org/source/world-development-indicators#.

WDI (2021*d*), 'Population, total(sp.pop.totl)'. data retrieved from World Development Indicators, https://databank.worldbank.org/source/world-development-indicators#.

Appendix

Table 7: Countries

1	Albania	2	Armenia
3	Austria	4	Azerbaijan
5	Belarus	6	Belgium
7	Bosnia and Herzegovina	8	Bulgaria
9	Bulgaria	10	Croatia
11	Cyprus	12	Czech Republic
13	Denmark	14	Finland
15	France	16	Georgia
17	Germany	18	Greece
19	Hungary	20	Ireland
21	Italy	22	Kazakhstan
23	Latvia	24	Lithuania
25	Luxembourg	26	(Moldova) Not included
27	Montenegro	28	Netherlands
29	North Macedonia	30	Poland
31	Portugal	32	Romania
33	Russian Federation	34	Serbia
35	Slovak Republic	36	Slovenia
37	Spain	38	Sweden
39	Tajikistan	40	Turkey
41	Ukraine	42	United Kingdom
43	Uzbekistan		