STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 - Master's Thesis in Economics
Academic Year 2018-2019

Catch-Up with Me if You Can

An empirical analysis of convergence of carbon emission intensity in the EU power sector

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Abstract

The anthropogenic impact on climate change is discernible and the power sector is known to be one of the main contributors of greenhouse gas emissions. This thesis takes a cross-country sectoral approach with the overall objective of analyzing convergence of carbon emission intensity in electricity generation across the power sectors in the EU. A univariate time-series approach is used to study stochastic convergence and a fixed effects estimator is applied to investigate beta-convergence. We employ a panel dataset of the current 28 EU member states spanning from 1995 to 2015. The results from three different panel unit root tests consistently provide support for the existence of stochastic convergence. The results provide strong support for the existence of beta-convergence and we conclude that more carbon intensive countries are catching up with the less carbon intensive countries. The results suggest that countries with a more stringent energy tax converge toward a lower path of carbon intensity, whilst wealthier countries tend to converge toward a higher path of carbon intensity. The speed of convergence is not found to be conditional on the development of the EU ETS carbon prices or the price of fossil fuels.

Keywords: carbon emission intensity, EU power sector, stochastic convergence, beta-convergence, environmental economics

JEL: Q40, Q54, Q58

Supervisor: Pamela Campa
Date submitted: May 13, 2019
Date examined: June 3, 2019
Discussants: Agnes Magnusson and Joel Blanke
Examiner: Mark Sanctuary

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1. Introduction

Climate change is an intensively discussed topic and is undoubtedly one of the major challenges that this planet faces. The lion share of evidence suggests that anthropogenic emissions of greenhouse gases (GHGs) – of which carbon dioxide is the most significant – has a considerable and discernible impact on climate change (Intergovernmental Panel on Climate Change [IPCC], 2018).

The power sector is one of the largest contributors of GHGs in the European Union (EU), contributing approximately 30% of total carbon emissions in 2015 (European Environment Agency [EEA], 2018). As it has been recognized to have a high ability to reduce emissions, the power sector is considered to play a key role in reaching the EU reduction target of 20% from 1990 levels by 2020 (European Union [EU] directive, 2009) as well as the long-term goal of EU climate neutrality by 2050.

A commonly applied concept within environmental economics is carbon intensity. Within the context of the power sector, carbon intensity relates to the ratio of carbon emissions[1] from electricity generation to gross electricity generation. This study investigates convergence of carbon intensity between countries in the EU power sector. It is relevant because the power sector is one of the biggest contributors of carbon emissions and the EU has implemented policies explicitly targeting the power sector. The high degree of integration, comprehensive environmental standards and common climate policy makes the 28 EU member countries[2] (EU28 henceforth) a unique and interesting case to study. As a political bloc, the EU requires all members to adopt, implement and enforce all EU rules. EU climate policy was to a great extent initiated during the early 1990's and the signing of the Kyoto Protocol in 1997 initiated the combat against climate change. With this in mind, we study the time period from 1995 to 2015.

Studying convergence of carbon intensity is important because it yield valuable insight into future carbon emissions and is useful for policy making. Further, the power sector is particularly well suited for cross-country comparison with regards to the carbon intensity as it produces a completely homogeneous good - electricity.

This study targets three main research questions:

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[1] As is standard practice, when measuring carbon emissions, we refer to the carbon equivalent of all greenhouse gases (mainly carbon dioxide, methane and nitrous oxide) released. This signifies the amount of CO_2 emissions that would have the equivalent impact on global warming and provides GHG emissions a common unit of measurement.

[2] The EU28 is defined as the 28 member states of the European Union as of 2013. See Appendix A for a complete list of countries.

1) *How has carbon intensity in the EU power sector evolved from 1995 to 2015?*
2) *Is the EU power sector converging toward a common path of carbon intensity or to different paths dependent on country characteristics?*
3) *Is the speed of convergence toward the path of carbon intensity different between countries?*

To answer these questions, we utilize a panel dataset of the EU28's power sector from 1995 to 2015. We answer the first research question by studying descriptive statistics and visualizing the data. To study convergence of the path of carbon intensity, we focus on two established convergence concepts; stochastic convergence and beta-convergence. Stochastic convergence is investigated by taking a time-series approach to test for a unit root in order to determine whether the time-series resembles a stationary process. The presence of stationarity supports stochastic convergence and implies that a shock to a carbon intensity time-series is only temporary and that the time-series reverts back to the mean. Empirically, we test if the time series resembles a unit root or stationary process. Within economic theory one might intuitively expect the carbon intensity series to be stationary over time. However, as this has not yet been tested, we examine this empirically. It is standard practice to conduct multiple unit root tests to ensure robustness of results, hence we employ the IPS test (Im, Pesaran & Shin, 2003), the Cross-sectionally augmented Dickey-Fuller (Pesaran, 2007) and the Hadri Lagrange Multiplier (Hadri, 2000) panel unit root tests. Stochastic convergence is a necessary but not sufficient condition for beta-convergence, thus if stochastic convergence persists, there can also be beta-convergence.

Beta-convergence has a foundation in neoclassical growth theory (Pettersson et al., 2014) and in the context of carbon intensity, it occurs when a country with high carbon intensity improves faster relative to a country with low carbon intensity. Beta-convergence can in turn be split into *absolute* and *conditional convergence.* Absolute convergence implies that the long-run path of carbon intensity is the same for all countries and conditional convergence allows for country differences in the path of carbon intensity. Economic theory would posit that absolute convergence indicates that all countries converge to the same level of carbon intensity in the long run, we test this explicitly in our regressions. In order to allow for cross-country variation in the path of carbon intensity, convergence can be made conditional on exogenous variables that are hypothesized to have an impact on the growth path of carbon intensity (Strazicich & List, 2003). In line with economic theory, conditional convergence indicates that the path of carbon intensity can differ considerably between countries due to differing country-specific structural characteristics. In this study, a fixed effects estimator is used to investigate beta-convergence, and EU membership, energy tax intensity and GDP per capita are included to test for conditional convergence. Further, we analyze if the price of emission allowances (carbon price) and the price of fossil fuels impact the rate at which countries approach their path of carbon intensity.

The results present convincing support for the existence of both stochastic and beta-convergence of carbon intensity in the EU power sector. Beta-convergence is found to be conditional on the energy tax of a country as well as on GDP per capita. This suggests that the studied countries converge to individual paths of carbon intensity. Countries with higher energy taxes tend to follow a lower path of carbon intensity, while countries with a higher GDP per capita follow a higher path. The speed of convergence does not appear to be affected by the carbon price and prices of fossil fuel.

The remainder of the thesis is organized as follows. Section 2 provide an introduction to the EU power sector and a background to the development of the EU climate policy. A theoretical framework is introduced in section 3 and a literature review of environmental convergence research is presented in section 4. Section 5 introduces the variables used, the data sources and descriptive statistics. Subsequently, section 6 presents the empirical framework employed to study stochastic and beta-convergence and is followed by the results in section 7. In section 8 we discuss the internal validity of the study as well as some policy implications of the results. Lastly, in section 9, our main conclusions are presented together with suggestions for further research.

2. Background

The section that follows provides a brief introduction to the EU power sector and the EU climate policy related to it. Both are essential in grasping the context in which this study is placed.

2.1. The EU Power Sector

A power sector is defined as the collection of all active installments contributing to *total gross electricity generation*[3]. This includes generation from combustion of fossil fuels such as coal, oil and gas, as well as generation from other energy sources such as nuclear and renewables. Carbon emissions from electricity generation arises from the combustion of fossil fuels, where a

[3] Defined as the gross electricity generation in all types of power plants, including the electricity used within the plant auxiliaries and in the transformers (European Commission [EC]], 2019a).

higher share of electricity from fossil fuels is associated with higher carbon intensity. Note that the carbon emissions do not include emissions from *primary energy production*[4].

From 1995 to 2015, annual carbon emissions from electricity generation within the EU28 decreased by 18% from 1,242 to 1,018 million tonne (Mt) CO_2 and electricity generation increased by 18,6% from 2,744 TWh[5] in 1995 to 3,255 TWh in 2015 (International Energy Agency [IEA], 2019a). In 2015, almost half of the electricity generated (44%) stemmed from fossil fuels, 26% was from nuclear and the remainder was generated from renewable energy sources, primarily hydro and wind (IEA, 2019a). There is significant variation regarding the relative importance of fossil fuels in electricity generation among the EU28. Hence, there is also considerable variation in the amount of carbon dioxide emitted as a by-product of electricity generation.

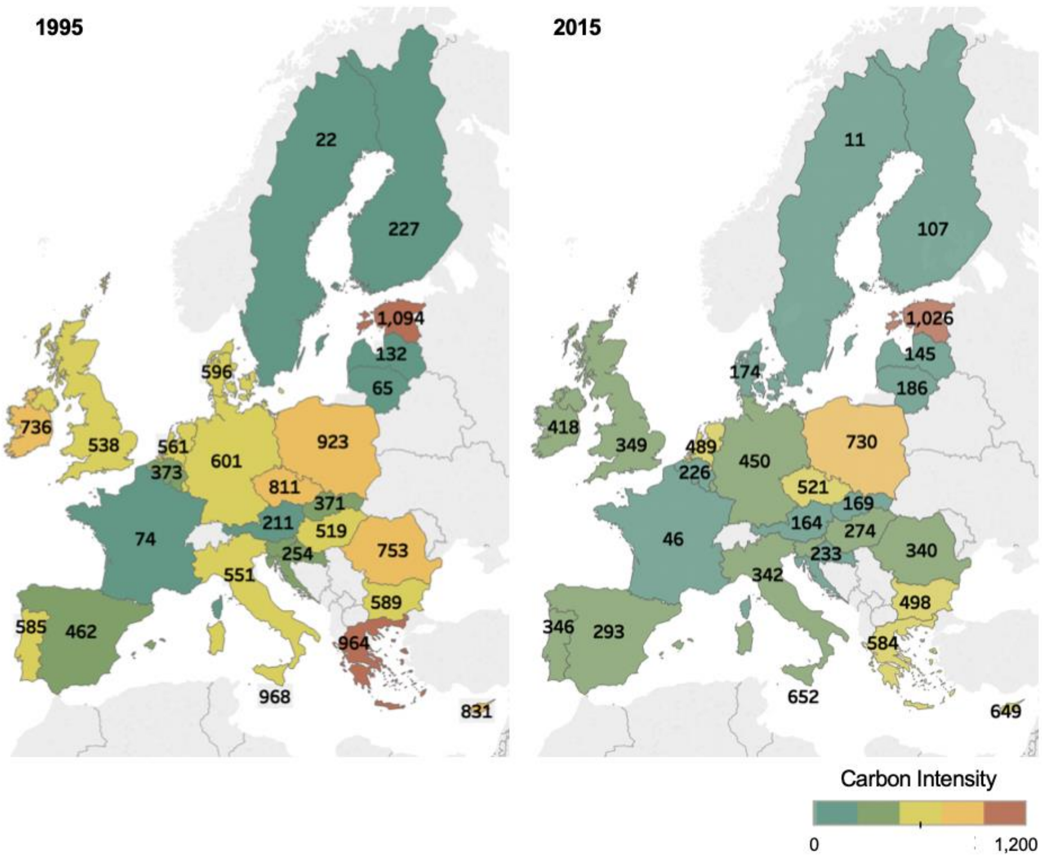

Figure 1: Carbon intensity (gCO2/kWh) of power sectors in the EU, 1995 and 2015.
Source: Author's rendering of data from IEA (2019a).

[4] Emissions from the extraction process of energy products from natural resources (for example coal mines or crude oil fields)(EC, 2019a).
[5] One terawatt hour (TWh) is equal to one billion kWh. To grasp this magnitude, relate it to the average 4-person household living in a house in Sweden consuming approximately 25 000 kWh annually for heating, electrical appliances and warm water.

Figure 1 presents carbon intensity in the power sector of the EU28 in 1995 and in 2015. In 1995, we observe a greater dispersion of carbon intensities, ranging from 22 gCO_2/kWh in Sweden to 1,094 gCO_2/kWh in Estonia. Almost all countries have improved their carbon intensity between 1995 to 2015. There are two main mechanisms by which a country can improve its carbon intensity: Firstly, by technological advancements improving the efficiency in electricity generation. This applies not only in generation from fossil fuels but also developments in the ability to extract energy from renewable energy sources such as solar and wind. Research and development in renewables is currently attracting an absolute majority of the attention and capital in this sector. Some important factors that determine the rate at which a country improves its carbon intensity include endowment of primary energy sources, past and current national policies and economic wealth.

Figure 2 presents the gross change in electricity generation from various energy sources[6] between 1995 and 2015. The EU power sectors' dependency on solid fuels (i.e. primarily coal), oil and nuclear has declined, with a reduced electricity generation from respective source of about 250, 170 and 40 TWh respectively. Gas as a source of electricity generation has increased the most by about 350 TWh. This is partly due to the reduction in gas prices following the developments in fracking[7] and shale gas. Note that gas has a lower carbon factor compared to solid fuels and oil[8], thus a switch from other fossil fuels to gas leads to a reduction in carbon intensity. Generation from renewable energy sources (i.e. hydro, wind and solar) have also increased, wind mostly so.

[6] Non-exclusive list of energy sources; change in geothermal, tidal and wave for example are negligible and excluded from the graph.

[7] The process of injecting liquids at high pressures into subterranean rocks, often shale, to cause micro cracks by which natural gases escape and can be extracted.

[8] This does not account for emissions in the extraction process of respective fuel, where for example fracking has been shown to produce excessive amounts of methane emissions.

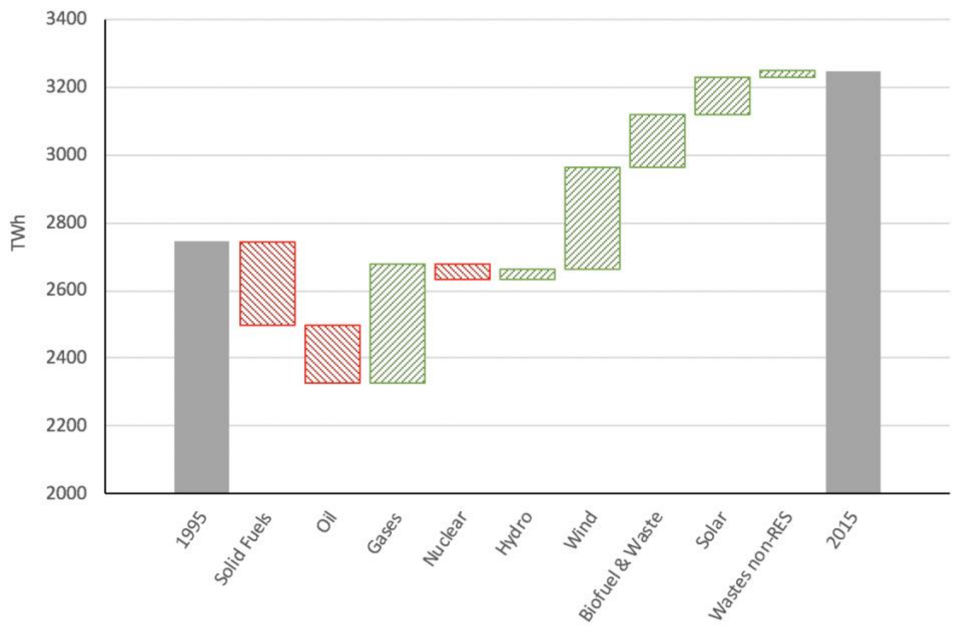

Figure 2: Gross change in energy sources in total gross electricity generation, 1995-2015.
Note: The solid bars correspond to the total EU electricity generation in 1995 and 2015 respectively. The dashed bars show the change in electricity generation from each energy source, where the red bars indicate a decrease and the green an increase. Source: Author's rendering of data from Eurostat (2018).

The European Commission also has a goal of integrating the European power market in order to produce a pan-European power market. This is considered to be most cost-effective way to secure a future power supply in the EU. Such a revision of the electricity market is believed to increase cross-border competition, improve energy flows and prepare the power grids for a higher share of intermittent renewable energy (European Commission [EC], 2019c). These are all considered factors which are vital in creating conditions for a sustainable and climate neutral power sector. An example of how such integration is occurring is the North Sea Link; a 1,400 MW power line connecting the UK with Norway and allowing the UK to buy electricity from the southern parts of Norway.

2.2. Climate Policy

The EU is committed to combating climate change, and climate policy is amongst the top priorities on both EU and national level. The EU climate debate was initiated following the IPCC[9] report in 1990, which was used in the preparation for the UNFCCC[10] negotiations later in 1990. In the same

[9] Intergovernmental Panel of Climate Change (IPCC).
[10] United Nations Framework Convention on Climate Change (UNFCCC).

year, EU leaders agreed on the first common EU climate goal; to stabilize the GHG emissions by 2000. Three main focus areas were identified: Reducing GHGs, promoting renewable energy sources and improving energy efficiency, all of which remain relevant areas in current EU climate policy. Note the distinction between an EU regulation – a binding legislation which must be applied across the EU; and an EU directive – a legislative act that sets out a goal for all EU countries to achieve, but implementation of achieving these goals are left to each state.

By 1997, various programmes (e.g. SAVE and ALTENER)[11] had been introduced but no reduction targets had yet been quantified. The Kyoto Protocol was adopted in 1997 and it identified developed countries (including the EU28) to have been historically responsible for the high GHG levels and to possess particular capabilities to combat climate change. As a consequence, binding reduction targets were assigned to EU countries. To fulfill these reduction targets, the European Commission launched the European Climate Change Programme (ECCP) in 2000 to examine and implement a range of policy instruments. One of the regulations implemented by the ECCP was to establish the EU Emission Trading System (EU ETS), in which emissions allowances are bought and traded. The EU ETS is a cap-and-trade system that regulates over 11,000 energy-intensive installations[12] in 31 countries[13] (EC, 2016). All regulated installations must surrender enough allowances to cover all of its annual emissions, otherwise fines are imposed. Generally, a sector is endowed a share of its allowances (via free allocation of allowances through a process known as grandfathering) and obliged to buy the excess demand at auction or in the secondary market. The price at which these allowances are bought in the secondary market is referred to as the carbon price. Since 2013, the power sector has been exempted from grandfathering and is required to buy all of its allowances. This is because the European Commission (EC) recognizes the EU power sector as a major contributor to EU's GHG emissions. Simultaneously, the EC motivates imposing more stringent policy targeted at power generators with the sector's high potential to lower emissions in cost efficient ways (EU, 2003) and its ability to pass-through increased costs from carbon abatement (EU, 2009) to end-users.

Beyond the reduction targets implemented by the Kyoto Protocol, the EU has set its own climate change mitigation targets. These include GHG reduction targets relative to 1990 emission levels of; 20% by 2020, 40% by 2030 and 80% by 2050. The 20% reduction by 2020 is part of the "20-20-20 by 2020 objective" in which the additional targets are a 20% increase in energy

[11] Specific Actions for Vigorous Energy Efficiency (SAVE) and ALTENER for promotion of renewable energy.
[12] These include power stations, industry, manufacturing and airlines operating within the EU.
[13] The EU28 plus Lichtenstein, Norway and Iceland.

efficiency as well as increasing renewables share of total EU electricity consumption of 20%. To meet these goals the *Climate and Energy Package.* The new package contained revisions to the EU ETS, and in 2008 the number of allowances in the EU ETS were reduced by 6,5% and have since 2013 been reduced annually by 1,74%. The intent is to gradually decrease the cap on emissions, thereby decreasing supply and increasing carbon prices to further incentivize installments to transition to fossil-free energy sources and limiting emissions of carbon dioxide.

To meet reduction targets set by the EU climate policy directives, most countries have implemented national climate policies. These national policies vary from subsidizing renewable energy sources by feed-in-tariffs, feed-in-premiums and investment aid to banning coal plants. For example, Germany has subsidized residential, commercial and centralized solar power with feed-in-tariffs and significant investment aid. As a result, the share of total electricity consumption from solar energy has gone from 0% to almost 7% in less than 20 years, placing Germany amongst the most solar power intense countries in the world. Consequently, this has contributed to an increased demand for solar components leading to a plunging price of solar components, something many EU countries have benefited from. Another example is Sweden, Poland and Romania, which have implemented quotas such that a minimum share of electricity supply has to be generated from renewable sources (Klessmann, 2014).

As part of the EU polluter pays principle, the EU has introduced an Energy Taxation directive[14] (EU, 2003), which encompass energy production and products for both transport and stationary purposes. Taxes are levied on fossil fuels, natural gas, coal, electricity and contains carbon dioxide taxes. The Energy Taxation directive outlines the structure and minimum tax levels; however, the implementation of the tax regimes is left to national governments.

3. Theoretical Framework

The following section introduces a detailed description of the main convergence concepts applied in this study. The empirical research on environmental convergence has grown extensively and two of the main convergence concepts that have emerged are *stochastic convergence* and *beta-convergence*. Beta-convergence can in turn be split into *absolute* and *conditional convergence.* If beta-convergence exists, one can also study the speed at which the country converges towards its path of carbon intensity.

[14] The energy taxation directive is formally known as the *Council Directive 2003/96/EC of 27 October 2003, restructuring the Community framework for the taxation of energy products and electricity.*

3.1. Stochastic Convergence

Carlino and Mills (1993) introduce the notion of *stochastic convergence.* If a set of economies exhibit stochastic convergence, it implies that shocks to carbon intensity in a country are only temporary and that carbon intensity will revert back to the sample mean. Econometrically, this means that if no unit root is detected when investigating univariate time-series, then the series are stationary and there is evidence of stochastic convergence. Carlino and Mills (1993) note that stochastic convergence is a relatively weak form of convergence. However, it is worthwhile investigating as it is a necessary, but not sufficient, condition for the beta-convergence.

3.2. Beta-Convergence

The concept of beta-convergence was initially introduced by Baumol (1986) and was first adopted in the context of environmental convergence by List and Gallet (1999). Beta-convergence occurs when a country with high carbon intensity decreases its carbon intensity faster relative to a country with low carbon intensity. This results in a so-called *Catch-up Effect* where countries converge in emission intensity in terms of growth rates.

The first type of beta-convergence, ***a*bsolute convergence** suggests that all countries converge toward the same path of carbon intensity, independent of country-specific characteristics[15] (Pettersson, Maddison, Acar & Söderholm, 2014). As illustrated in figure 3, countries A and B starts at different levels of carbon intensity, but A catch up with B and they converge towards a common path P.

On the other hand, there is **conditional convergence**, which allows for countries to converge to different paths of carbon intensity based on country-specific characteristics. As illustrated in figure 3, country C and country D converge toward individual paths P1 and P2. Conditional convergence is studied by making convergence conditional on exogenous variables believed to have an impact on the path of carbon intensity (Strazicich & List, 2003). Consequently, a set of countries will only converge to the same path conditional on them sharing similar characteristics, elsewise they converge to different paths of carbon intensity.

[15] Country characteristics such as for example wealth, endowment of natural resources or topographical conditions favoring for example hydro-generation as in the case of Sweden or Norway.

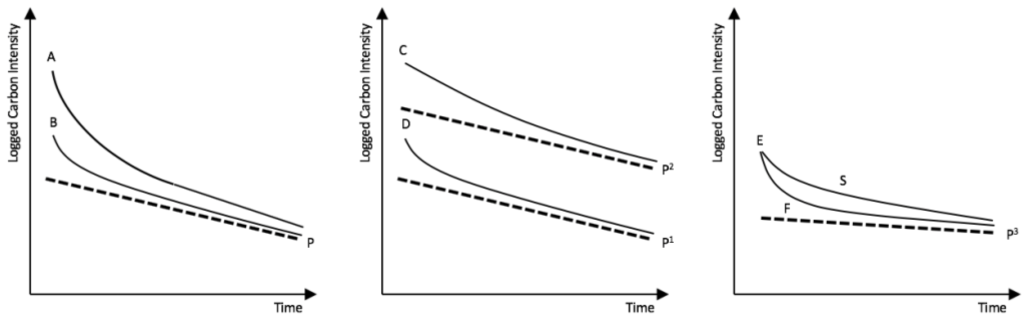

Figure 3. Illustration of convergence concepts.
Note: Absolute convergence (left), conditional convergence (middle) and speed of convergence (right).
Source: Author's illustration.

Based on these definitions of absolute and conditional convergence, it is not possible for a set of countries to exhibit absolute convergence (along the same path) whilst simultaneously converging conditionally (along individual paths), hence we define them as mutually exclusive.

Another concept that will be discussed is ***speed of convergence***. This refers to the speed at which a country converges towards the long run path; a slower speed implies that it takes longer, whilst a faster speed implies the opposite. In figure 3, the speed of convergence of country E indicates whether it converges faster (along F) or slower (along S). Note that the speed of convergence can also differ in conditional convergence, between countries exemplified by country C and D in the same figure.

The *Catch-up Theory* paints an appealing picture of growth theory, especially for the more carbon intensive countries. However, there are extensions to growth theory emphasizing that a country does not necessarily have to catch-up just because it is lagging behind. For one, Abramovitz' (1986) argues that in order for a country to catch up, it has to be capable of adopting the more efficient technology employed by better performing countries. This requires establishing relationships with more developed countries to enable such technological spill-over, something that is likely facilitated by the common membership of the EU. However, it is important to note that generation technologies might not be completely transferable across all states due to different geographical conditions and resource endowment. For example, the flat topography of The Netherlands provides limited benefits of adopting hydro-related technology from Sweden, but perhaps larger gains from advancements in wind power from Denmark.

The various convergence concepts have been applied to a wide array of research topics, and over the past 20 years they have also begun to gain popularity among environmental economists. A brief introduction and review of this body of research follows.

4. Literature Review

In the following section, we present an overview of the relevant literature of stochastic and beta-convergence. We highlight how our study places in the context of previous literature and what our main contributions are.

Environmental convergence is gaining popularity as a field of research. Some of the most commonly studied measures are carbon emissions per capita (Brock & Taylor, 2010; Jobert, Karanfil & Tykhonenko, 2010; Strazicich & List, 2003), carbon intensity of GDP (Hao, Liao & Wei, 2015) and carbon intensity of output (Brännlund, Lundgren & Söderholm, 2015). This study is most closely related to the field investigating carbon intensity of output, with electricity generation being the output good. Methodological approaches and conclusions can to a great extent be extrapolated and adopted from previous studies to our own, hence the following literature review will cover studies utilizing different measures.

4.1. Stochastic Convergence

Strazicich and List (2003) is one of the first papers to explicitly study stochastic convergence in the context of environmental economics and do so by studying emission per capita. As they define it, finding that the time-series are stationary suggests stochastic convergence. This means that shocks are only temporary and that the time-series reverts back to the sample mean. In general, results support stochastic convergence of emissions per capita among developed countries such as the OECD and the EU (e.g. Romero-Ávila, 2008; Westerlund & Basher, 2008; Strazicich & List, 2003), whilst the results for developing and global samples tend to suggest divergence.

Stochastic convergence is commonly tested for by taking a time-series approach and employing unit root tests. Researchers have not agreed on a preferred unit root test when investigating stochastic convergence, and standard procedure has become to employ a set of different unit root tests to ensure the robustness of the results. Conflicting results from various studies (see Strazicich and List (2003) vs Barassi, Cole and Elliott (2008)) indicate that the adoption of several unit root tests is warranted to ensure validity of the results. Commonly used tests include the augmented Dickey Fuller (ADF), the Cross-sectionally augmented ADF (Pesaran, 2007), the Hadri-LM (Hadri, 2000) and the Im, Pesaran and Shin (2003) unit root test.

Different properties of the respective tests refer to higher or lower power to reject the null hypothesis depending on the characteristics of the data. For example, the Hadri-LM unit root test tests the null of stationarity instead of the unit root null as the other tests do. This gives it a higher power to reject the null in the event that a series follows a non-stationary process. The use of different unit root tests is further discussed in section 6.1.

4.2. Beta-Convergence

In the empirical literature, there are differing definitions of absolute and conditional beta-convergence. Brock and Taylor (2010) and Jobert et al. (2010) claim to find both absolute and conditional convergence. Another set of literature defines absolute and conditional convergence as mutually exclusive; if a set of countries are conditionally converging to their individual paths, then cannot simultaneously converge toward a common path (Strazicich & List, 2003; Brännlund et al., 2015). In this thesis, we have adopted the latter interpretation of absolute and conditional convergence, as outlined in section 3.

Pettersson et al. (2014) reviewed the existing literature on carbon emissions per capita between different sets of countries and across different time spans. Whether one investigates carbon emissions per capita or utilizes an intensity measure, results tend to be sensitive to the set of countries investigated and time span studied. As Pettersson et al. (2014) and Strazicich and List (2003) argue, more encompassing samples (such as global samples), often show divergence in per capita emissions. This might be due to significant differences in levels of development, natural resource endowments, dysfunctional governmental regulatory bodies or industry structures. The fact that more similar subsets of countries, or subsets of industries, demonstrate convergence could also be explained by spillover effects and countries mimicking each other's environmental policies (Brännlund et al., 2015). Multiple studies investigate conditional convergence in the OECD (Brock & Taylor, 2010; Strazicich & List, 2003) and emissions per capita have been found to be conditional on for example the price of fuel as well as on average winter temperatures.

Jobert et al. (2010) study EU countries to find that they converge conditional on industry share of GDP, but that GDP per capita is not an important factor. They also find that there are differences in the speed of convergence at which each country moves towards the path of carbon intensity. They conclude that the decline in carbon emission per capita is due to the efforts of new EU member countries and not the efforts of older members. Jobert el al. (2010) argue that the disparities in the carbon emissions convergence path makes a clear case as to why a "*one size fits all*" climate policy for the EU countries is unfounded. Hao et al. (2015) study stochastic convergence of carbon intensity as a measure of carbon emissions relative to GDP in a panel dataset of 29 Chinese provinces from 1995 to 2011. They assert that beta-convergence suggests that policy makers should set a higher reduction target for provinces with high carbon intensities as they would reduce emissions even without an explicitly set reduction target. In their studied sample of Chinese provinces, they also find that richer provinces are more likely to exhibit rapid convergence than their poorer counterparts. This suggests that policy makers may have to differentiate not only based on a province's carbon intensity but also on their relative wealth.

One of the few papers that has studied convergence of carbon intensity relative to output is Brännlund et al. (2015). They investigate carbon emission intensity among 14 Swedish industries and find that the industries are converging. The results suggest that industries converge conditional on price of fossil fuels. Brännlund et al. (2015) do not find convergence across sectors to be conditional on them being regulated by the EU ETS. This is tested for by including a dummy variable taking on the value of 1 if more than 10% of the firms in a sector are regulated by the EU ETS.

Investigating environmental convergence presents several methodological and econometrical difficulties. Empirical results have been shown to not only be sensitive to the data and time period studied, but also to the choice of econometric approach (Pettersson et al., 2014). Within the beta-convergence literature, cross-sectional and panel data approaches are commonly adopted. List and Gallet (1999) and Strazicich and List (2003) are two of the novel papers in environmental economics to focus on beta-convergence and both utilize the cross-sectional approach originally proposed by Baumol (1986) to test for convergence in per capita emissions. The cross-sectional approach regresses the logged growth rate of emissions between the initial and current period on the initial level of emissions. In the cross-sectional approach, beta-convergence is determined by testing for significance of the coefficient on the initial logged per capita emissions level, and tests the hypothesis that countries converge depending on their initial levels of intensity.

Islam (1995) proposes a panel data approach to test for beta-convergence. Using a fixed effects model is desirable as it allows us to control for unobserved country or year fixed effects. This approach is adopted by Van (2005) and Brännlund et al. (2014). When utilizing a panel data approach, beta-convergence[16] is determined by testing for significance of the coefficient on the independent variables of interest[17]. In the panel-data approach, a negative and significant beta coefficient would indicate convergence to a common path of carbon intensity; countries with higher carbon intensities would, on average, reduce their carbon intensity more than countries with a lower carbon intensity. In addition, conditional beta-convergence is investigated by

[16] This is often referred to as the beta-coefficient, hence the notion of beta-convergence.
[17] Brännlund et al (2014) utilizes lagged carbon intensity as the main variable of interest while Van (2005) investigates lagged carbon emissions per capita.

including a set of exogenous control variables capturing heterogeneity in country-specific characteristics. This means that the null of absolute convergence is expressed as: $H_0\colon \beta < 0\ and\ \gamma = 0$, with an alternative hypothesis of conditional convergence specified as: $H_1\colon \beta < 0\ and\ \gamma \neq 0$, where γ is a vector of the control variables coefficients.

Both the cross-sectional and panel data approach has been criticized to produce biased results due to the independent variables possibly being correlated with past and current realizations of the error term (Baltalgi, 2008). Using an exogenous Instrumental Variable (IV) or the Generalized Methods of Moments (GMM) have been argued to be an alternative approach that resolves such issues (Arellano & Bond, 1991; Blundell & Bond, 1998). Jobert et al. (2010) applies yet another approach; the Bayesian shrinkage estimator. They argue that the Bayesian shrinkage estimator lies between the extreme assumptions of cross-sectional homogeneity and heterogeneity of the slope coefficients made by cross-sectional or panel data approaches respectively. They describe it as “a weighted average of the overall pooled estimate and the separate time series estimates based on each cross-section” (Jobert et al. 2010).

In summary, previous research uses a variety of techniques to investigate environmental convergence across countries, or sectors within a country. Carbon emissions per capita or emission intensity by GDP are the most commonly analyzed variables.

4.3. Placement in Literature

With a foundation in economic theory and previous research, our contributions are summarized as follows:

- We extend the state of knowledge regarding environmental convergence by investigating carbon intensity in the EU power sector. This cross-country sectoral approach is novel within convergence studies and provides an important step in understanding the evolution of the EU power sector.

- Our findings provide a useful tool for EU and national policy makers in the design and evaluation of climate policies for the power sector.

- We evaluate how the path of carbon intensity is influenced by EU membership, energy taxes intensity and GDP per capita. Additionally, we provide insight into the role of fossil fuel prices and carbon price fluctuations impact speed of convergence.

5. Data

In this following section, we describe the main carbon intensity variable and five other variables that will be used in the study. Each measure is explained, and their respective data source is accounted for. A motivation and discussion of each variable follows in section 6. The section ends with some descriptive statistics of the data employed.

5.1. Description of Variables and Data

The group of countries investigated in this study is the current set of 28 EU member states and the time period we study is between 1995 and 2015. (See appendix A for a full list of countries studied)

Carbon Intensity (I). Carbon intensity is a measure of the amount of greenhouse gases (GHG) released as a by-product of electricity generation. As such, we define carbon intensity as the ratio of carbon emissions produced in electricity generation over total gross electricity generated:

$$I_{it} = \frac{Carbon\ Emissions_{it}}{Electricity\ Generated_{it}} = \frac{g\ CO_{2\,it}}{kWh_{it}} \tag{1}$$

where i refers to a country and t to the year of the observation. Carbon emissions is the GHG emissions measured in grams of carbon equivalents (gCO_2) and electricity is measured in kilowatt hours (kWh). Data for carbon intensity is obtained from the International Energy Agency (IEA, 2019a)[18]. The IEA uses a bottom up Tier 1[19] approach to estimate carbon emissions from the power sector, as suggested by the IPCC (2006). The carbon emissions attributed to electricity generation are estimated by multiplying the fuel inputs by their respective carbon factor (see Appendix B). The IEA obtain the quantity of electricity generated from national records and these encompass all electricity generated in a country.

EU Membership (EU). We create an EU dummy variable capturing whether a country is an EU member or not in any given year. It takes the value zero for years when a country is not an

[18] Observations for carbon intensity for Luxembourg 1995 to 1997 are missing. Calculations were made based on the total carbon emissions from electricity and heat divided by total electricity generated. The emissions for the electricity sector were isolated by multiplying total emissions from electricity and heat (the numerator) by the average factor of CO_2 emissions produced by the electricity compared to heat sector in Luxembourg from 1998 to 2015.

[19] See Appendix B for detail on the Tier 1 approach.

EU member and the value of one when it is. It is based on a country's year of entry into the EU as reported by the European Commission (2019b), see Appendix A.

GDP per capita (GDPpc). The data of GDP per capita for the EU28 are collected from the World Bank (2019). It encompasses the sum of gross domestic production each year, divided by the midyear population. The data is in constant 2010 U.S. dollars. It is first converted from national currencies into euros and then converted into U.S. dollars. For GDP per capita data prior to the introduction of the euro in 1999[20], all historical values are irrevocably translated to euro using a fixed euro conversion rate[21]. The GDP data is adjusted using the European Union Harmonized Index Consumer Price (HICP), a consumer price index representing the developments in the prices of all goods and services in the EU (European Central Bank [ECB], 2019).

Energy tax intensity (ETI). The ETI variable is computed by dividing total *energy tax revenue*[22] by the total *carbon emissions from the energy sector*. ETI is defined as follows:

$$ETI_{it} = \frac{energy\ tax\ revenue_{it}(€)}{carbon\ emissions\ energy\ sector(kg\ CO2_{it})} \tag{2}$$

where i and t refers to country i and year t. The unit on ETI is € / kg CO_2. The numerator is the energy tax revenue, taken from Eurostat (2019) and is available from 1995 to 2015. Energy tax revenue encompasses taxes paid to national governments by all sectors of the economy, including producers and households. The tax base includes taxes imposed on energy production and on energy products used for transport and stationary purposes. Importantly, revenues from carbon emission allowances as part of the EU ETS are also included in energy tax revenues. The denominator of total carbon emissions from the energy sector[23] is estimated using a Tier 1 approach and adopts IPCC sectoral definition for the energy sector (IEA, 2018). The data was obtained from the IEA (2019b) database. The main reason we develop an intensity measure is for cross-country comparability. One should note that the definitions of the energy sectors adopted

[20] With the exception of Greece who adopted the euro in 2001.
[21] The approach chosen by the OECD to compute pre-1999 GDP is based on a (moving) weighted average of a country's value change in GDP in USD. This approach excludes exchange rate effects and therefore also price movements. See Schreyer and Suyker (2002) for further details.
[22] Note that the EU definition of the energy sector is not equivalent to a tax on the power / electricity generation sector. The energy sector encompasses energy products for transport, stationary purposes (including the carbon content of fuels and emissions of greenhouse gases).
[23] Carbon emissions from energy sector is defined by the IPCC as carbon dioxide released from fuel combustion activity by the energy industry, manufacturing industry, construction, transport and other sectors. (IPCC, 2006).

by the EU and the IPCC are different. Hence the ETI measure should not be understood as the tax rate on carbon emissions, but as a proxy for a country's commitment to utilizing market measures to combat climate change (see section 6.3.1.2 for more details).

Carbon Price (CP). Carbon price is the explicit price paid for an EU ETS emission allowance. A power generator in the EU is required to supply one such allowance for every tonne of CO_2 equivalent emissions produced. Data on daily carbon prices is collected from the EEA (2019) and the annual average of the daily settlement prices is computed. The unit of measure is 2015 euro per allowance (€/EUA) after deflation using the HICP. Prior to the introduction of the EU ETS, there was no explicit carbon price and hence, we set the carbon price equal to zero for the period 1995-2005.

Weighted Price of Fossil Fuels (WPF). WPF is defined as the price of oil, gas and coal, weighted by their respective share in total gross electricity generation of the EU[24]:

$$WPF_t = \sum_{f=1}^{F} \frac{e_{ft}}{E_t} * P_{ft} \tag{3}$$

Where the subscripts t and f denote the year and type of fossil fuel respectively. e_{ft} and E_t is the electricity generated from fuel f in year t and the total electricity generated in period t respectively. Finally, P_{ft} is the price of fuel f in period t. To create WPF, data on fossil fuel prices are gathered from *British Petroleum* (2019). The price of oil is proxied by the price of Brent Oil, a benchmark oil price used worldwide. The price of coal is equated with the *Northwest Europe Coal Marker Price,* and gas price is proxied by the *Average Import German Price*. For comparability, all fuel prices are presented in 2015 US dollar per megawatt hour ($/MWh). Prices are adjusted for inflation using the EU HICP. Electricity generation from each respective fuel source as well as total EU electricity generation is collected from Eurostat (2018).

5.2. Descriptive Statistics

Table 1 presents the descriptive statistics of carbon intensity, GDP per capita and energy tax intensity. From 1995 to 2015, the average carbon intensity in electricity generation, decreased 32,8% from 530 gCO_2/kWh to 356 gCO_2/kWh. The standard deviations indicate a large spread across the member countries. We note a large variation within the EU28 with regard to GDP per capita and energy tax intensity. Comparing 1995 to 2015, the mean and median GDP per capita and energy tax intensity increased while carbon intensity decreased. With regard to energy tax

[24] EU common prices are used in this study. A discussion of this follows in section 6.2.1.3.

intensity, there are no data available for Croatia (prior to 2003), Hungary (prior to 2004) and Cyprus (prior to 2007).

Table 1. Descriptive statistics

	Carbon Intensity (gC02/kWh)		GDP per capita (2010 USD)		Energy Tax Intensity (€ / kg CO2)	
	1995	**2015**	**1995**	**2015**	**1995**	**2015**
Average	530.24	355.96	16,298	33,730	32.54	86.26
Standard deviation	293.66	228.07	11,573	21,939	24.98	45.71
Max	1,094.09	1,025.51	52,300	107,235	85.74	225.32
Median	556.01	316.52	15,074	26,608	32.91	77.60
Min	22.18	10.78	2,645	7,612	1.02	26.45
# of observations	28	28	28	28	25	28

Note: The constant 2010 USD and € are deflated with an EU HICP with 2015=100.

The time-series for carbon intensity (figure 4) and in time series of weighted price of fossil fuels and carbon price (figure 5) are presented above. Studying carbon intensity in figure 4 allows for some preliminary observations. Firstly, we observe a general downward trend, which is consistent with the reduced average carbon intensity (indicated by dashed blue line). However, two countries display a slight increase in carbon intensity, namely Lithuania and Latvia. From figure 5, we notice considerable variation in both carbon price and weighted price of fossil fuels over the study period. For carbon price, it was the highest at 20,24€ when it was first introduced in 2006 before falling to almost 0€ in 2008 during the financial crisis.

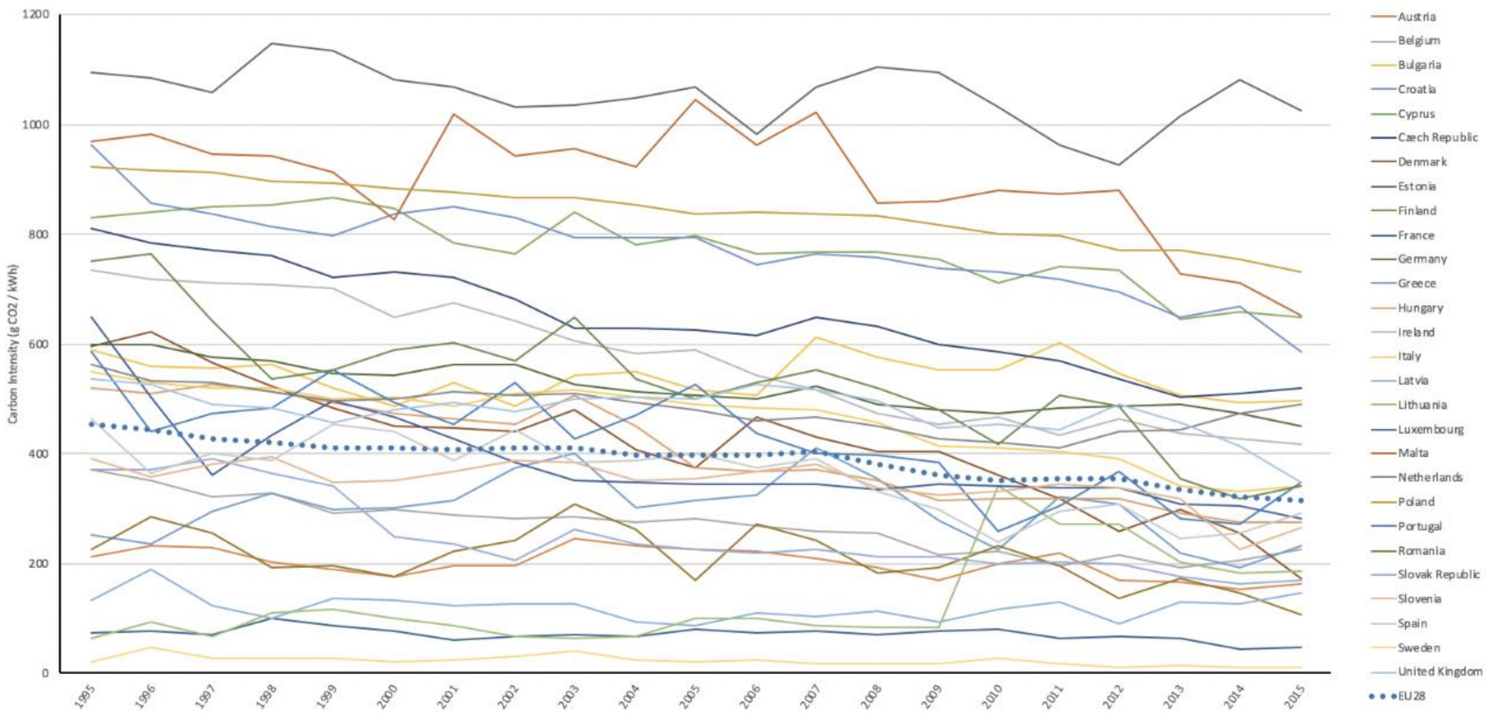

Figure 4. Carbon intensity (gCO_2/kWh) for each country as well as the EU28 average from 1995 to 2015. Source: Author's renderings of data from IEA (2019a)

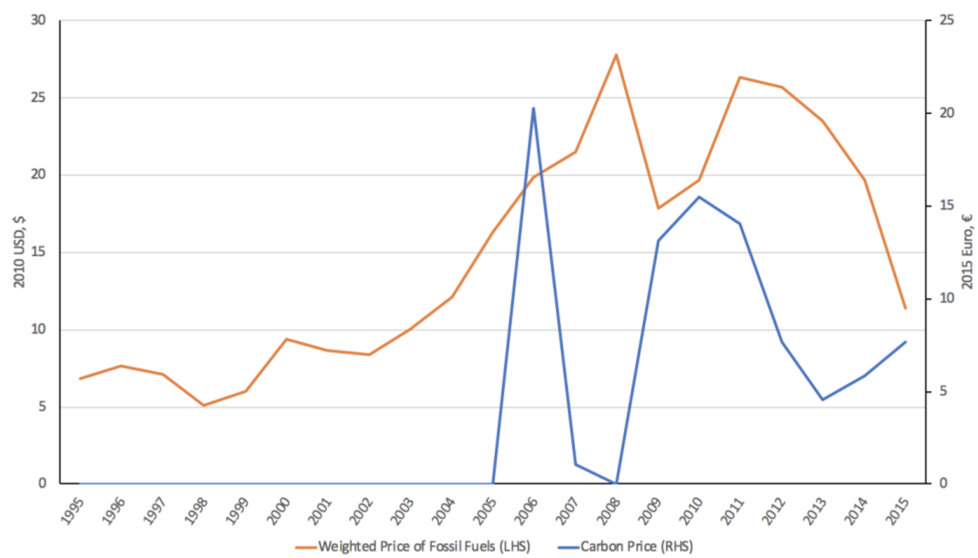

Figure 5. Weighted price of fossil fuels (WPF) and Carbon price (CP)
Note: WPF is in 2010 USD on the left axis and CP in 2015 Euro on the right axis. Both are deflated using HICP. Source: Author's renderings of data from BP (2018) and EEA (2019).

The time series for our other variables: carbon price, energy tax intensity and GDP per capita are illustrated in Appendix C.

6. Empirical Framework

In the following section, we motivate why it is relevant to investigate carbon intensity, outline the empirical approach adopted to investigate stochastic convergence, beta-convergence and the speed of convergence. Stochastic convergence is a necessary condition for beta-convergence; hence we start by introducing the empirical approach utilized to study stochastic convergence and then move on to beta-convergence.

6.1. Carbon Intensity

This study concerns carbon intensity in electricity generation in the EU28. Carbon intensity is a suitable measure when investigating the supply side of electricity as it is a fair basis of comparison across countries and provides an actionable standard for power generators to work toward. Given the important role of the power sector in meeting international emission reduction targets and the direct measure of a negative by-product (carbon emissions) from a desirable output (electricity), it is interesting to study the time path of carbon intensity in electricity production. Further, with the continued integration of the EU power sector, it is important to study convergence of carbon intensity as the presence of divergence could potentially lead to substantial transfers through trading of EU ETS emission allowances and relocation of power generation.

6.2. Stochastic Convergence

We investigate stochastic convergence of carbon intensity of the EU28 based on univariate time-series analysis by adopting the approach proposed by Carlino and Mills (2013). We create a *yearly relative carbon intensity* variable (RI) by taking the logarithm of the ratio of each country's carbon intensity relative to the EU average as follows:

$$RI_{it} = ln(\frac{I_{it}}{\overline{I_t}}) \tag{4}$$

where RI_{it} refers to the carbon intensity of country i in year t, and $\overline{I_t}$ is the EU28 average carbon intensity in year t. A unit root in the above log ratio would indicate a non-stationary time-series and that shocks to carbon intensity are permanent. Rejection of a unit root would suggest stationarity and stochastic convergence (Strazicich & List, 2003). Note that creating the relative carbon intensity variable also serves to demean the data for common time effects across the countries, such as a global shock to fuel supply or prices.

Within the stochastic convergence literature, there is no agreement on which the ideal unit root tests to apply is (Hao et al., 2015). Hence, in line with what has become standard practice, we present three unit root tests with different asymptotic assumptions and null hypothesis. Firstly, in line with current convergence literature, the IPS panel unit root test presented by Im, Pesaran and Shin (2002) is utilized. The assumption of cross-sectional independence in the IPS test has received critiqued as being unrealistic as many studies find that macro time-series tend to exhibit significant cross-sectional correlation (Baltagi, 2008). Failing to account for cross-sectional dependence would result in considerably biased results. Cross sectional-dependance between the EU28 is likely due to the high degree of integration, common legislative framework and significant trade-intensity. This potentially leads to a degree of innovation and technological spread that could in theory cause a correlation between development of the carbon intensity of respective country's power sector. Hence, we employ the *Cross-sectionally augmented ADF (CADF)* unit root test suggested by Pesaran (2007) which is able to account for cross-sectional dependance.

Both the IPS and CADF consider the null hypothesis of a unit root. This is the standard approach to test for stationarity in a panel, but as Hadri (2000) asserts, these standard unit root tests lack power to accurately test for relevant alternative hypotheses. These tests sometimes erroneously fail to reject the unit root null for many economic series that are actually stationary processes. With this in mind, as a complement to the IPS and CADF unit root tests, we employ the Hadri Lagrange Multiplier (Hadri-LM)(Hadri, 2000) test to investigate the null that time-series are stationary versus the alternative that at least one time-series contains a unit root. Utilizing the IPS and CADF unit root tests limits us to test whether at least one time-series contains a unit root whilst the Hadri-LM test allows us to investigate whether all time-series are stationary and thereby whether the prerequisites for beta-convergence are fulfilled.

6.2.1. Im, Pesaran and Shin (IPS) Panel Unit Root Test

The IPS (Im et al., 2003) pools separate time-series estimates and tests the pooled value for a unit root, this results in a higher power to detect stationarity (Chatfield, 2016).

As a first step, the IPS performs an Augmented Dickey Fuller (ADF) test on each country's RI time-series and then executes a testing procedure based on an average of each country's ADF test statistics. To correct for possible higher-order serial correlation we include the first-difference lagged terms (i.e. augmentations), $\Delta RI_{i,t-j}$. The number of augmented terms is allowed to vary across the sampled countries and the optimal number of augmented terms is determined by employing a *general-to-specific* approach as suggested by Philips and Perron (1988) (see section table 10a in appendix F). For each time-series, the ADF test takes the form:

$$\Delta RI_{it} = \alpha_i + \beta_i RI_{i,t-1} + \theta_i t + \sum_{j=1}^{\rho_i} \gamma_{ij} \; \Delta RI_{i,t-j} + \varepsilon_{it} \tag{5}$$

where ΔRI_{it}=$RI_{it} - RI_{i,t-1}$ is the difference in relative carbon intensity in two subsequent periods, α_i is the country-specific constant term and $\theta_i t$ is a linear time trend. β_i is the coefficient of interest and tests for the presence of a unit root in the specific time-series, ρ_i is the number of augmentations for country i and $\gamma_{ij}$is the estimated coefficient for each of the first-differenced augmentations. Lastly, ε_{it} is the contemporaneous error term assumed to be independently and identically distributed with a mean of zero and finite variance. After conducting the ADF regression test for each country, the IPS statistic is calculated as:

$$IPS\ statistic \;=\; \sqrt{N}\,\frac{\bar{t}_{NT} - E(t_{iT}|\beta_i = 0)}{\sqrt{Var(t_{iT}|\beta_i = 0)}} \tag{6}$$

$$\bar{t}_{NT} = N^{-1} \sum_{i=1}^{N} t_{iT} \tag{7}$$

where N refers to the number of countries and T is the number of years. $\bar{t}$ is the average t-statistic of estimates of β_i across all countries and periods and E is the expectation operator. IPS test report the critical values of $E(t_{iT} \,|\, \beta_i = 0)$ and $Var(t_{iT} \,|\, \beta_i = 0)$ for different values of T and k, where T is the number of years, and k is the number of augmented terms included in each equation. The expectation, variances and critical values for t-statistics can be found in Appendix D. The hypotheses tested in the IPS panel unit root is:

$$H_0 \colon \beta_i = 0, for\ all\ i \tag{8}$$

$$H_1 \colon \beta_i < 0\ for\ i\ = 1,2, \ldots, N_1\ and\ \beta_i = 0\ for\ i = N_1 + 1, N_1 + 2, \ldots, N \tag{9}$$

Failure to reject the unit root null hypothesis would indicate that carbon intensity of all individual time-series resembles a non-stationary series with shocks having permanent effects. Conversely, rejecting the null would suggests that at least one country's carbon intensity time-series resembles a stationary series.

6.2.2. Cross-sectionally Augmented ADF Panel Unit Root Test

To account for cross-sectional dependence, we proceed with performing the *Cross-sectionally augmented ADF (CADF) panel* unit root test suggested by Pesaran (2007). This approach augments the traditional ADF unit root test with cross-sectional averages of lagged levels and first-differences of the individual time-series. These terms are included in the CADF to account for cross-sectional dependence. The CADF is a single common factor model, which imposes the restriction that the countries possess one common unobserved factor[25]. The test is based on a dynamic linear heterogeneous panel data model is specified as follows:

$$RI_{it} = (1 - \phi_i)u_i + \phi_i RI_{i,t-1} + u_{it} \tag{10}$$

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \tag{11}$$

Where $(1 - \phi_i)u_i$ is a country-specific intercept and u_{it} is the error term containing a common factor component capturing the cross-sectional dependence. f_t refers to the unobserved common factor and ε_{it} is the idiosyncratic error term. This means that f_t captures the cross-sectional dependance. By first-differencing RI_{it}, we can combine and express equations 10 and 11 into the expression:

$$\Delta RI_{it} = \alpha_i + \beta_i RI_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \tag{12}$$

Where $\alpha_i = (1 - \phi_i)u_i$, $\beta_i = -(1 - \phi_i)$ and $\Delta RI_{it} = RI_{it} - RI_{i,t-1}$.The unit root null hypothesis (where $\phi_i = 1$) and alternative hypothesis test are identical to the IPS and as follows:

$$H_0: \beta_i = 0 \; for \; all \; i \tag{13}$$

$$H_1: \beta_i < 0 \; for \; i = 1,2,\dots,N_1 \; and \; \beta_i = 0 \; for \; i = N_1 + 1, N_1 + 2, \dots, N \tag{14}$$

The simple CADF regression is as follows:

[25]In this study, we do not extend our analysis to encompasses several factors for simplicity reasons. We propose that future research investigate stochastic convergence with unit root tests that account for multiple factors.

$$\Delta RI_{it} = \alpha_i + \beta_i RI_{i,t-1} + d_0 \overline{RI}_{t-1} + d_1 \Delta\overline{RI}_t + \varepsilon_{it} \tag{15}$$

where $\overline{RI}_{t-1}$ refers to the lagged cross-sectional average at time t-1 of all N observations and $\Delta\overline{RI}_t$ refers to the difference in averages between time t and t-1. These are included to capture the effects of cross-sectional dependance. Pesaran (2007) argues that including these terms sufficiently proxy the unobserved common factor (f_t).

In order to address potential serial correlation in the error term or in the common factor, the regression is augmented with lagged first differences of RI_{it} and $\overline{RI}_t$ where the degree of augmentation is chosen by the SBC (see table 10b in Appendix F). This yields the regressions:

$$\Delta RI_{it} = \alpha_i + \beta_i RI_{i,t-1} + d_0 \overline{RI}_{t-1} + \sum_{j=0}^{p} d_{j+1}\, \Delta\overline{RI}_{t-j} + \sum_{k=1}^{p} c_k\, \Delta RI_{i,t-k} + \varepsilon_{it} \tag{16}$$

From the augmented regression, the t-statistic of β_i for each country is referred to as the $CADF_i$. The t-statistic based on this regression should be devoid of the unobserved common factor (f_t) and therefore free of cross-sectional dependence. $CADF_i$ is then averaged in order to obtain the CIPS statistic:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i \tag{17}$$

The resulting CIPS-statistics is in turn compared to the critical values in Appendix D. The null hypothesis is that all series are non-stationary while the alternative hypothesis suggests that at least one series is stationary.

6.2.3. Hadri Lagrange-Multiplier Panel Unit Root Test

Hadri (2000) proposes a residual-based Lagrange Multiplier (LM) test with a null hypothesis of stationarity. The alternative hypothesis is that at least one time-series follow a unit root process, and thus is non-stationary. Employing the Hadri-LM test brings about two benefits. First, the test has more power to reject the null in the event that the series resemble a non-stationary process. Second, it allows us to investigate whether all time-series are stationary and thereby fulfilling the prerequisites for beta-convergence.

When applying the Hadri-LM test in the context of stochastic convergence, failure to reject the null hypothesis would mean that carbon intensity for all countries resembles a stationary series. Rejection of the null would indicate that at least one country has a unit root and that there is divergence over time. In accordance with Hadri (2000), we consider the following model:

$$RI_{it} = x_{it} + \beta_i t + \varepsilon_{it} \tag{18}$$

$$x_{it} = x_{i,t-1} + \mu_{it} \tag{19}$$

Consider that x_{it} is a random walk process and both ε_{it} and μ_{it} are idiosyncratic error terms following a normal distribution, $N \sim (0, \sigma^2)$. Using backward substitution, we find:

$$RI_{it} = x_{i0} + \beta_i t + \sum_{s=1}^{t} \mu_{is} + \varepsilon_{it} \tag{20}$$

$$Let\ v_{it} = \sum_{s=1}^{t} \mu_{is} + \varepsilon_{it} \tag{21}$$

The Hadri-LM test considers the following hypothesis:

$$H_0 : \frac{\sigma_\mu^2}{\sigma_\epsilon^2} = 0 \tag{22}$$

$$H_1 : \frac{\sigma_\mu^2}{\sigma_\epsilon^2} > 0 \tag{23}$$

Under the stationary null hypothesis, σ_μ^2 (the variance of μ) is zero indicating that μ is constant over time. This means that $\varepsilon_{it} = v_{it}$ and RI_{it} would follow a trend stationary process.

The LM-statistic accounts for cross-sectional dependance and is given by:

$$\widehat{LM} = N^{-1} \sum_{i=1}^{N} \left(T^{-2} \sum_{t=1}^{T} \frac{S_{i\,t}^2}{\sigma_{\epsilon,i}^2} \right) \tag{24}$$

where S_{it} is the partial sum of the residuals and $\sigma_{\epsilon,i}^2$ the variance of the error term ϵ_i defined as:

$$S_{it} = \sum_{j=1}^{t} \hat{\epsilon}_{ij} \tag{25}$$

$$\hat{\sigma}_{\epsilon,i}^2 = \sum_{t=1}^{T} \hat{\epsilon}_{it} \tag{26}$$

As proposed in Hadri (2000), the test-statistic is given by $Z = \sqrt{N}(\widehat{LM} - \xi_1) / \varsigma$, where ξ_1 is $\frac{1}{6}$ and ς is $\frac{11}{6300}$. Large positive values of the Z-statistic would lend support to rejecting the null. The power of the test as proposed by Hadri (2000) is presented in Appendix D.

6.2.4. Selection of Lag Length

Accurately determining the number of augmented terms for each country is essential to avoid loss of power in the IPS and CADF panel unit root test. Including unnecessary lags reduces the power of the test and including too few lags inhibits the regression's ability to capture the error process of the coefficient and leads to inaccurate estimation of the standard errors (Chatfield, 2016).

To identify the optimal number of lags for each country's time series, we employ the Schwarz Bayesian Criteria (SBC). The SBC assists us in selecting the most suitable model out of the different number of lags tested. An alternative selection criterion would have been the Akaike Information Criteria (AIC). However, we argue that the SBC is a more appropriate measure as we ensure that a more parsimonious (restrictive) model is selected. This reduces the risk of overfitting the model due to the inclusion of unnecessary lags. In addition, using only the minimal number of lags does not reduce the degrees of freedom of the model more than necessary and thereby the power of the unit root tests will not be lowered.

Table 2. Overview of tests

	IPS	CADF	Hadri-LM
Country-specific convergence coefficient	✓	✓	✓
Cross-sectional dependance	✗	✓	✓
Unit root null hypothesis	✓	✓	✗

Additionally, we utilize the Ljung-Box-Q test to verify that the residuals of the models selected by the SBC mimic the properties of a white noise process. In the event that this is not the case, we employ a specific-to-general method by adding further augmentations to the models and iterate with the Ljung-Box-Q test until the residuals resembles a white noise process. In this manner, we ensure that all the serial correlation in the data has been captured within each country-specific model. We follow Hyndman and Athanasopoulos (2013) to ensure that we choose a sufficiently large number of lags in the Ljung-Box-Q test to capture any troublesome correlations. They suggest a rule-of-thumb to use lags=min(10, T/5), which in our case is lags=min(10, 5)[26]. We present the results of these tests in table 10a-b in Appendix F.

6.3. Beta-Convergence

To investigate beta-convergence, we construct a Change in Carbon Intensity (CCI) variable tracking the change in carbon intensity by taking the logarithm of the ratio of each country's carbon intensity in period t and t-1 as follows:

$$CCI_{it} = ln(\frac{I_{it}}{I_{i,t-1}}) \tag{27}$$

where I_{it} refers to the carbon intensity of country i at time t. If the CCI_{it} is greater than zero, it suggests that the country's power sector is becoming more carbon intensive and a CCI_{it} smaller than zero implies that the country's power sector is becoming less carbon intensive.

6.3.1. Empirical Approach

In investigating beta-convergence, we adopt the panel-data framework suggested by Islam (1995). Various specifications of the model will be estimated, including permutations of control variables that will be introduced successively. The main model is expressed as:

$$CCI_{it} = ln(\frac{I_{it}}{I_{i,t-1}}) = \alpha + \beta ln(I_{i,t-1}) + \gamma \boldsymbol{X}_{it} + \lambda \boldsymbol{Z_{it}} + \eta_t + \delta_i + v_{it} \tag{28}$$

where CCI_{it} is as defined in equation 27. $I_{i,t-1}$ is the lagged carbon intensity and the β-coefficient is the main coefficient of interest in determining beta-convergence. $\boldsymbol{X}_{it}$ is a vector of country-specific control variables that will be used in investigating conditional convergence and $\boldsymbol{Z_{it}}$ is a vector of interaction terms used to allow for cross-country heterogeneity in the speed of convergence. η_t and δ_i are year and country fixed effects respectively.

Equation 28 is estimated on the panel dataset of the EU28 from 1995 to 2015. We investigate whether convergence is conditional on EU membership, GDP per capita and the energy tax intensity in a country. Further, the weighted price of fossil fuels and the carbon price of emission allowances is interacted with the lagged carbon intensity to test if the speed of

[26] T=21 hence T/5=4,2 but we round up and use 5 lags to ensure we capture all serial correlation.

convergence varies between countries. A motivation and discussion of the choice of variables is presented in section 6.3.1.1.

A two-way fixed effects estimation with country and time fixed effects (FE) is used to reduce potential bias from omitted or unobservable variables. The time FE capture variation that is constant across countries in any given period, but changes over time. An example of such variation is EU common policy or carbon price of emission allowances. The country FE accounts for variation between countries that remain constant within a country over time. This could be differences in geographical or topographical conditions for solar, hydro or wind power.

The standard errors are clustered on a country level and robust for heteroskedasticity in all the estimated specifications. Clustered standard errors are used as we expect there to be within country correlation of the standard errors over time. This choice of standard errors is further discussed in section 6.4.2.

6.3.1.1. Basic Model

In investigating beta-convergence, the basic model estimates the lagged carbon intensity on the change of carbon intensity between two consecutive periods. This approach is suggested by Islam (1995) and adopted by Brännlund et al. (2015) to study carbon intensity. To test for beta-convergence, the null hypothesis of no beta-convergence is tested against the alternative hypothesis of beta-convergence[27]:

$$H_0: \beta = 0 \tag{29}$$

$$H_1: \beta < 0 \tag{30}$$

Hence, a negative and significant beta-coefficient suggests that a country with a higher carbon intensity in one period is expected to exhibit a greater improvement in carbon intensity in the following period.

6.3.1.2. Conditional Models

We proceed to investigate whether the EU28 converge toward a common path of carbon intensity or if they converge towards individual paths of carbon intensity conditional on country-specific characteristics. We do this by appending the basic model with permutations of control variables.

[27] Note that we are performing a two-sided hypothesis test and not a one-sided hypothesis test. It is rather the conditions for beta-convergence that is one-sided.

If a control is found to be significant, it suggests that it has an impact on the path of carbon intensity to which a country converges. The null hypothesis of absolute convergence is tested against the alternative of conditional convergence as follows:

$$H_0: \beta < 0 \; and \; \gamma = 0 \tag{31}$$

$$H_1: \beta < 0 \; and \; \gamma \neq 0 \tag{32}$$

where γ is the vector of coefficients on the control variables included: EU Membership, GDP Per Capita and energy tax intensity. The selection of control variables is key when investigating conditional convergence and the inclusion of different control variables are likely to impact the estimation results (Jobert et al., 2010). We motivate our choice of control variables as follows:

EU Membership (EU). Membership in the EU requires a country to adhere to EU environmental regulation and policy. Given the strict policies regulating the power sector, it is feasible to hypothesize that joining the EU applies pressure on producers of GHG emissions to reduce emissions as implementing the polluter pays principle is part of EU environmental policy. To this end, we introduce a dummy EU variable, taking the value zero for years when a country is not an EU member and the value one when it is.

GDP per capita (GDPpc). A standard measure of wealth is GDP per capita and it has repeatedly been considered in convergence studies (Hao et al., 2015; Jobert et al., 2010). We hypothesize that wealth is an important determinant of a country's path of carbon intensity. Therefore, we include a measure of GDP per capita to investigate if carbon intensity in the EU power sector converges to different paths conditional on wealth.

Energy tax intensity (ETI). Finally, as a proxy for international climate commitment, an energy tax intensity (ETI) measure is included. Such a proxy is appropriate as taxes are one of the premier market-based policy tools used to influence the behavior of both producers and consumers (Eurostat, 2019). Energy taxes were implemented in response to the EU (2003) Energy Taxation directive regarding the taxation of energy products and electricity. As Eurostat (2019) clarifies, the energy tax base is on anything that has a proven negative impact on the environment. The Energy Taxation directive only sets minimum levels of taxation, member states are free to set their national rates in line with their target objectives, hence there is significant variation in how individual regimes employ energy taxes. We argue that national stringency of energy taxes is a suitable indicator of a country's national climate commitment. For example, Sweden has one of the highest energy and carbon taxes in the world, which Ackva and Hoppe

(2018) argues has been highly effective in reducing emissions and has contributed strongly to Sweden's climate leadership.

6.3.1.3. Speed Models

Lastly, we control for the carbon price of emission allowances in the EU ETS and the weighted price of fossil fuels to investigate if these have an effect on the speed of convergence in the EU28. In the basic and conditional models, the speed of convergence is assumed to be homogenous as the beta-coefficient is the same for all countries. In the speed models, we allow speed of convergence to vary by interacting the carbon price and weighted price of fossil fuel variables with lagged carbon intensity. The null of homogenous speed of convergence is tested against the alternative of differences in speed of convergence. The tested hypothesis is:

$$H_0: \beta < 0 \ and \ \lambda = 0 \tag{33}$$

$$H_1: \beta < 0 \ and \ \lambda \neq 0 \tag{34}$$

where λ is the vector of coefficients on the interaction terms. The inclusion of respective interaction term is motivated as follows:

Weighted Price of Fossil Fuels (WPF). *WPF* is included as it is hypothesized to be an important factor determining the speed of convergence. Brännlund et al. (2014) and Strazicich and List (2003) claim that higher carbon intensity implies a greater exposure to changes in fuel prices, and thus makes more economic sense to undertake abatement measures to reduce emissions following an increase in prices.

Carbon Price (CP). A similar logic is applied to motivate the inclusion of *CP*. Emission allowances is a market-based policy instrument that is implemented with the intention of making GHG emissions costly and to incentivize abatement efforts. Emission allowances are traded on an EU exchange and hence, the carbon price is the same for all countries. The inclusion of *CP* is to investigate the effect of a change in carbon price on the speed of convergence by interacting it with lagged carbon intensity and thereby allowing for heterogeneity between countries.

Note that since they are common across all countries, the main effects of CP and WPF are captured by the time fixed effects and are therefore not explicitly included in the estimated models.

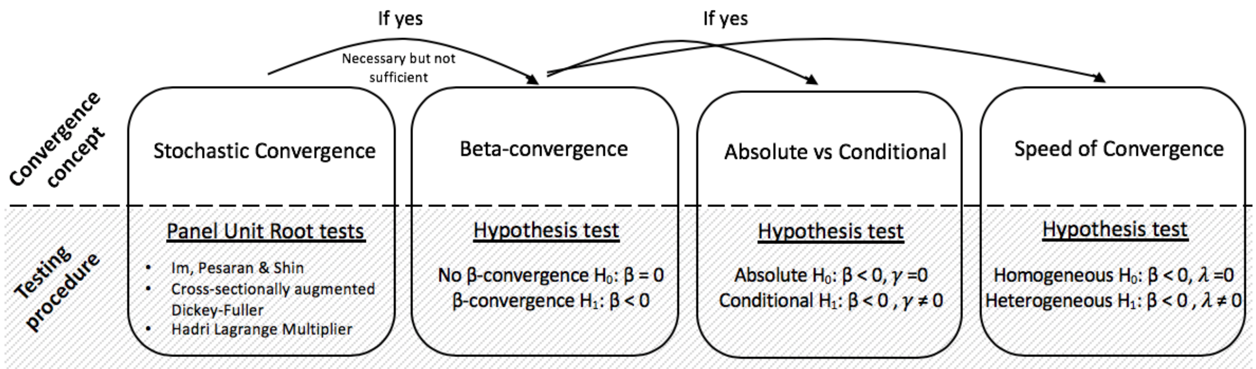

Figure 6. Summary of convergence concepts and testing procedures.
Note: If stochastic convergence prevails, there can be beta-convergence. In turn, if beta-convergence is found, absolute vs conditional and speed of convergence can be investigated. Source: Author's own rendering.

6.4. Robustness Checks

6.4.1. OLS to Verify Beta-Convergence

There have been several concerns with regard to fixed effects estimation in a dynamic panel setting. Inherent to this is the concern of endogeneity of the lagged carbon intensity variable and the error term. The within transformation of the fixed effect estimator removes the average of the independent variable ($I_{i,t-1} - \bar{I}_{i.}$) and the error term (v_{it}-$\bar{v}_{i.}$) respectively. But because $\bar{v}_{i.}$ contains $v_{i,t-1}$, which in turn $I_{i,t-1}$ is correlated with, $I_{i,t-1}$ will still be correlated with the error term through $\bar{v}_{i.}$[28].

As Roodman (2009) specifies, the risk is that the coefficient on our lagged carbon intensity variable of interest is biased by variation that should actually be attributed to the country's fixed effects. For example, carbon intensity is inherently linked to a country's dependence on hydro energy which is in turn largely determined by its topography. Based on Monte Carlo simulations that have been run, the correlation between the lagged carbon intensity variable and the transformed error term can be shown to be negative. Hence, fixed effects estimation can lead to coefficients being downward biased[29] (Bond, 2002; Nickell,1981).

Inspired by Bond (2002), we utilize an OLS estimation to, in combination with the fixed effects estimation, create an upper and lower bound on the beta-coefficient. This is possible because the estimators are likely to be biased in opposite directions. The fixed effects produce a lower bound on the true beta-coefficient due to the downward bias explained above. The OLS

[28] See Baltalgi (2008), section 8.1. for more details on dynamic panel bias.
[29] Judson and Owen (1999) suggest that even with T=30, the bias on the true value of coefficients could be as much as 20%.

estimate on the other hand, provides an upper bound due to the correlation of the lagged carbon intensity variable with the country-specific fixed effects in the error term, $u_i + v_{it}$. Bond (2002) finds that standard results from OLS estimation with omitted variables tend to indicate an upward bias in the produced estimates, thereby producing an upper bound on the beta-coefficient.

6.4.2. Bootstrapped Standard Errors

A key assumption when applying clustered standard errors at a country level is that error terms are correlated within a country but uncorrelated across countries. Given the nature of common EU climate policy and technology spillover, it is plausible to hypothesize that error terms are correlated across countries. Further, as a rule of thumb, one should only employ clustering of standard errors with 30 or more clusters, but we only have 28 country clusters. Hence, as a robustness check, we employ bootstrapped standard errors[30] to ensure that our findings are robust.

Bootstrapping standard errors refers to a non-parametric approach to estimating standard errors. As we are uncertain about the distribution of the error terms, bootstrapping sidesteps this by utilizing random draws with replacement from the entire dataset. The bootstrapped standard errors in a sample is the standard error of an estimator across many repeated draws with replacement. The non-parametric nature of bootstrapped standard errors allows us to avoid making assumptions regarding the distribution of the variables by observing an approximation of the sampling distribution of interest. Bootstrapping typically requires the sample to be representative of the target population, but as we study the entire target population this is not an issue. The approach also requires that a sufficient number of replications are run to estimate reliable standard errors. To ensure this, we employ estimations with 100 replications, above which there are negligible improvements in estimation (Goodhue, Lewis & Thompson, 2012)

7. Results

The empirical results consist of two main sections. In the first, we consider carbon intensity of the EU28 power sector by presenting results on both aggregate and country level. The second part presents the results from our analysis of stochastic and beta-convergence.

[30] Note that standard errors are bootstrapped across the entire population and not bootstrapped in clusters. This allows us to account for correlation of the standard errors across countries.

7.1 Carbon Intensity at Aggregate and Country Level

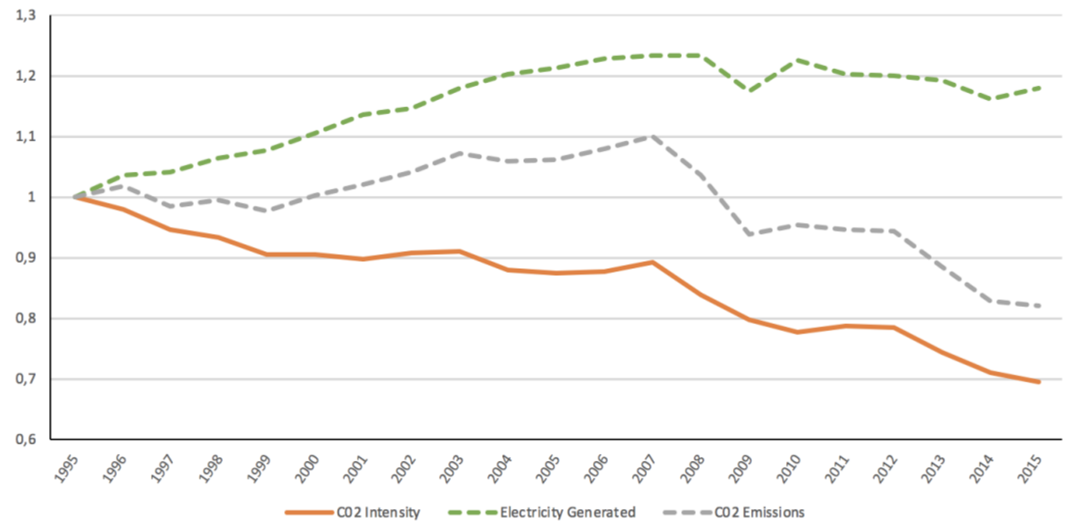

Figure 7. EU Index of carbon intensity, aggregate electricity generation and aggregate carbon emissions from 1995 to 2015.
Source: Author's rendering of data from Eurostat (2018).

Figure 7 displays an index of the total EU28 carbon intensity, total gross electricity generation and total CO_2 emissions from 1995 to 2015. Across the entire period we observe both *relative decoupling* and *absolute decoupling*. Relative decoupling refers to the decline in carbon emissions per unit of energy produced, this is indicated by a decrease in the carbon intensity index. Absolute decoupling means that the absolute level of emissions has decreased despite an increase in electricity generation. Relative decoupling is a requirement for an economy to sustain growth in electricity generation without having an increasingly negative impact on the environment. The two main channels enabling this are improving efficiency in electricity generation and transitioning to less carbon intensive energy sources. We interestingly see that the decline in carbon emissions was initiated in 2008, whilst the electricity generation grew in 2008 and did not decline until 2009. From figure 12 in Appendix E, we note that there is a sharp increase in oil price relative to the gas price up until mid-2008. Hence, we hypothesize that the high oil price incentivized power generators to switch from oil to the relatively cheaper and cleaner natural gas, leading to a decrease in carbon emissions. In 2009 we see a drop in gross electricity generation following the economic downturn, coupled by a further decline in carbon emissions.

The box plot in figure 8 depicts the carbon intensity across power sectors of the EU28 from 1995 to 2015. The graph is consistent with the overall decreasing carbon intensity seen in figure 7, but it also reveals that the range of carbon intensities is decreasing over time. This suggests that there is indeed an improvement in the carbon intensity in the power sector and is a first indication of that the EU28 are to some extent converging towards a lower level of carbon intensity.

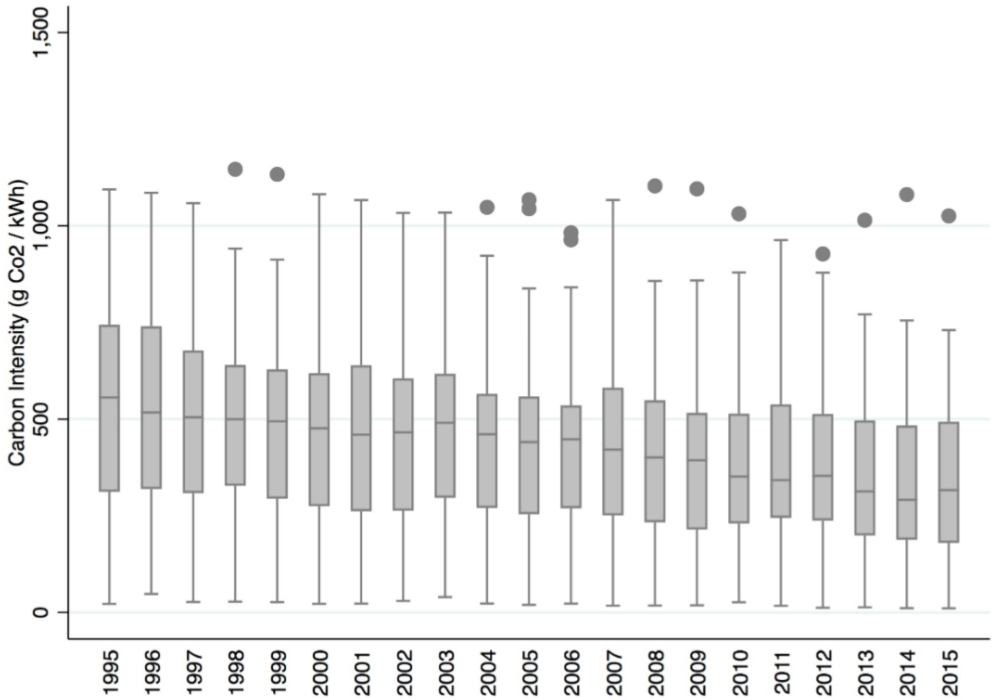

Figure 8. Box plot of carbon intensity.

Note: The box spans between the first and third quartile and the line within it representing the EU28 median. The whiskers indicate the maximum/minimum for each respective year or extends 1,5 interquartile ranges (third-first quartile) from the box, with dots representing outliers. Source: Author's rendering of data from Eurostat (2018).

In figure 9, we plot the carbon intensity of each EU28 member state in 1995 and in 2015, as well as the EU average (yellow bar). In line with earlier findings, the figure illustrates that most EU members decreased their carbon intensity between 1995 and 2015, albeit to different extents. Country-level analysis of the changes in carbon intensity from electricity generation reveals some interesting findings. Most EU member states, with the exception of Latvia and Lithuania, decreased in carbon intensity over the studied period. Countries with a relatively high carbon intensity, such as Malta, Romania, Luxembourg and Poland, improved considerably during the same period. Sweden and France were the least carbon intensive countries in 1995 and after reductions, continue to be the least carbon intensive countries in 2015.

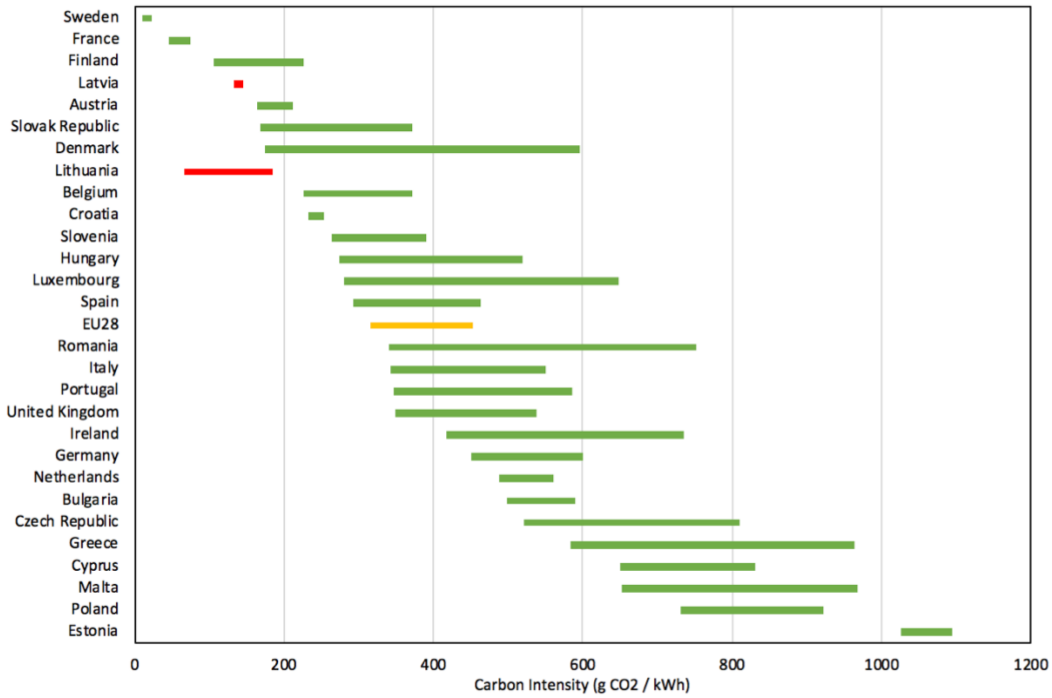

Figure 9: CO_2 intensity of EU member states: 1995, 2015 and changes between the two years.

Note: A green bar indicates a decrease in carbon intensity, while a red bar indicates an increase. The reference line for plotting the bars is in ascending order of each country's carbon intensity in 2015 – specifically, these refer to the values to the left of the green bars and to the right of the red bars.

Source: Author's rendering of data from Eurostat (2018).

7.2. Convergence Results

We find support for both stochastic and beta-convergence of carbon intensity in the EU power sector. These findings are robust across the different unit root tests employed for stochastic convergence, and for beta-convergence both across specifications and various robustness checks. Our findings of stochastic convergence suggest that the entire panel is stationary and that each carbon intensity time-series reverts back to the mean of the EU28 after a shock. The beta-convergence results suggest that convergence is conditional on GDP per capita and energy tax intensity in a country.

7.2.1. Stochastic Convergence

The number of lags selected by the SBC and the results of the Ljung-Box-Q for the IPS and CADF test are presented in Appendix F.

Table 3 presents the results from the battery of panel unit root tests performed on the dataset. The time-series tested is the logarithm of relative carbon intensity, *RI*. The tests are initially performed by allowing individual intercepts to differ. However, as visual inspection of the time series suggests a downward trend, we also include a specification that allows for a time trend. Under the null hypothesis of the IPS and the CADF, the individual time-series have a unit root and the alternative hypothesis is that at least one time-series is stationary. The Hadri-LM test tests the null that all individual time-series are stationary, with the alternative hypothesis being that at least one time-series contains a unit root. The consistent results across the IPS and CADF suggest that the results are insensitive to allowing for cross-sectional dependence.

Table 3. Results from panel unit root tests

	IPS	**CADF**	**Hadri-LM**
Individual Intercepts	-17,378***	-4,064***	-2,031
	(0,000)	(0,000)	(0,979)
Individual Intercepts & Trend	-15,058***	-4,203***	-1,799
	(0,000)	(0,000)	(0,964)
Null hypothesis	Unit root	Unit root	Stationarity

Note: P-values are presented in parentheses: *** $p < 0{,}01$, ** $p < 0{,}05$, * $p < 0{,}1$.

The IPS and the CADF panel unit root tests produce highly significant results in both specifications. These results reject the unit root null hypothesis at a 1% significance level in favor of the alternative hypothesis that at least one time-series is stationary. The third panel unit root test, the Hadri-LM, fails to reject the null hypothesis that all the time series are stationary. All results are consistent whether or not a time trend is allowed for.

The Hadri-LM test indicates that there is stochastic convergence among the EU28. This is supported by the results of the IPS and CADF that indicate that at least one time series is stationary. This consistency provides robustness to the results. Stochastic convergence indicates that a shock to carbon intensity of any one of the EU28 is only temporary, and that it converges back to the average EU level. The existence of stochastic convergence implies that the necessary conditions for beta-convergence are fulfilled. Hence, we move on to investigate absolute and conditional convergence as well as the speed of convergence.

7.2.2. Beta-Convergence

Table 4 presents the regression results of the specifications that have been estimated using fixed effects. The dependent variable is the logarithm of the change in carbon intensity between two consecutive periods. In all models, time and country fixed effects are included to control for time and country invariant omitted variables that may bias the estimates. The full specifications including coefficients on the country and year dummies are presented in Appendix G.

Table 4. Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(I_{t-1})$	-0,335***	-0,343***	-0,368***	-0,367***	-0,344***	-0,383***	-0,417***	-0,434***	-0,355***	-0,471***
	(0,0810)	(0,0781)	(0,0647)	(0,0645)	(0,0861)	(0,0692)	(0,109)	(0,113)	(0,0689)	(0,0880)
EU_t		0,0495		0,00162		0,0307	-0,00934	0,0210	0,0125	-0,00619
		(0,0329)		(0,0294)		(0,0309)	(0,0277)	(0,0288)	(0,0313)	(0,0285)
$\ln(GDPpc_t)$			0,221**	0,219*		0,294**	0,240**	0,317**	0,198*	0,236**
			(0,107)	(0,111)		(0,135)	(0,107)	(0,133)	(0,0981)	(0,106)
$\ln(ETI_t)$					0,0143	-0,0661**		-0,0686**		
					(0,0230)	(0,0295)		(0,0292)		
$\ln(I_{t-1})*\ln(WPF_t)$							0,0188	0,0195		0,0485***
							(0,0200)	(0,0197)		(0,0121)
$\ln(I_{t-1})*(CP_t)$									-0,00247	-0,00460**
									(0,00201)	(0,00178)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0,223	0,231	0,244	0,244	0,227	0,257	0,247	0,260	0,251	0,266
Adjusted R^2	0,154	0,161	0,175	0,173	0,153	0,182	0,175	0,184	0,180	0,195
Countries	28	28	28	28	28	28	28	28	28	28
N	588	588	588	558	558	558	588	558	588	588

Note: Country level clustered standard errors in parentheses: *** $p < 0,01$, ** $p < 0,05$, * $p < 0,1$. The dependent variable being estimated is the *change in carbon intensity*.

Across all specifications, we note that the coefficient on the lagged carbon intensity variable, $I_{i,t-1}$, is negative and highly significant at the 1% level[31]. Its significance across specifications provides robustness and yields strong support for the existence of beta-convergence.

Model 1 is the basic model containing only the lagged carbon intensity variable. The beta-coefficient is negative and significant, this suggests countries which are more carbon intense exhibit a greater improvement in carbon intensity in the following period. The beta-coefficient is interpreted as a country with a 1% lower carbon intensity decreasing carbon intensity 0,34% slower. Hence, the less carbon intensive a country is, the slower it improves and thereby countries still at a higher carbon intensity improves faster and catches up.

In model 2, the regression is appended with a dummy for EU membership, which is found to be insignificant. This indicates that becoming an EU member has not had an impact on the path of carbon intensity. In model 3, GDP per capita (GDPpc) is added to the basic model and it is found to be significant at the 5% level. Hence, we reject absolute convergence in favor of convergence conditional on GDPpc. The significant and positive coefficient on GDPpc suggests that the EU28 do not converge along the same path of carbon intensity. Rather, countries with higher GDPpc converge toward a higher path of carbon intensity (all else equal). In model 4, both the GDPpc variable and the EU dummy are included. The EU dummy remains insignificant while

[31] Whilst employing conventional significance levels, we acknowledge their arbitrariness and maintain a healthy skepticism in our interpretations.

GDPpc is significant only at the 10% level. Energy tax intensity (ETI) is introduced in isolation in model 5 and is not found to be significantly different from zero. In model 6, when we also control for GDPpc and EU membership, ETI is found to be significant at the 5% level. ETI remains significant in model 8 when the interaction of WPF and lagged intensity is included. As the coefficient on ETI is negative and significant, countries who employ a more stringent energy tax converge along a lower path of carbon intensity.

The speed of convergence (the magnitude of the beta-coefficient) does not change significantly in any of the basic or conditional models (model 1-6). The interaction of WPF with the lagged carbon intensity variable is estimated across models 7,8 and 10 to investigate speed of convergence. The WPF interaction is only significant when estimated along with carbon price in model 10 but is insignificant across all other specifications. This leads us to reject that the speed of convergence is influenced by the weighted price of the fossil fuels. In model 9 and 10, carbon price (CP) and its interaction with the lagged carbon intensity variable is included to test for differences in the speed of convergence. The interaction of CP is significant only in model 10 but insignificant in model 9. This inconsistency puts the reliability of the estimated effect under question and we reject that the speed of convergence is influenced by CP. CP is not included in combination with ETI in any model because CP is a direct component of ETI.

7.2.3. Robustness Check

Results from the full set of robustness checks are presented in Appendix H. The results of the robustness checks support the findings of conditional beta-convergence presented in our main fixed effects estimations. As in our main specification, the beta coefficient is negative and significant in most specifications, this supports the finding of beta-convergence. In addition, ETI and GDPpc are consistently significant across the bootstrapped specifications; this supports the finding of conditional beta-convergence.

With OLS estimation, we note that in the simple specification, the specification with the EU dummy only, and the specification with carbon price (models 1, 2 and 9), the OLS estimate of the beta-coefficient is insignificant, this might point to an upper bound which does not support beta-convergence. However, when the most relevant controls are included (GDPpc and ETI), the beta-coefficient is found to be negative and significant - this supports the existence of conditional convergence. In estimating the upper bounds on the beta coefficient utilizing OLS, we note that it is considerably smaller in magnitude compared to the fixed effects estimation - however the coefficient remains negative and significant.

With regard to estimations from bootstrapped standard errors, the magnitude of the estimated coefficients is the same as with fixed effects estimation (as is to be expected) while standard errors are smaller compared to the clustered standard errors. As the results of the estimation with bootstrapping are consistent, the initial concern of having less than 30 country clusters is unlikely to have caused considerable bias in the estimation of standard errors in the original fixed effects estimation with country clusters.

8. Discussion

8.1. Internal Validity and Limitations

In this section, we discuss the internal validity of our study. This includes a critical reflection of the data used, estimation methods adopted and limitations of our study.

8.1.1. Data

The carbon intensity measure is obtained from the International Energy Agency (IEA). The numerator presents carbon emissions from fossil fuels consumed in electricity generation while the denominator presents total gross electricity generated. These values are provided by national governments. There is a risk that energy statistics at the national level have been collected using different criteria and definitions. This implies that there might be a degree of measurement error in our data, which potentially creates a problem for cross-country comparability. It is entirely possible that even after standardization and adjustments by the IEA[32], that there are unavoidable measurement error persists at an individual power plant level. These systematic measurement errors can bias results in both stochastic and beta-convergence.

The IEA estimates carbon emissions by a *Tier 1* approach (see Appendix B). The *Tier 1* approach computes carbon emissions by multiplying fuel consumption by a carbon factor that is assumed to be constant across the EU28 and time. As the IEA (2018) admits, this assumes that there is no change in emission efficiency of the power plants over the entire time period. However, the IPCC (2006) concludes that there is limited heterogeneity between various combustion technologies with regard to the quantity of CO_2 emissions. Therefore, we consider this to be a limited source of bias in our results.

[32] The IEA has made considerable efforts to ensure that data is in line with the United Nations International Recommendations on Energy Statistics (IEA, 2018). It has identified most of differences in national definitions and adjusted the data to meet international definitions.

8.1.2. Unit Root Tests

The validity of estimates from the unit root tests rely on certain asymptotic assumptions. In practice, this means that the tests perform best for large T and at least moderate N (Phillips & Moon, 2000). Whilst "large" and "moderate" lack explicit values, our panel of T=21 and N=28 is in the vicinity of what previous literature using the same unit root tests employs (Hao et al., 2015; Lee & Chang, 2009; Strazicich & List, 2002), and we consider the asymptotic assumptions to have been fulfilled.

Performing three different panel unit root tests acts as a robustness check, and the results all support the same conclusion of stochastic convergence. However, all three tests have certain traits in common. Firstly, in all cases the time trends are limited to linear time trends and the possibility of a non-linear time trend may reduce the validity of the linear tests. We emphasize that we find stochastic convergence when a linear trend is included and leave investigating non-linear time trends as a point for future research. Secondly, neither of the tests allow for structural breaks in the time-series. As we have a relatively limited dataset, it is difficult to allow for a structural break while ensuring that there are sufficient observations pre-and-post break to allow for robust estimation.

8.1.3 Beta-Convergence

In employing fixed effects estimation, endogeneity may lead to estimates being biased and inconsistent. This could be due to independent variables being determined within the model, omitted variables being correlated with the independent variables or measurement error. The fixed effects included in our models account for variables that are time-invariant or country-invariant. However, a potential source of omitted variable bias are factors that vary across time and country and are correlated with any of the independent variables. Such an omitted variable could be national climate policy such as coal bans or subsidies for renewables. These country specific factors change over time and are thus not controlled for in a fixed effects approach. Adopting an Instrumental Variable (IV) approach such as applying an exogenous IV or Generalized Methods of Moments (GMM) may be useful to verify our results[33] and to address some of concerns with omitted variables and reverse causality.

A potential weakness in the WPF variable is the lack of country variation within the variable. Ideally, we would have like to have country specific prices for the respective fossil fuels

[33] As Bond (2002) advises, if one uses the GMM estimator to obtain an estimate on the beta-coefficient, the estimation should be compared with the bounds created by OLS and fixed effects estimation - this is the approach that we have adopted in our robustness checks (see section 7.2.3.).

as we suspect that the price of fuels varies across the EU. However, due to data unavailability such variation remains unaccounted for. An alternative approach to introduce cross-country variation would be to weigh the common fossil fuel price by for example the relative dependency on each fossil fuel in a country. This would be desirable as a country with less fossil fuels in their energy mix would naturally be less sensitive to changes in fuel prices. However, switching from fossil fuels and thereby decreasing fossil fuel dependency is one of the main mechanisms through which a country can improve its carbon intensity. Hence, a channel through which carbon intensity improves is through the fossil fuel mix component of WPF and if included it would be a bad control. Including bad controls could lead to misinterpretation of the estimated beta-coefficient as the mechanism through which the independent variable affects the outcome is limited when holding the bad control constant (Angrist & Pischke, 2008).

8.2. Policy Implications of Results

The main objective of this thesis is to investigate the development and convergence of carbon intensity in the EU power sector. In light of our findings, we discuss them in relation to climate and energy policy and possible implications for future policy making. Considering the basis of this discussion is limited to carbon intensity, we recognize the limitations in our policy implications and evaluations to only encompass aspects in regards of carbon intensity related to the power sector. Additional criteria such as social impact on for example income or employment is left outside of the scope of this paper.

Regarding stochastic convergence, stationarity means that following a structural change or sudden change in the power sector with regards to carbon emissions, the carbon intensity time-series will revert to the EU average. Importantly, stationarity indicates that it is possible to forecast future movements in the carbon intensity series by examining its past behavior. This ability to forecast might be helpful for policy makers in target setting and climate negotiations.

As a result of beta-convergence in carbon intensity, countries with more carbon intensive power sectors exhibit a higher rate of improvement compared to less carbon intensive power sectors. This conclusion is coherent with the *catch-up theory* and is useful for consideration in climate policy negotiations. Beta-convergence is also an important conclusion considering the European Commission's goal to integrate the EU power market and create a pan-European power market. If we had found divergence, there could potentially be substantial transfers of resources following a trade-deficit of electricity in more carbon intensity countries due to higher cost of electricity generation from fossil fuels. However, as the carbon intensity in the EU28 power sector is found to converge, this concern is likely to be less important.

Convergence of carbon intensity is not found to be conditional on being an EU member. Whilst we hypothesized that entering the EU would affect the development of a country's carbon intensity in the power sector, the conditions that have to be satisfied by a country before being eligible for membership may bias the estimate. As part of satisfying the *Copenhagen Criteria* (a set of requirements to join the EU), a country has to show that they are willing and able to adopt, implement and enforce all current EU rules, the "*acquis*" (EC, 2019d). These rules cover a set of 35 policy areas, one of which directly regulates the energy sector. Amongst others, the energy acquis regulates state aid to the coal sector as well as requires the country to promote renewable energy sources and energy efficiency. Given the adoption and implementation of standards and rules of the energy acquis prior to actually becoming an EU country, it is feasible to argue that the dummy of EU membership does not provide a discrete break in the country's climate and energy policies.

Convergence is found to be conditional on GDP per capita. We find an increase in GDP per capita to be coupled with a slower rate of change in carbon intensity and convergence toward a higher path of carbon intensity. A possible explanation for this is that in practice, an increase in GDP per capita is highly correlated with an increased demand for electricity. This in turn, means that the electricity generators will have to increase production in order to meet the higher demand. The source of this increased generation is likely to come from fossil fuel plants as capacity of renewable sources is less flexible and often require additional investments, which due to long lead times might not be possible in the short run. In line with Jobert et al. (2010), one should also note that given convergence conditional on GPD per capita, a 'one-size fits all" type of EU environmental policy might not be appropriate in the context of carbon emissions reduction targets. We also find convergence to be conditional on energy tax intensity (ETI). EU countries that demonstrate a higher commitment to combating climate change by enforcing more strict environmental tax regimes tend to converge towards a lower path of carbon intensity. This points to the usefulness of market-based incentives in reducing carbon emissions and is intuitive as a high ETI makes emissions more costly for firms.

The results on speed of convergence yields mixed results. Carbon price (CP) is found to have a negative effect, hence increase the speed of convergence, in one of the specifications. This is the intended and hypothesized effect of the EU ETS and it is intuitive as making GHG emissions more costly is likely to incentivize power generators to undertake abatement efforts to reduce emissions. The weak effect of carbon price could also be due to the distorted price development since the introduction of the EU ETS with prices close to zero for some periods. Further, the effects of more recent revisions to the EU ETS such as the requirement for power generators to since 2013 buy 100% of their allowances may not yet have been fully realized in the studied data. Future development of the EU ETS, like the introduction of the *market stability reserve*[34] in 2019, may more efficiently incentivize abatement efforts. WPF and CP would be expected to have similar effects on the speed of convergence as they both make usage of fossil fuels more costly. As our results regarding speed of convergence are not consistent across various specifications, the relationship between carbon intensity and CP/WPF warrants further research.

9. Conclusion

In this paper, we have analyzed carbon intensity within the EU28 power sector from 1995 to 2015. The key empirical issue addressed is whether carbon intensity in the EU power sectors converges along the same path or if they converge along individual paths conditional on country characteristics. The motivation for studying carbon intensity in the EU power sector is two-fold. Firstly, the power sector is responsible for a large share of EU's carbon emissions, hence, it is warranted to conduct a cross-country sectoral analysis of the time path of carbon intensity. Secondly, convergence of carbon intensity provides a useful tool for EU and national policy makers in the design and evaluation of climate policies for the power sector. The empirical approach can be split into an analysis of the evolution of carbon intensity and an investigation of stochastic and beta-convergence.

The analysis of carbon intensity shows that there has been relative decoupling (a decreasing carbon intensity in electricity generation) as well as absolute decoupling (a decrease of total carbon emissions) in the EU power sector. The average carbon intensity level has improved by 40,4% from 1995 to 2015. The dispersion in levels of carbon intensities has decreased across the studied period.

In analyzing stochastic convergence, we construct a relative carbon intensity measure, which is each country's carbon intensity divided by the EU mean. We adopt an univariate time-series approach and utilize the IPS (Im et al., 2003), CADF (Pesaran, 2007) and Hadri-LM (Hadri, 2000) panel unit root tests to test for stationarity. We find stationarity across all EU28 carbon intensity time-series and thereby conclude the existence of stochastic convergence. One of the implications of finding stochastic convergence is that we are able to forecast future developments in the carbon intensity series based on its past developments.

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[34] A market intervention with the purpose to deal with the surplus of allowances and to make the EU ETS more resilient to future economic shocks (EC, 2018).

In studying beta-convergence, we adopt a panel data approach utilizing a fixed effects estimator. The main independent variable is lagged carbon intensity and the main dependent variable is the year-on-year change in carbon intensity of electricity generation. Absolute and conditional convergence is tested for and assumed to be mutually exclusive. We investigate whether convergence is conditional on EU membership, GDP per capita as well as energy tax intensity. Further, we test if carbon prices and fossil fuel prices affect the speed of convergence. Based on our findings, we reject the absolute convergence hypothesis in favor of conditional convergence. We find support for countries converging conditional on GDP per capita and the level of energy taxes levied. Conditional convergence based on energy tax intensity means that countries that implement a higher energy tax tend to converge toward a lower path of carbon intensity. The results suggest that countries with higher GDP per capita converge toward a higher path of carbon intensity. We find that becoming an EU member has had no effect on the path of carbon intensity. There is some indication of heterogeneity in the speed of convergence across countries, but our results are inconclusive. We caution against extrapolating our convergence results beyond the context of the EU and the time period we study. However, the importance of GDP per capita and energy tax intensity in the path of carbon intensity is likely to translate to power sectors outside the studied sample.

This study is the first to investigate carbon intensity within the power sector and yields some interesting insights. As a next step, we suggest that future research further investigate convergence within the EU power sector with other techniques or extend this body of research to other countries. The previously outlined potential issues with endogeneity call for alternative estimation methods such as an Instrumental Variable or GMM approach to verify our beta-convergence results. The results of our paper also suggest it would be useful to consider other variables that might alter the path of carbon intensity within the EU. Future research could also extend investigation to other convergence concepts within the EU power sector such as sigma convergence which investigate the dispersion within countries or club convergence to investigate convergence between different groups of countries. It would also be interesting to investigate stochastic and beta-convergence in carbon intensity of electricity generation amongst other sets of countries such as the OECD or on a global level in aid in our understanding of effective climate change measures.

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Appendix A: EU28 Member Countries

Table 5. EU member countries and date of entry

Date of Entry	Country
1958-01-01	Belgium
	France
	Germany
	Italy
	Luxembourg
	Netherlands
1973-01-01	Denmark
	Ireland
	United Kingdom
1981-01-01	Greece
1986-01-01	Portugal
	Spain
1995-01-01	Austria
	Finland
	Sweden
2004-05-01	Cyprus
	Czechia
	Estonia
	Hungary
	Latvia
	Lathiuania
	Malta
	Poland
	Slovakia
	Slovenia
2007-01-01	Bulgaria
	Romania
2013-07-01	Croatia

Source: Author’s rendering of data from IEA (2019)

Appendix B: IPCC Tier 1

The IPCC Tier 1 approach of calculating total GHG emissions in carbon equivalent is as follows:

First, calculations are based on the quantity of consumed fossil fuel and the respective emission factor (a measure of emissions per unit of fuel combusted) as follows:

$$Emissions_{GHG,fuel} = Fuel\ Consumption_{Fuel} * Emission\ Factor_{GHG,Fuel} \qquad (35)$$

The quantity of fuel combusted is obtained through national energy statistics and the emission factors are average default emission factor. The GHG emissions are the summed up across fuel types in order to obtain the total emissions from electricity generation as follows:

$$Emissions_{GHG} = \sum_{fuels} Emissions_{GHG,fuel} \qquad (36)$$

As mentioned in our data, a Tier 1 approach is adopted by the IEA. It has been noted that Tier 1 approaches fail to consider the efficiencies and combustion technologies of specific power plants. In addition, relative to the Tier 3 approach, a Tier 1 estimation does not account for operation conditions, quality of maintenance and the age of equipment. These measures are considered in Tier 2 and Tier 3 approaches - however, at the time of writing, this data is unavailable on such a granular level, and might be an appropriate avenue for future research. However, within the scientific literature, combustion technology and operating conditions are regarded to be of importance only for methane and nitrous oxide while they are relatively unimportant for carbon dioxide (which form the majority of GHGs released) (IPCC, 2006). Hence, in our opinion, our data remains reliable.

Appendix C: Time-series of variables

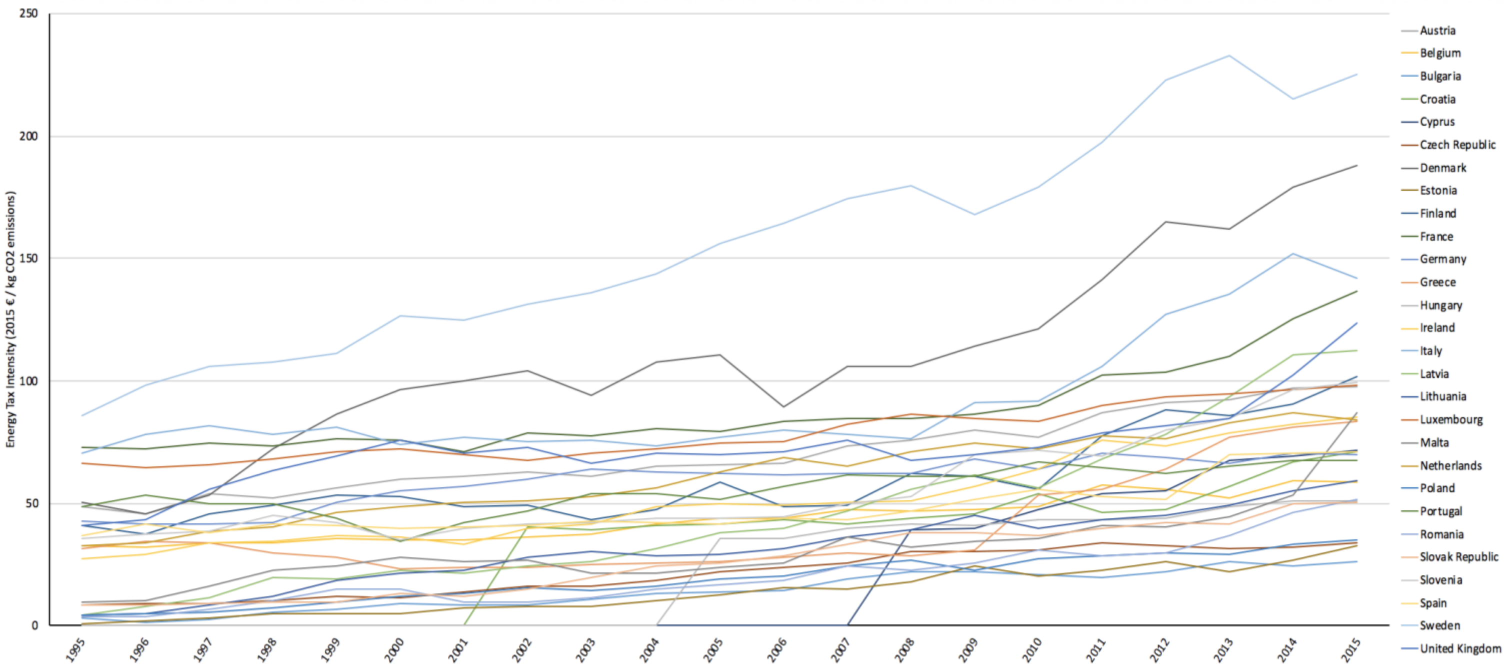

Figure 10. Energy tax intensity (ETI in 2015 US $ / MWh) from 1995 to 2015.
Source: Author's rendering of data from BP (2019) and Eurostat (2018).

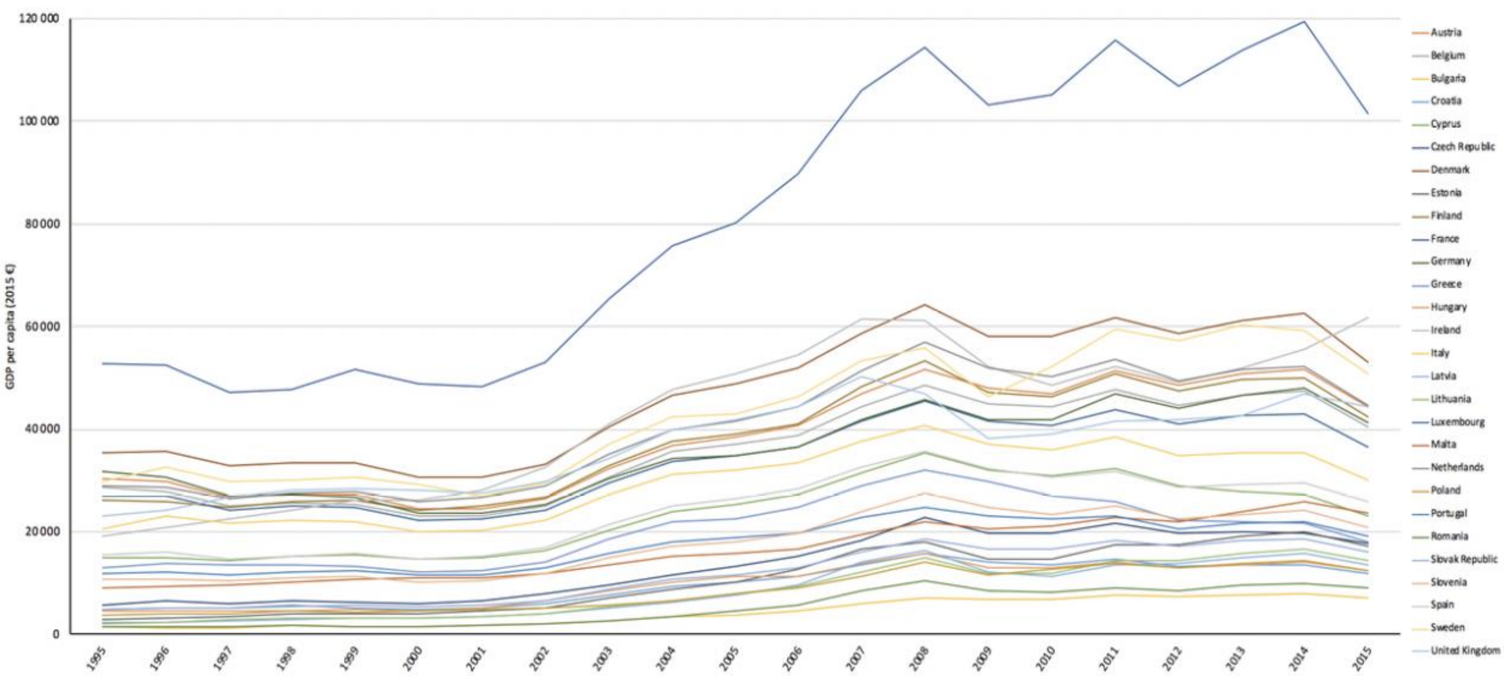

Figure 11. GDP per capita (current USD) from 1995 to 2015.
Source: Author's rendering of data from World Bank (2019).

Appendix D: Panel Unit Root Tests: Critical Values

Table 6. IPS panel unit root test - critical values

Case A: Only intercepts

N\T	5	10	15	20	25	30	40	50	60	70	100
1 percent											
5	−3,79	−2,66	−2,54	−2,50	−2,46	−2,44	−2,43	−2,42	−2,42	−2,40	−2,40
7	−3,45	−2,47	−2,38	−2,33	−2,32	−2,31	−2,29	−2,28	−2,28	−2,28	−2,27
10	−3,06	−2,32	−2,24	−2,21	−2,19	−2,18	−2,16	−2,16	−2,16	−2,16	−2,15
15	−2,79	−2,14	−2,10	−2,08	−2,07	−2,05	−2,04	−2,05	−2,04	−2,04	−2,04
20	−2,61	−2,06	−2,02	−2,00	−1,99	−1,99	−1,98	−1,98	−1,98	−1,97	−1,97
25	−2,51	−2,01	−1,97	−1,95	−1,94	−1,94	−1,93	−1,93	−1,93	−1,93	−1,92
50	−2,20	−1,85	−1,83	−1,82	−1,82	−1,82	−1,81	−1,81	−1,81	−1,81	−1,81
100	−2,00	−1,75	−1,74	−1,73	−1,73	−1,73	−1,73	−1,73	−1,73	−1,73	−1,73
5 percent											
5	−2,76	−2,28	−2,21	−2,19	−2,18	−2,16	−2,16	−2,15	−2,16	−2,15	−2,15
7	−2,57	−2,17	−2,11	−2,09	−2,08	−2,07	−2,07	−2,06	−2,06	−2,06	−2,05
10	−2,42	−2,06	−2,02	−1,99	−1,99	−1,99	−1,98	−1,98	−1,97	−1,98	−1,97
15	−2,28	−1,95	−1,92	−1,91	−1,90	−1,90	−1,90	−1,89	−1,89	−1,89	−1,89
20	−2,18	−1,89	−1,87	−1,86	−1,85	−1,85	−1,85	−1,85	−1,84	−1,84	−1,84
25	−2,11	−1,85	−1,83	−1,82	−1,82	−1,82	−1,81	−1,81	−1,81	−1,81	−1,81
50	−1,95	−1,75	−1,74	−1,73	−1,73	−1,73	−1,73	−1,73	−1,73	−1,73	−1,73
100	−1,84	−1,68	−1,67	−1,67	−1,67	−1,67	−1,67	−1,67	−1,67	−1,67	−1,67
10 percent											
5	−2,38	−2,10	−2,06	−2,04	−2,04	−2,02	−2,02	−2,02	−2,02	−2,02	−2,01
7	−2,27	−2,01	−1,98	−1,96	−1,95	−1,95	−1,95	−1,95	−1,94	−1,95	−1,94
10	−2,17	−1,93	−1,90	−1,89	−1,88	−1,88	−1,88	−1,88	−1,88	−1,88	−1,88
15	−2,06	−1,85	−1,83	−1,82	−1,82	−1,82	−1,81	−1,81	−1,81	−1,81	−1,81
20	−2,00	−1,80	−1,79	−1,78	−1,78	−1,78	−1,78	−1,78	−1,78	−1,77	−1,77
25	−1,96	−1,77	−1,76	−1,75	−1,75	−1,75	−1,75	−1,75	−1,75	−1,75	−1,75
50	−1,85	−1,70	−1,69	−1,69	−1,69	−1,69	−1,68	−1,68	−1,68	−1,68	−1,69
100	−1,77	−1,64	−1,64	−1,64	−1,64	−1,64	−1,64	−1,64	−1,64	−1,64	−1,64

Case B: Intercepts and linear time trends

N\T	5	10	15	20	25	30	40	50	60	70	100
1 percent											
5	−8,12	−3,42	−3,21	−3,13	−3,09	−3,05	−3,03	−3,02	−3,00	−3,00	−2,99
7	−7,36	−3,20	−3,03	−2,97	−2,94	−2,93	−2,90	−2,88	−2,88	−2,87	−2,86
10	−6,44	−3,03	−2,88	−2,84	−2,82	−2,79	−2,78	−2,77	−2,76	−2,75	−2,75
15	−5,72	−2,86	−2,74	−2,71	−2,69	−2,68	−2,67	−2,65	−2,66	−2,65	−2,64
20	−5,54	−2,75	2,67	−2,63	−2,62	−2,61	−2,59	−2,60	−2,59	−2,58	−2,58
25	−5,16	−2,69	−2,61	−2,58	−2,58	−2,56	−2,55	−2,55	−2,55	−2,54	−2,54
50	−4,50	−2,53	−2,48	−2,46	−2,45	−2,45	−2,44	−2,44	−2,44	−2,44	−2,43
100	−4,00	−2,42	−2,39	−2,38	−2,37	−2,37	−2,36	−2,36	−2,36	−2,36	−2,36
5 percent											
5	−4,66	−2,98	−2,87	−2,82	−2,80	−2,79	−2,77	−2,76	−2,75	−2,75	−2,75
7	−4,38	−2,85	−2,76	−2,72	−2,70	−2,69	−2,68	−2,67	−2,67	−2,66	−2,66
10	−4,11	−2,74	−2,66	−2,63	−2,62	−2,60	−2,60	−2,59	−2,59	−2,58	−2,58
15	−3,88	−2,63	−2,57	−2,55	−2,53	−2,53	−2,52	−2,52	−2,52	−2,51	−2,51
20	−3,73	−2,56	−2,52	−2,49	−2,48	−2,48	−2,48	−2,47	−2,47	−2,46	−2,46
25	−3,62	−2,52	−2,48	−2,46	−2,45	−2,45	−2,44	−2,44	2,44	−2,44	−2,43
50	−3,35	−2,42	−2,38	−2,38	−2,37	−2,37	−2,36	−2,36	−2,36	−2,36	−2,36
100	−3,13	−2,34	−2,32	−2,32	−2,31	−2,31	−2,31	−2,31	−2,31	−2,31	−2,31
10 percent											
5	−3,73	−2,77	−2,70	−2,67	−2,65	−2,64	−2,63	−2,62	−2,63	−2,62	−2,62
7	−3,60	−2,68	−2,62	−2,59	−2,58	−2,57	−2,57	−2,56	−2,56	−2,55	−2,55
10	−3,45	−2,59	−2,54	−2,52	−2,51	−2,51	−2,50	−2,50	−2,50	−2,49	−2,49
15	−3,33	−2,52	−2,47	−2,46	−2,45	−2,45	−2,44	−2,44	−2,44	−2,44	−2,44
20	−3,26	−2,47	−2,44	−2,42	−2,41	−2,41	−2,41	−2,40	−2,40	−2,40	−2,40
25	−3,18	−2,44	−2,40	−2,39	−2,39	−2,38	−2,38	−2,38	−2,38	−2,38	−2,38
50	−3,02	−2,36	−2,33	−2,33	−2,33	−2,32	−2,32	−2,32	−2,32	−2,32	−2,32
100	−2,90	−2,30	−2,29	−2,28	−2,28	−2,28	−2,28	−2,28	−2,28	−2,28	−2,28

Source: Im et al. (2003)

Table 7. Expectation and variances for t-statistics

	Moments of t_{iT}		Moments of t_{iT}	
T	$E(t_T)$	$Var(t_T)$	$E(t_T)$	$Var(t_T)$
6	−1,125	0,497	−1,520	1,745
7	−1,178	0,506	−1,514	1,414
8	−1,214	0,506	−1,501	1,228
9	−1,244	0,527	−1,501	1,132
10	−1,274	0,521	−1,504	1,069
15	−1,349	0,565	−1,514	0,923
20	−1,395	0,592	−1,522	0,851
25	−1,423	0,609	−1,520	0,809
30	−1,439	0,623	−1,526	0,789
40	−1,463	0,639	−1,523	0,77
50	−1,477	0,656	−1,527	0,76
100	−1,504	0,683	−1,532	0,735
500	−1,526	0,704	−1,531	0,715
1000	−1,526	0,702	−1,529	0,707
∞	−1,533	0,706	−1,533	0,706

Source: Im et al. (2003)

Table 8. Critical values of cross-sectional augmented Dickey-Fuller panel unit root test

Critical values of average of individual cross-sectionally augmented Dickey-Fuller distribution (T=30, N=30)					
Case 1: No intercept and no trend		Case 2: Intercept only		Case 3: Intercept and trend	
	Critical values		Critical values		Critical values
1%	-1.74	1%	-2.30	1%	-2.81
5%	-1.57	5%	-2.15	5%	-2.66
10%	-1.47	10%	-2.07	10%	-2.58

Table 9. Power of Hadri LM panel unit root test

$\frac{\sigma_\mu^2}{\sigma_\epsilon^2}$	0,0001	0,001	0,01	0,1	1	100	10000
Intercept Only	0,0566	0,0844	0,4258	0,9996	1	1	1
Intercept & Trend	0,0427	0,0477	0,131	0,9685	1	1	1

In Hadri (2000), the asymptotic distribution of each test is shown to be normal, the moments of the asymptotic tests are derived exactly and do not require previous similar studies, the use of moments estimated through Monte Carlo simulation.

Appendix E: Price of Fossil Fuels

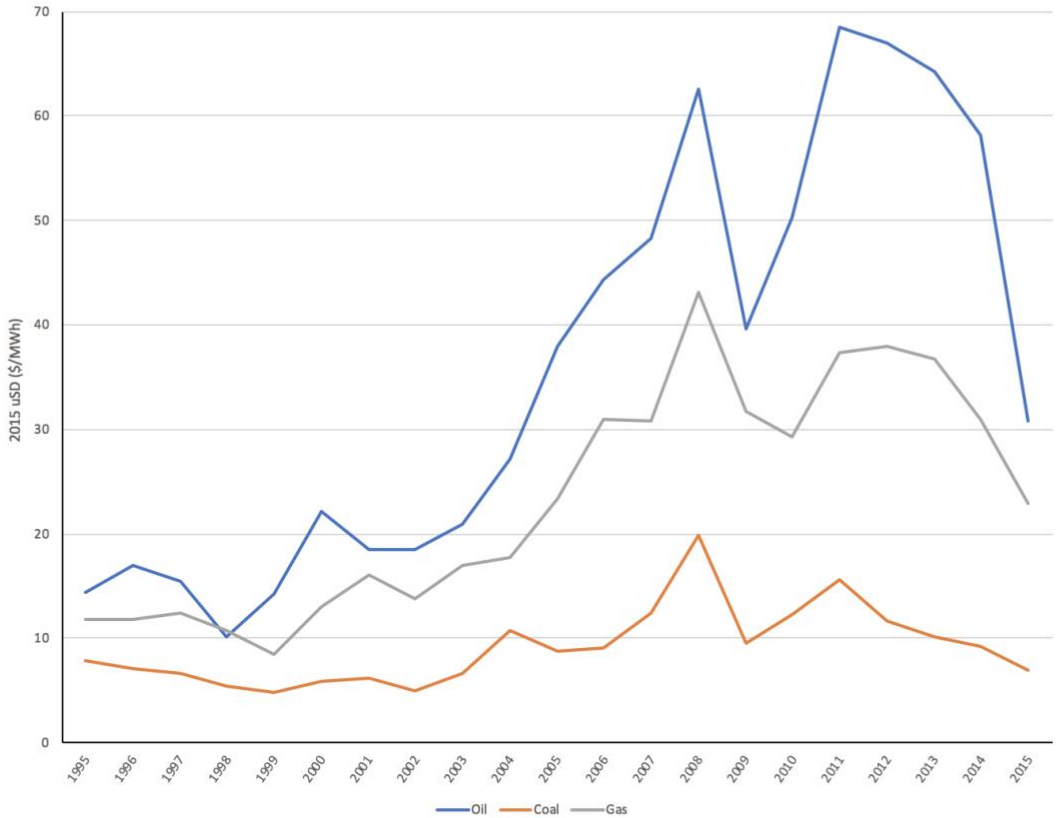

Figure 12. Price of fossil fuels in 2015 USD per MWh equivalents.
Source: Author's rendering of data from BP, 2019.

Appendix F: Results Portmanteau White-Noise Test

Table 10a: Results IPS lags - Portmanteau White Noise Test (Ljung-Box-Q)

		Number of lags in Portmanteau White Noise Test (IPS)				
Country	**# of lags selected**	**1**	**2**	**3**	**4**	**5**
Austria	0	0.516	0.712	0.642	0.566	0.660
Belgium	1	0.517	0.250	0.401	0.441	0.428
Bulgaria	0	0.570	0.187	0.164	0.212	0.059
Croatia	2	0.187	0.316	0.276	0.066	0.115
Cyprus	0	0.295	0.157	0.114	0.100	0.160
Czech Republic	0	0.749	0.776	0.573	0.735	0.399
Denmark	0	0.511	0.170	0.179	0.263	0.386
Estonia	2	0.373	0.670	0.712	0.830	0.825
Finland	2	0.940	0.993	0.986	0.850	0.926
France	0	0.163	0.376	0.582	0.707	0.811
Germany	0	0.725	0.578	0.574	0.645	0.734
Greece	0	0.335	0.399	0.601	0.745	0.856
Hungary	0	0.998	0.284	0.463	0.553	0.695
Ireland	0	0.625	0.819	0.919	0.792	0.868
Italy	0	0.176	0.175	0.220	0.179	0.214
Latvia	2	0.495	0.579	0.772	0.853	0.838
Lithuania	0	0.415	0.716	0.501	0.595	0.635
Luxembourg	3	0.733	0.286	0.435	0.572	0.663
Malta	1	0.918	0.814	0.752	0.655	0.750
Netherlands	1	0.957	0.987	0.904	0.854	0.913
Poland	0	0.173	0.274	0.288	0.275	0.226
Portugal	2	0.973	0.979	0.960	0.857	0.889
Romania	0	0.952	0.052	0.115	0.180	0.270
Slovak Republic	0	0.849	0.874	0.117	0.203	0.269
Slovenia	0	0.073	0.167	0.294	0.428	0.533
Spain	1	0.764	0.550	0.533	0.694	0.780
Sweden	2	0.992	0.414	0.430	0.509	0.633
UK	0	0.986	0.998	0.228	0.310	0.399

Note: Column 2 reports the number of lags selected by the SBC and when needed, augmented with additional lags following the Portmanteau White Noise Test. The values reported are P-values from the Portmanteau White Noise Test (Ljung-Box-Q test).

Table 10b: Results CADF Lags - Portmanteau White Noise Test (Ljung-Box-Q)

		Number of lags in Portmanteau White Noise Test (CADF)				
Country	# of lags selected	1	2	3	4	5
Austria	0	0.595	0.745	0.842	0.932	0.585
Belgium	1	0.197	0.407	0.614	0.768	0.385
Bulgaria	0	0.194	0.166	0.167	0.210	0.058
Croatia	2	0.208	0.240	0.251	0.123	0.189
Cyprus	0	0.360	0.176	0.127	0.107	0.162
Czech Repub	0	0.868	0.972	0.297	0.445	0.270
Denmark	0	0.705	0.234	0.381	0.542	0.508
Estonia	2	0.368	0.548	0.726	0.859	0.816
Finland	1	0.703	0.181	0.307	0.413	0.554
France	0	0.204	0.383	0.587	0.740	0.847
Germany	0	0.656	0.598	0.613	0.657	0.774
Greece	0	0.617	0.681	0.799	0.783	0.730
Hungary	0	0.963	0.231	0.398	0.470	0.616
Ireland	0	0.601	0.827	0.912	0.855	0.919
Italy	0	0.174	0.185	0.256	0.218	0.253
Latvia	0	0.856	0.783	0.910	0.797	0.876
Lithuania	0	0.465	0.765	0.448	0.589	0.656
Luxembourg	2	0.433	0.405	0.494	0.441	0.272
Malta	0	0.060	0.127	0.133	0.188	0.268
Netherlands	1	0.711	0.550	0.751	0.780	0.534
Poland	0	0.169	0.273	0.290	0.278	0.234
Portugal	1	0.396	0.096	0.092	0.167	0.139
Romania	1	0.973	0.006	0.192	0.314	0.415
Slovak Repul	0	0.752	0.807	0.096	0.175	0.225
Slovenia	0	0.068	0.130	0.252	0.342	0.475
Spain	0	0.339	0.183	0.330	0.433	0.548
Sweden	1	0.833	0.587	0.305	0.351	0.483
UK	0	0.986	0.998	0.228	0.310	0.399

Note: Column 2 reports the number of lags selected by the SBC and when needed, augmented with additional lags following the Portmanteau White Noise Test. The values reported are P-values from the Portmanteau White Noise Test (Ljung-Box-Q test).

Table 10a(b) presents the number of lags selected to be used in the IPS(CADF) panel unit root test. The lags where selected by firstly regressing each model with various augmentations and cross-sectional means in the case of the CADF, then based on the SBC for respective model choosing the best model. To ensure that the model captures all significant serial correlation, we compute the Portmanteau White Noise Test (also referred to as the Ljung-Box-Q test) with five lags to. Column 3-7 report the P-values for the null of no serial correlation with each lag. In each case we find insufficient support for a rejection of the null hypothesis and therefore conclude that the model sufficiently captures all serial correlation. In the Portmanteau White Noise test, we have to specify the number of lags for which we want to test for serial correlation. For non-seasonal data such as the panel used here, Hyndman and Athanasopoulos (2013) recommend the number of lags to be selected by: #lags=min(10, T/5), which implies approximately five and we therefore check for serial correlation five lags back.

Appendix G: Results Beta-Convergence

Table 11a. Complete regression results (1/2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(I_{t-1})$	-0,335***	-0,343***	-0,368***	-0,367***	-0,344***	-0,383***	-0,417***	-0,434***	-0,355***	-0,471***
	(0,0810)	(0,0781)	(0,0647)	(0,0645)	(0,0861)	(0,0692)	(0,109)	(0,113)	(0,0689)	(0,0880)
EU_t		0,0495		0,00162		0,0307	-0,00934	0,0210	0,0125	-0,00619
		(0,0329)		(0,0294)		(0,0309)	(0,0277)	(0,0288)	(0,0313)	(0,0285)
$\ln(GDPpc_t)$			0,221**	0,219*		0,294**	0,240**	0,317**	0,198*	0,236**
			(0,107)	(0,111)		(0,135)	(0,107)	(0,133)	(0,0981)	(0,106)
$\ln(ETI_t)$					0,0143	-0,0661**		-0,0686**		
					(0,0230)	(0,0295)		(0,0292)		
$\ln(I_{t-1})*\ln(WPF_t)$							0,0188	0,0195		0,0485***
							(0,0200)	(0,0197)		(0,0121)
$\ln(I_{t-1})*(CP_t)$									-0,00247	-0,00460**
									(0,00201)	(0,00178)
Constant	2,094***	2,107***	0,114	0,138	2,102***	-0,298	0,0160	-0,424	0,252	0,0364
	(0,533)	(0,524)	-1300	-1341	(0,619)	-1513	-1329	-1517	-1224	-1306
Austria	-0,285***	-0,292***	-0,349***	-0,348***	-0,292***	-0,376***	-0,353***	-0,381***	-0,343***	-0,350***
	(0,0719)	(0,0694)	(0,0528)	(0,0519)	(0,0770)	(0,0576)	(0,0561)	(0,0621)	(0,0524)	(0,0539)
Belgium	-0,199***	-0,204***	-0,242***	-0,241***	-0,197***	-0,292***	-0,243***	-0,295***	-0,239***	-0,241***
	(0,0476)	(0,0459)	(0,0349)	(0,0343)	(0,0579)	(0,0441)	(0,0362)	(0,0464)	(0,0342)	(0,0348)
Bulgaria	0,0489***	0,0781***	0,483**	0,478**	0,0761*	0,522**	0,513**	0,556**	0,446**	0,507**
	(0,00916)	(0,0174)	(0,204)	(0,207)	(0,0375)	(0,225)	(0,204)	(0,225)	(0,186)	(0,203)
Croatia	-0,145***	-0,107*	0,0854	0,0839	-0,133***	0,152	0,0971	0,167	0,0719	0,0952
	(0,0410)	(0,0568)	(0,136)	(0,136)	(0,0419)	(0,146)	(0,136)	(0,146)	(0,124)	(0,134)
Cyprus	0,168***	0,193***	0,248***	0,248***	0,196***	0,277***	0,250***	0,275***	0,246***	0,250***
	(0,0381)	(0,0338)	(0,0335)	(0,0330)	(0,0465)	(0,0401)	(0,0344)	(0,0402)	(0,0333)	(0,0342)
Czech Republic	0,101***	0,125***	0,282***	0,281***	0,123***	0,270***	0,294***	0,282***	0,269***	0,291***
	(0,0238)	(0,0217)	(0,0768)	(0,0763)	(0,0264)	(0,0759)	(0,0767)	(0,0774)	(0,0702)	(0,0768)
Denmark	-0,0841***	-0,0851***	-0,180***	-0,179***	-0,0905***	-0,188***	-0,186***	-0,195***	-0,172***	-0,185***
	(0,0108)	(0,0104)	(0,0413)	(0,0426)	(0,00980)	(0,0465)	(0,0423)	(0,0470)	(0,0390)	(0,0423)
Estonia	0,280***	0,307***	0,542***	0,540***	0,315***	0,517***	0,559***	0,534***	0,522***	0,555***
	(0,0625)	(0,0563)	(0,104)	(0,103)	(0,0560)	(0,101)	(0,106)	(0,106)	(0,0976)	(0,106)
Finland	-0,295***	-0,302***	-0,350***	-0,350***	-0,300***	-0,386***	-0,353***	-0,390***	-0,346***	-0,352***
	(0,0669)	(0,0646)	(0,0495)	(0,0488)	(0,0740)	(0,0552)	(0,0522)	(0,0590)	(0,0485)	(0,0497)
France	-0,637***	-0,652***	-0,710***	-0,710***	-0,658***	-0,730***	-0,713***	-0,733***	-0,704***	-0,707***
	(0,155)	(0,150)	(0,122)	(0,122)	(0,163)	(0,131)	(0,127)	(0,137)	(0,119)	(0,122)
Germany	0,0344***	0,0350***	0,0235**	0,0236**	0,0379***	0,00736	0,0229**	0,00612	0,0242**	0,0230**
	(0,00647)	(0,00624)	(0,00983)	(0,0102)	(0,00577)	(0,0150)	(0,0101)	(0,0149)	(0,00931)	(0,00981)
Greece	0,160***	0,164***	0,269***	0,268***	0,174***	0,263***	0,278***	0,272***	0,258***	0,275***
	(0,0387)	(0,0373)	(0,0430)	(0,0431)	(0,0351)	(0,0437)	(0,0457)	(0,0469)	(0,0419)	(0,0455)
Hungary	-0,0687***	-0,0489**	0,179	0,176	-0,106***	0,158	0,197	0,180	0,157	0,193
	(0,0146)	(0,0235)	(0,127)	(0,129)	(0,0308)	(0,142)	(0,126)	(0,140)	(0,115)	(0,124)
Ireland	0,0504***	0,0517***	0,0112	0,0117	0,0574***	-0,0261	0,00905	-0,0300	0,0140	0,00919
	(0,0133)	(0,0128)	(0,0276)	(0,0286)	(0,0118)	(0,0402)	(0,0282)	(0,0399)	(0,0261)	(0,0277)
Italy	-0,0126***	-0,0129***	-0,00241	-0,00255	-0,0162***	0,0155	-0,000893	0,0178	-0,00412	-0,00124
	(0,00367)	(0,00354)	(0,00732)	(0,00760)	(0,00442)	(0,0134)	(0,00699)	(0,0129)	(0,00635)	(0,00675)
Latvia	-0,446***	-0,436***	-0,188	-0,191	-0,449***	-0,145	-0,167	-0,121	-0,211	-0,169
	(0,115)	(0,117)	(0,202)	(0,207)	(0,132)	(0,227)	(0,201)	(0,224)	(0,185)	(0,196)
Lithuania	-0,448***	-0,439***	-0,197	-0,200	-0,447***	-0,175	-0,180	-0,156	-0,216	-0,179
	(0,120)	(0,122)	(0,203)	(0,208)	(0,142)	(0,224)	(0,204)	(0,223)	(0,188)	(0,200)
Luxembourg	-0,107***	-0,109***	-0,323***	-0,320***	-0,110***	-0,388***	-0,339***	-0,408***	-0,302***	-0,334***
	(0,0159)	(0,0153)	(0,0962)	(0,0994)	(0,0158)	(0,121)	(0,0977)	(0,121)	(0,0897)	(0,0974)
Malta	0,207***	0,233***	0,374***	0,373***	0,226***	0,384***	0,383***	0,393***	0,363***	0,380***
	(0,0514)	(0,0459)	(0,0654)	(0,0638)	(0,0464)	(0,0668)	(0,0666)	(0,0703)	(0,0618)	(0,0667)
Netherlands	0,0151***	0,0150***	-0,0368	-0,0362	0,0178***	-0,0670*	-0,0406	-0,0723**	-0,0319	-0,0395
	(0,000711)	(0,000685)	(0,0246)	(0,0255)	(0,00502)	(0,0354)	(0,0250)	(0,0352)	(0,0229)	(0,0248)
Poland	0,197***	0,222***	0,505***	0,502***	0,223***	0,524***	0,526***	0,547***	0,479***	0,520***
	(0,0452)	(0,0402)	(0,129)	(0,129)	(0,0408)	(0,138)	(0,130)	(0,141)	(0,119)	(0,130)
Portugal	-0,0466***	-0,0478***	0,0733	0,0719	-0,0443**	0,0948	0,0848	0,108	0,0597	0,0825
	(0,0118)	(0,0114)	(0,0645)	(0,0670)	(0,0166)	(0,0758)	(0,0640)	(0,0739)	(0,0585)	(0,0631)
Romania	0,0177*	0,0468**	0,402**	0,398**	0,0396	0,450**	0,430**	0,481**	0,368**	0,423**
	(0,00866)	(0,0173)	(0,181)	(0,183)	(0,0294)	(0,201)	(0,180)	(0,201)	(0,164)	(0,179)
Slovak Republic	-0,235***	-0,220***	-0,0264	-0,0284	-0,225***	-0,0245	-0,00995	-0,00689	-0,0448	-0,0116
	(0,0546)	(0,0596)	(0,135)	(0,137)	(0,0761)	(0,145)	(0,134)	(0,143)	(0,122)	(0,131)
Slovenia	-0,104***	-0,0850**	0,0174	0,0166	-0,102***	0,0487	0,0243	0,0570	0,00970	0,0234
	(0,0265)	(0,0337)	(0,0747)	(0,0750)	(0,0326)	(0,0849)	(0,0745)	(0,0850)	(0,0680)	(0,0732)
Spain	-0,0965***	-0,0989***	-0,0500	-0,0506	-0,0934***	-0,0635	-0,0447	-0,0582	-0,0563	-0,0459
	(0,0247)	(0,0238)	(0,0396)	(0,0410)	(0,0325)	(0,0420)	(0,0389)	(0,0406)	(0,0357)	(0,0376)
Sweden	-1,055***	-1,079***	-1,209***	-1,208***	-1,094***	-1,224***	-1,215***	-1,230***	-1,198***	-1,207***
	(0,250)	(0,241)	(0,191)	(0,189)	(0,257)	(0,203)	(0,199)	(0,213)	(0,186)	(0,190)

Note: Table 11a continues in table 11b.

Table 11b. Complete regression results (2/2)

Year = 1996	0,0442	0,0439	0,0315	0,0316	0,0542	0,0418	0,0170	0,0267	0,0331	-0,00318
	(0,0511)	(0,0508)	(0,0473)	(0,0485)	(0,0557)	(0,0542)	(0,0475)	(0,0530)	(0,0493)	(0,0463)
Year = 1997	-0,0396*	-0,0397*	-0,0639***	-0,0637***	-0,0549**	-0,0691***	-0,0700***	-0,0752***	-0,0613***	-0,0754***
	(0,0195)	(0,0194)	(0,0183)	(0,0184)	(0,0204)	(0,0184)	(0,0208)	(0,0211)	(0,0182)	(0,0202)
Year = 1998	0,0152	0,0145	-0,0223	-0,0218	0,00757	-0,0120	0,00599	0,0171	-0,0176	0,0577*
	(0,0464)	(0,0458)	(0,0320)	(0,0334)	(0,0472)	(0,0407)	(0,0384)	(0,0402)	(0,0348)	(0,0339)
Year = 1999	-0,000579	-0,00119	-0,0456**	-0,0451*	-0,00441	-0,0274	-0,0348	-0,0162	-0,0403	-0,00954
	(0,0348)	(0,0343)	(0,0220)	(0,0241)	(0,0334)	(0,0314)	(0,0247)	(0,0288)	(0,0266)	(0,0247)
Year = 2000	-0,0441	-0,0447	-0,104***	-0,103***	-0,0548*	-0,0936***	-0,145***	-0,136**	-0,0968***	-0,198***
	(0,0291)	(0,0287)	(0,0220)	(0,0236)	(0,0280)	(0,0285)	(0,0474)	(0,0536)	(0,0239)	(0,0356)
Year = 2001	-0,0136	-0,0147	-0,0870***	-0,0861**	-0,0210	-0,0765*	-0,121***	-0,111**	-0,0781**	-0,160***
	(0,0338)	(0,0330)	(0,0283)	(0,0335)	(0,0338)	(0,0384)	(0,0435)	(0,0500)	(0,0335)	(0,0374)
Year = 2002	-0,0104	-0,0115	-0,0954***	-0,0944***	-0,0183	-0,0832**	-0,126***	-0,115***	-0,0853***	-0,159***
	(0,0278)	(0,0270)	(0,0261)	(0,0330)	(0,0247)	(0,0320)	(0,0301)	(0,0326)	(0,0294)	(0,0309)
Year = 2003	0,0229	0,0218	-0,0731*	-0,0720	0,00784	-0,0697	-0,125**	-0,123**	-0,0619	-0,189***
	(0,0358)	(0,0354)	(0,0418)	(0,0480)	(0,0349)	(0,0491)	(0,0521)	(0,0556)	(0,0448)	(0,0494)
Year = 2004	-0,0756**	-0,0941***	-0,184***	-0,183***	-0,0864**	-0,183***	-0,254***	-0,256***	-0,176***	-0,352***
	(0,0336)	(0,0278)	(0,0388)	(0,0392)	(0,0337)	(0,0404)	(0,0802)	(0,0838)	(0,0363)	(0,0638)
Year = 2005	-0,0368	-0,0559	-0,160***	-0,159***	-0,0479	-0,159***	-0,265**	-0,267**	-0,150***	-0,413***
	(0,0493)	(0,0415)	(0,0414)	(0,0430)	(0,0445)	(0,0447)	(0,117)	(0,120)	(0,0408)	(0,0869)
Year = 2006	-0,0166	-0,0358	-0,155***	-0,154***	-0,0256	-0,155***	-0,283**	-0,287**	0,148	0,0789
	(0,0428)	(0,0344)	(0,0445)	(0,0476)	(0,0407)	(0,0495)	(0,125)	(0,127)	(0,229)	(0,241)
Year = 2007	-0,0236	-0,0462	-0,177***	-0,176***	-0,0351	-0,178***	-0,314**	-0,320**	-0,150***	-0,483***
	(0,0363)	(0,0311)	(0,0577)	(0,0572)	(0,0335)	(0,0579)	(0,141)	(0,142)	(0,0484)	(0,108)
Year = 2008	-0,0840**	-0,107***	-0,246***	-0,245***	-0,0971***	-0,250***	-0,412**	-0,422**	-0,233***	-0,652***
	(0,0365)	(0,0277)	(0,0586)	(0,0598)	(0,0299)	(0,0615)	(0,162)	(0,164)	(0,0539)	(0,117)
Year = 2009	-0,0934**	-0,116***	-0,245***	-0,244***	-0,108**	-0,242***	-0,361***	-0,362***	-0,0448	-0,173
	(0,0436)	(0,0327)	(0,0494)	(0,0526)	(0,0391)	(0,0530)	(0,119)	(0,122)	(0,146)	(0,169)
Year = 2010	-0,0198	-0,0433	-0,179***	-0,178***	-0,0352	-0,176**	-0,306*	-0,307*	0,0547	-0,0722
	(0,0990)	(0,0869)	(0,0546)	(0,0596)	(0,0897)	(0,0693)	(0,152)	(0,159)	(0,207)	(0,225)
Year = 2011	-0,0556	-0,0788	-0,223***	-0,222***	-0,0718	-0,218***	-0,383**	-0,383**	-0,00882	-0,238
	(0,0530)	(0,0466)	(0,0586)	(0,0564)	(0,0481)	(0,0561)	(0,171)	(0,174)	(0,170)	(0,209)
Year = 2012	-0,0991	-0,122**	-0,272***	-0,271***	-0,116**	-0,265***	-0,429**	-0,427**	-0,148	-0,449**
	(0,0612)	(0,0544)	(0,0615)	(0,0605)	(0,0566)	(0,0620)	(0,175)	(0,178)	(0,106)	(0,164)
Year = 2013	-0,131**	-0,157***	-0,310***	-0,308***	-0,150***	-0,301***	-0,456***	-0,453***	-0,229***	-0,542***
	(0,0582)	(0,0474)	(0,0582)	(0,0602)	(0,0493)	(0,0626)	(0,151)	(0,155)	(0,0699)	(0,125)
Year = 2014	-0,154**	-0,180***	-0,340***	-0,339***	-0,174***	-0,329***	-0,468***	-0,461***	-0,242**	-0,490***
	(0,0650)	(0,0554)	(0,0653)	(0,0658)	(0,0567)	(0,0687)	(0,143)	(0,148)	(0,0917)	(0,132)
Year = 2015	-0,113	-0,139**	-0,308***	-0,307***	-0,135**	-0,297***	-0,379***	-0,369***	-0,184*	-0,263**
	(0,0687)	(0,0596)	(0,0676)	(0,0653)	(0,0568)	(0,0639)	(0,0958)	(0,0983)	(0,105)	(0,119)
R^2	0,223	0,231	0,244	0,244	0,227	0,257	0,247	0,260	0,251	0,266
Adjusted R^2	0,154	0,161	0,175	0,173	0,153	0,182	0,175	0,184	0,180	0,195
Countries	28	28	28	28	28	28	28	28	28	28
N	588	588	588	558	558	558	588	558	588	588

Note: Bootstrapped standard errors in parentheses: *** p < 0,01, ** p < 0,05, * p < 0,1. The dependent variable being estimated is the lagged carbon intensity. The reference group is the United Kingdom in 1995.

Appendix H. Robustness Check Results

Table 12a. Regression results OLS vs FE (1/2)

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS	FE	OLS
$\ln(I_{t-1})$	-0,335***	-0,0136	-0,343***	-0,0138	-0,368***	-0,0155*	-0,367***	-0,0153*	-0,344***	-0,0216***	-0,383***	-0,0264***	-0,417***	-0,0569*	-0,434***	-0,0678**	-0,355***	-0,00409	-0,471***	-0,116***
	(0,0810)	(0,00877)	(0,0781)	(0,00872)	(0,0647)	(0,00756)	(0,0645)	(0,00749)	(0,0861)	(0,00773)	(0,0692)	(0,00855)	(0,109)	(0,0296)	(0,113)	(0,0303)	(0,0689)	(0,00582)	(0,0880)	(0,0174)
EU_t			0,0495	-0,00433			0,00162	0,0223			0,0307	0,0504*	-0,00934	0,0176	0,0210	0,0463*	0,0125	0,0283	-0,00619	0,0198
			(0,0329)	(0,0100)			(0,0294)	(0,0176)			(0,0309)	(0,0251)	(0,0277)	(0,0197)	(0,0288)	(0,0266)	(0,0313)	(0,0199)	(0,0285)	(0,0200)
$\ln(GDPpc_t)$					0,221**	-0,0141**	0,219*	-0,0213**			0,294**	0,000646	0,240**	-0,0193**	0,317**	0,00262	0,198*	-0,0237**	0,236**	-0,0201**
					(0,107)	(0,00540)	(0,111)	(0,00868)			(0,135)	(0,00706)	(0,107)	(0,00886)	(0,133)	(0,00742)	(0,0981)	(0,00970)	(0,106)	(0,00924)
$\ln(ETI_t)$									0,0143	-0,0216***	-0,0661**	-0,0404***			-0,0686**	-0,0408***				
									(0,0230)	(0,00745)	(0,0295)	(0,0142)			(0,0292)	(0,0139)				
$\ln(I_{t-1})*\ln(WPF_t)$																	-0,00247	-0,00262	-0,00460**	-0,00479***
																	(0,00201)	(0,00156)	(0,00178)	(0,00151)
$\ln(I_{t-1})*(CP_t)$													0,0188	0,0163	0,0195	0,0161			0,0485***	0,0474***
													(0,0200)	(0,0132)	(0,0197)	(0,0135)			(0,0121)	(0,00640)
Constant	2,094***	0,0467	2,107***	0,0504	0,114	0,191***	0,138	0,245***	2,102***	0,151***	-0,298	0,199***	0,0160	0,292***	-0,424	0,247***	0,252	0,197***	0,0364	0,293***
	(0,533)	(0,0533)	(0,524)	(0,0542)	-1300	(0,0574)	-1341	(0,0705)	(0,619)	(0,0481)	-1513	(0,0595)	-1329	(0,0593)	-1517	(0,0524)	-1224	(0,0665)	-1306	(0,0612)
Austria	-0,285***		-0,292***		-0,349***		-0,348***		-0,292***		-0,376***		-0,353***		-0,381***		-0,343***		-0,350***	
	(0,0719)		(0,0694)		(0,0528)		(0,0519)		(0,0770)		(0,0576)		(0,0561)		(0,0621)		(0,0524)		(0,0539)	
Belgium	-0,199***		-0,204***		-0,242***		-0,241***		-0,197***		-0,292***		-0,243***		-0,295***		-0,239***		-0,241***	
	(0,0476)		(0,0459)		(0,0349)		(0,0343)		(0,0579)		(0,0441)		(0,0362)		(0,0464)		(0,0342)		(0,0348)	
Bulgaria	0,0489***		0,0781***		0,483**		0,478**		0,0761*		0,522**		0,513**		0,556**		0,446**		0,507**	
	(0,00916)		(0,0174)		(0,204)		(0,207)		(0,0375)		(0,225)		(0,204)		(0,225)		(0,186)		(0,203)	
Croatia	-0,145***		-0,107*		0,0854		0,0839		-0,133***		0,152		0,0971		0,167		0,0719		0,0952	
	(0,0410)		(0,0568)		(0,136)		(0,136)		(0,0419)		(0,146)		(0,136)		(0,146)		(0,124)		(0,134)	
Cyprus	0,168***		0,193***		0,248***		0,248***		0,196***		0,277***		0,250***		0,275***		0,246***		0,250***	
	(0,0381)		(0,0338)		(0,0335)		(0,0330)		(0,0465)		(0,0401)		(0,0344)		(0,0402)		(0,0333)		(0,0342)	
Czech Republic	0,101***		0,125***		0,282***		0,281***		0,123***		0,270***		0,294***		0,282***		0,269***		0,291***	
	(0,0238)		(0,0217)		(0,0768)		(0,0763)		(0,0264)		(0,0759)		(0,0767)		(0,0774)		(0,0702)		(0,0768)	
Denmark	-0,0841***		-0,0851***		-0,180***		-0,179***		-0,0905***		-0,188***		-0,186***		-0,195***		-0,172***		-0,185***	
	(0,0108)		(0,0104)		(0,0413)		(0,0426)		(0,00980)		(0,0465)		(0,0423)		(0,0470)		(0,0390)		(0,0423)	
Estonia	0,280***		0,307***		0,542***		0,540***		0,315***		0,517***		0,559***		0,534***		0,522***		0,555***	
	(0,0625)		(0,0563)		(0,104)		(0,103)		(0,0560)		(0,101)		(0,106)		(0,106)		(0,0976)		(0,106)	
Finland	-0,295***		-0,302***		-0,350***		-0,350***		-0,300***		-0,386***		-0,353***		-0,390***		-0,346***		-0,352***	
	(0,0669)		(0,0646)		(0,0495)		(0,0488)		(0,0740)		(0,0552)		(0,0522)		(0,0590)		(0,0485)		(0,0497)	
France	-0,637***		-0,652***		-0,710***		-0,710***		-0,658***		-0,730***		-0,713***		-0,733***		-0,704***		-0,707***	
	(0,155)		(0,150)		(0,122)		(0,122)		(0,163)		(0,131)		(0,127)		(0,137)		(0,119)		(0,122)	
Greece	0,0344***		0,0350***		0,0235**		0,0236**		0,0379***		0,00736		0,0229**		0,00612		0,0242**		0,0230**	
	(0,00647)		(0,00624)		(0,00983)		(0,0102)		(0,00577)		(0,0150)		(0,0101)		(0,0149)		(0,00931)		(0,00981)	
Germany	0,160***		0,164***		0,269***		0,268***		0,174***		0,263***		0,278***		0,272***		0,258***		0,275***	
	(0,0387)		(0,0373)		(0,0430)		(0,0431)		(0,0351)		(0,0437)		(0,0457)		(0,0469)		(0,0419)		(0,0455)	
Hungary	-0,0687***		-0,0489**		0,179		0,176		-0,106***		0,158		0,197		0,180		0,157		0,193	
	(0,0146)		(0,0235)		(0,127)		(0,129)		(0,0308)		(0,142)		(0,126)		(0,140)		(0,115)		(0,124)	
Ireland	0,0504***		0,0517***		0,0112		0,0117		0,0574***		-0,0261		0,00905		-0,0300		0,0140		0,00919	
	(0,0133)		(0,0128)		(0,0276)		(0,0286)		(0,0118)		(0,0402)		(0,0282)		(0,0399)		(0,0261)		(0,0277)	
Italy	-0,0126***		-0,0129***		-0,00241		-0,00255		-0,0162***		0,0155		-0,000893		0,0178		-0,00412		-0,00124	
	(0,00367)		(0,00354)		(0,00732)		(0,00760)		(0,00442)		(0,0134)		(0,00699)		(0,0129)		(0,00635)		(0,00675)	
Latvia	-0,446***		-0,436***		-0,188		-0,191		-0,449***		-0,145		-0,167		-0,121		-0,211		-0,169	
	(0,115)		(0,117)		(0,202)		(0,207)		(0,132)		(0,227)		(0,201)		(0,224)		(0,185)		(0,196)	
Lithuania	-0,448***		-0,439***		-0,197		-0,200		-0,447***		-0,175		-0,180		-0,156		-0,216		-0,179	
	(0,120)		(0,122)		(0,203)		(0,208)		(0,142)		(0,224)		(0,204)		(0,223)		(0,188)		(0,200)	
Luxembourg	-0,107***		-0,109***		-0,323***		-0,320***		-0,110***		-0,388***		-0,339***		-0,408***		-0,302***		-0,334***	
	(0,0159)		(0,0153)		(0,0962)		(0,0994)		(0,0158)		(0,121)		(0,0977)		(0,121)		(0,0897)		(0,0974)	
Malta	0,207***		0,233***		0,374***		0,373***		0,226***		0,384***		0,383***		0,393***		0,363***		0,380***	
	(0,0514)		(0,0459)		(0,0654)		(0,0638)		(0,0464)		(0,0668)		(0,0666)		(0,0703)		(0,0618)		(0,0667)	
Netherlands	0,0151***		0,0150***		-0,0368		-0,0362		0,0178***		-0,0670*		-0,0406		-0,0723**		-0,0319		-0,0395	
	(0,000711)		(0,000685)		(0,0246)		(0,0255)		(0,00502)		(0,0354)		(0,0250)		(0,0352)		(0,0229)		(0,0248)	
Poland	0,197***		0,222***		0,505***		0,502***		0,223***		0,524***		0,526***		0,547***		0,479***		0,520***	
	(0,0452)		(0,0402)		(0,129)		(0,129)		(0,0408)		(0,138)		(0,130)		(0,141)		(0,119)		(0,130)	
Portugal	-0,0466***		-0,0478***		0,0733		0,0719		-0,0443**		0,0948		0,0848		0,108		0,0597		0,0825	
	(0,0118)		(0,0114)		(0,0645)		(0,0670)		(0,0166)		(0,0758)		(0,0640)		(0,0739)		(0,0585)		(0,0631)	
Romania	0,0177*		0,0468**		0,402**		0,398**		0,0396		0,450**		0,430**		0,481**		0,368**		0,423**	
	(0,00866)		(0,0173)		(0,181)		(0,183)		(0,0294)		(0,201)		(0,180)		(0,201)		(0,164)		(0,179)	
Slovak Republic	-0,235***		-0,220***		-0,0264		-0,0284		-0,225***		-0,0245		-0,00995		-0,00689		-0,0448		-0,0116	
	(0,0546)		(0,0596)		(0,135)		(0,137)		(0,0761)		(0,145)		(0,134)		(0,143)		(0,122)		(0,131)	
Slovenia	-0,104***		-0,0850**		0,0174		0,0166		-0,102***		0,0487		0,0243		0,0570		0,00970		0,0234	
	(0,0265)		(0,0337)		(0,0747)		(0,0750)		(0,0326)		(0,0849)		(0,0745)		(0,0850)		(0,0680)		(0,0732)	
Spain	-0,0965***		-0,0989***		-0,0500		-0,0506		-0,0934***		-0,0635		-0,0447		-0,0582		-0,0563		-0,0459	
	(0,0247)		(0,0238)		(0,0396)		(0,0410)		(0,0325)		(0,0420)		(0,0389)		(0,0406)		(0,0357)		(0,0376)	
Sweden	-1,055***		-1,079***		-1,209***		-1,208***		-1,094***		-1,224***		-1,215***		-1,230***		-1,198***		-1,207***	
	(0,250)		(0,241)		(0,191)		(0,189)		(0,257)		(0,203)		(0,199)		(0,213)		(0,186)		(0,190)	

Note: Table 12a continues in table 12b.

Table 12b. Regression results OLS vs FE (2/2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year = 1996	0,0442	0,0439	0,0315	0,0316	0,0542	0,0418	0,017	0,0267	0,0331	-0,00318
	-0,0498	-0,0451	-0,0434	-0,0427	-0,0473	-0,0548	-0,0453	-0,0486	-0,0423	-0,0427
Year = 1997	-0,0396	-0,0397	-0,0639*	-0,0637*	-0,0549	-0,0691	-0,0700*	-0,0752	-0,0613	-0,0754*
	-0,04	-0,0421	-0,0355	-0,0369	-0,0363	-0,0424	-0,036	-0,0477	-0,0378	-0,0393
Year = 1998	0,0152	0,0145	-0,0223	-0,0218	0,00757	-0,012	0,00599	0,0171	-0,0176	0,0577
	-0,0336	-0,037	-0,0338	-0,034	-0,0357	-0,0402	-0,0537	-0,0534	-0,0351	-0,044
Year = 1999	-0,000579	-0,00119	-0,0456	-0,0451	-0,00441	-0,0274	-0,0348	-0,0162	-0,0403	-0,00954
	-0,033	-0,0343	-0,0311	-0,0337	-0,0307	-0,0343	-0,0375	-0,0396	-0,0324	-0,0318
Year = 2000	-0,0441	-0,0447	-0,104***	-0,103***	-0,0548*	-0,0936**	-0,145***	-0,136***	-0,0968***	-0,198***
	-0,034	-0,0305	-0,0309	-0,0336	-0,0314	-0,037	-0,0534	-0,0437	-0,0339	-0,0543
Year = 2001	-0,0136	-0,0147	-0,0870**	-0,0861**	-0,021	-0,0765**	-0,121**	-0,111**	-0,0781**	-0,160***
	-0,0326	-0,0331	-0,0346	-0,0381	-0,0321	-0,0385	-0,0488	-0,0449	-0,0345	-0,0493
Year = 2002	-0,0104	-0,0115	-0,0954**	-0,0944**	-0,0183	-0,0832*	-0,126**	-0,115***	-0,0853*	-0,159***
	-0,0357	-0,0317	-0,0401	-0,0447	-0,0361	-0,0439	-0,0497	-0,0429	-0,0438	-0,0491
Year = 2003	0,0229	0,0218	-0,0731	-0,072	0,00784	-0,0697	-0,125*	-0,123**	-0,0619	-0,189***
	-0,0377	-0,039	-0,0469	-0,0453	-0,0415	-0,051	-0,0711	-0,056	-0,049	-0,0661
Year = 2004	-0,0756**	-0,0941***	-0,184***	-0,183***	-0,0864**	-0,183***	-0,254***	-0,256***	-0,176***	-0,352***
	-0,0352	-0,033	-0,0411	-0,0434	-0,036	-0,0515	-0,0856	-0,0644	-0,0446	-0,0797
Year = 2005	-0,0368	-0,0559	-0,160***	-0,159***	-0,0479	-0,159***	-0,265**	-0,267***	-0,150***	-0,413***
	-0,038	-0,0384	-0,0461	-0,0462	-0,0351	-0,0525	-0,119	-0,088	-0,0504	-0,117
Year = 2006	-0,0166	-0,0358	-0,155***	-0,154***	-0,0256	-0,155***	-0,283*	-0,287***	0,148	0,0789
	-0,0352	-0,0366	-0,0537	-0,0512	-0,0346	-0,053	-0,145	-0,104	-0,24	-0,212
Year = 2007	-0,0236	-0,0462	-0,177***	-0,176***	-0,0351	-0,178***	-0,314**	-0,320***	-0,150**	-0,483***
	-0,0322	-0,0312	-0,0513	-0,0533	-0,0364	-0,0604	-0,157	-0,117	-0,0584	-0,141
Year = 2008	-0,0840**	-0,107***	-0,246***	-0,245***	-0,0971***	-0,250***	-0,412**	-0,422***	-0,233***	-0,652***
	-0,034	-0,0297	-0,0531	-0,0574	-0,0322	-0,0625	-0,188	-0,137	-0,0587	-0,17
Year = 2009	-0,0934***	-0,116***	-0,245***	-0,244***	-0,108***	-0,242***	-0,361***	-0,362***	-0,0448	-0,173
	-0,0332	-0,0299	-0,0516	-0,0582	-0,0334	-0,0622	-0,132	-0,0977	-0,155	-0,153
Year = 2010	-0,0198	-0,0433	-0,179***	-0,178***	-0,0352	-0,176***	-0,306*	-0,307***	0,0547	-0,0722
	-0,0684	-0,0577	-0,0557	-0,0562	-0,0567	-0,0608	-0,162	-0,118	-0,216	-0,198
Year = 2011	-0,0556	-0,0788**	-0,223***	-0,222***	-0,0718*	-0,218***	-0,383**	-0,383***	-0,00882	-0,238
	-0,0372	-0,0325	-0,059	-0,0658	-0,0403	-0,0662	-0,184	-0,131	-0,172	-0,19
Year = 2012	-0,0991**	-0,122***	-0,272***	-0,271***	-0,116***	-0,265***	-0,429**	-0,427***	-0,148	-0,449***
	-0,0439	-0,0444	-0,0694	-0,0716	-0,0426	-0,0709	-0,178	-0,136	-0,103	-0,166
Year = 2013	-0,131***	-0,157***	-0,310***	-0,308***	-0,150***	-0,301***	-0,456***	-0,453***	-0,229***	-0,542***
	-0,0408	-0,0355	-0,0579	-0,0656	-0,0428	-0,075	-0,167	-0,123	-0,0768	-0,148
Year = 2014	-0,154***	-0,180***	-0,340***	-0,339***	-0,174***	-0,329***	-0,468***	-0,461***	-0,242***	-0,490***
	-0,0387	-0,0386	-0,0674	-0,0741	-0,0445	-0,0834	-0,146	-0,108	-0,0927	-0,139
Year = 2015	-0,113**	-0,139***	-0,308***	-0,307***	-0,135***	-0,297***	-0,379***	-0,369***	-0,184*	-0,263**
	-0,0449	-0,0443	-0,0713	-0,0782	-0,0457	-0,0852	-0,0931	-0,0847	-0,109	-0,117
R^2	0,223	0,231	0,244	0,244	0,227	0,257	0,247	0,260	0,251	0,266
Adjusted R^2	0,154	0,161	0,175	0,173	0,153	0,182	0,175	0,184	0,180	0,195
Countries	28	28	28	28	28	28	28	28	28	28
N	588	588	588	588	558	558	588	558	588	588

Note: Country level standard errors in parentheses: *** $p < 0,01$, ** $p < 0,05$, * $p < 0,1$. The dependent variable being estimated is the lagged carbon intensity. The reference group is the United Kingdom in 1995.

Table 13a. Regression Results with Bootstrapped Standard Errors (1/2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(I_{t-1})$	-0,335***	-0,343***	-0,368***	-0,367***	-0,344***	-0,383***	-0,417***	-0,434***	-0,355***	-0,471***
	(0,0470)	(0,0490)	(0,0541)	(0,0553)	(0,0518)	(0,0539)	(0,0725)	(0,0606)	(0,0523)	(0,0724)
EU_t		0,0495**		0,00162		0,0307	-0,00934	0,0210	0,0125	-0,00619
		(0,0231)		(0,0232)		(0,0320)	(0,0258)	(0,0321)	(0,0255)	(0,0265)
$\ln(GDPpc_t)$			0,221***	0,219**		0,294***	0,240***	0,317***	0,198**	0,236***
			(0,0784)	(0,0880)		(0,0937)	(0,0824)	(0,0901)	(0,0834)	(0,0798)
$\ln(ETI_t)$					0,0143	-0,0661**		-0,0686**		
					(0,0253)	(0,0325)		(0,0329)		
$\ln(I_{t-1})*\ln(WPF_t)$							0,0188	0,0195		0,0485***
							(0,0219)	(0,0173)		(0,0184)
$\ln(I_{t-1})*(CP_t)$									-0,00247	-0,00460***
									(0,00207)	(0,00164)
Constant	2,094***	2,107***	0,114	0,138	2,102***	-0,298	1,447**	0,970	0,252	0,873
	(0,294)	(0,367)	(0,689)	(0,778)	(0,365)	(0,975)	(0,661)	(0,750)	(0,873)	(0,771)
Austria	-0,285***	-0,292***	-0,349***	-0,348***	-0,292***	-0,376***	-0,353***	-0,381***	-0,343***	-0,350***
	(0,0481)	(0,0560)	(0,0486)	(0,0576)	(0,0525)	(0,0488)	(0,0505)	(0,0580)	(0,0533)	(0,0564)
Belgium	-0,199***	-0,204***	-0,242***	-0,241***	-0,197***	-0,292***	-0,243***	-0,295***	-0,239***	-0,241***
	(0,0362)	(0,0376)	(0,0370)	(0,0360)	(0,0382)	(0,0398)	(0,0380)	(0,0444)	(0,0346)	(0,0409)
Bulgaria	0,0489**	0,0781***	0,483***	0,478***	0,0761	0,522***	0,513***	0,556***	0,446***	0,507***
	(0,0224)	(0,0294)	(0,136)	(0,156)	(0,0532)	(0,174)	(0,148)	(0,145)	(0,167)	(0,149)
Croatia	-0,145***	-0,107**	0,0854	0,0839	-0,133**	0,152	0,0971	0,167*	0,0719	0,0952
	(0,0450)	(0,0535)	(0,0934)	(0,0893)	(0,0595)	(0,102)	(0,0850)	(0,0873)	(0,0896)	(0,0825)
Cyprus	0,168***	0,193***	0,248***	0,248***	0,196***	0,277***	0,250***	0,275***	0,246***	0,250***
	(0,0297)	(0,0347)	(0,0413)	(0,0410)	(0,0397)	(0,0506)	(0,0353)	(0,0466)	(0,0412)	(0,0407)
Czech Republic	0,101***	0,125***	0,282***	0,281***	0,123***	0,270***	0,294***	0,282***	0,269***	0,291***
	(0,0244)	(0,0286)	(0,0622)	(0,0692)	(0,0457)	(0,0732)	(0,0612)	(0,0646)	(0,0695)	(0,0665)
Denmark	-0,0841***	-0,0851**	-0,180***	-0,179***	-0,0905***	-0,188***	-0,186***	-0,195***	-0,172***	-0,185***
	(0,0311)	(0,0335)	(0,0476)	(0,0505)	(0,0342)	(0,0492)	(0,0528)	(0,0446)	(0,0504)	(0,0452)
Estonia	0,280***	0,307***	0,542***	0,540***	0,315***	0,517***	0,559***	0,534***	0,522***	0,555***
	(0,0402)	(0,0494)	(0,0963)	(0,105)	(0,0763)	(0,111)	(0,0943)	(0,0993)	(0,107)	(0,100)
Finland	-0,295***	-0,302***	-0,350***	-0,350***	-0,300***	-0,386***	-0,353***	-0,390***	-0,346***	-0,352***
	(0,0591)	(0,0647)	(0,0642)	(0,0721)	(0,0704)	(0,0605)	(0,0715)	(0,0643)	(0,0722)	(0,0624)
France	-0,637***	-0,652***	-0,710***	-0,710***	-0,658***	-0,730***	-0,713***	-0,733***	-0,704***	-0,707***
	(0,0912)	(0,116)	(0,0994)	(0,102)	(0,116)	(0,0985)	(0,0944)	(0,100)	(0,0991)	(0,112)
Greece	0,0344*	0,0350*	0,0235	0,0236	0,0379**	0,00736	0,0229	0,00612	0,0242	0,0230
	(0,0189)	(0,0207)	(0,0182)	(0,0212)	(0,0182)	(0,0186)	(0,0178)	(0,0198)	(0,0209)	(0,0176)
Germany	0,160***	0,164***	0,269***	0,268***	0,174***	0,263***	0,278***	0,272***	0,258***	0,275***
	(0,0309)	(0,0338)	(0,0469)	(0,0517)	(0,0423)	(0,0520)	(0,0445)	(0,0488)	(0,0509)	(0,0505)
Hungary	-0,0687***	-0,0489*	0,179**	0,176**	-0,106***	0,158	0,197**	0,180**	0,157	0,193**
	(0,0244)	(0,0276)	(0,0793)	(0,0899)	(0,0315)	(0,106)	(0,0863)	(0,0853)	(0,0980)	(0,0834)
Ireland	0,0504**	0,0517**	0,0112	0,0117	0,0574**	-0,0261	0,00905	-0,0300	0,0140	0,00919
	(0,0223)	(0,0227)	(0,0254)	(0,0259)	(0,0249)	(0,0349)	(0,0264)	(0,0308)	(0,0276)	(0,0242)
Italy	-0,0126	-0,0129	-0,00241	-0,00255	-0,0162	0,0155	-0,000893	0,0178	-0,00412	-0,00124
	(0,0201)	(0,0184)	(0,0191)	(0,0182)	(0,0204)	(0,0211)	(0,0183)	(0,0215)	(0,0196)	(0,0165)
Latvia	-0,446***	-0,436***	-0,188*	-0,191	-0,449***	-0,145	-0,167	-0,121	-0,211	-0,169
	(0,0847)	(0,101)	(0,106)	(0,116)	(0,107)	(0,151)	(0,115)	(0,119)	(0,128)	(0,118)
Lithuania	-0,448***	-0,439***	-0,197	-0,200	-0,447***	-0,175	-0,180	-0,156	-0,216	-0,179
	(0,0936)	(0,0922)	(0,136)	(0,132)	(0,103)	(0,164)	(0,121)	(0,113)	(0,133)	(0,116)
Luxembourg	-0,107***	-0,109***	-0,323***	-0,320***	-0,110***	-0,388***	-0,339***	-0,408***	-0,302***	-0,334***
	(0,0317)	(0,0307)	(0,0701)	(0,0835)	(0,0259)	(0,0909)	(0,0865)	(0,0838)	(0,0887)	(0,0838)
Malta	0,207***	0,233***	0,374***	0,373***	0,226***	0,384***	0,383***	0,393***	0,363***	0,380***
	(0,0339)	(0,0457)	(0,0650)	(0,0727)	(0,0506)	(0,0669)	(0,0636)	(0,0630)	(0,0742)	(0,0726)
Netherlands	0,0151	0,0150	-0,0368	-0,0362	0,0178	-0,0670**	-0,0406	-0,0723**	-0,0319	-0,0395
	(0,0227)	(0,0203)	(0,0288)	(0,0293)	(0,0200)	(0,0321)	(0,0313)	(0,0315)	(0,0306)	(0,0275)
Poland	0,197***	0,222***	0,505***	0,502***	0,223***	0,524***	0,526***	0,547***	0,479***	0,520***
	(0,0315)	(0,0412)	(0,101)	(0,117)	(0,0570)	(0,123)	(0,108)	(0,107)	(0,120)	(0,109)
Portugal	-0,0466	-0,0478	0,0733	0,0719	-0,0443	0,0948	0,0848	0,108**	0,0597	0,0825
	(0,0392)	(0,0377)	(0,0524)	(0,0569)	(0,0436)	(0,0650)	(0,0604)	(0,0526)	(0,0594)	(0,0566)
Romania	0,0177	0,0468	0,402***	0,398***	0,0396	0,450***	0,430***	0,481***	0,368**	0,423***
	(0,0277)	(0,0349)	(0,127)	(0,140)	(0,0500)	(0,159)	(0,134)	(0,130)	(0,151)	(0,134)
Slovak Republic	-0,235***	-0,220***	-0,0264	-0,0284	-0,225***	-0,0245	-0,00995	-0,00689	-0,0448	-0,0116
	(0,0398)	(0,0473)	(0,0753)	(0,0867)	(0,0561)	(0,108)	(0,0822)	(0,0820)	(0,0946)	(0,0809)
Slovenia	-0,104***	-0,0850***	0,0174	0,0166	-0,102***	0,0487	0,0243	0,0570	0,00970	0,0234
	(0,0267)	(0,0316)	(0,0454)	(0,0467)	(0,0296)	(0,0563)	(0,0421)	(0,0452)	(0,0531)	(0,0495)
Spain	-0,0965**	-0,0989***	-0,0500	-0,0506	-0,0934***	-0,0635	-0,0447	-0,0582	-0,0563	-0,0459
	(0,0389)	(0,0350)	(0,0365)	(0,0363)	(0,0353)	(0,0396)	(0,0369)	(0,0400)	(0,0371)	(0,0389)
Sweden	-1,055***	-1,079***	-1,209***	-1,208***	-1,094***	-1,224***	-1,215***	-1,230***	-1,198***	-1,207***
	(0,157)	(0,181)	(0,167)	(0,169)	(0,184)	(0,162)	(0,166)	(0,180)	(0,154)	(0,192)

Note: Table 13a continues in table 13b.

Table 13b. Bootstrapped Standard Errors (2/2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year = 1996	0,0442	0,0439	0,0315	0,0316	0,0542	0,0418	0,017	0,0267	0,0331	-0,00318
	-0,0498	-0,0451	-0,0434	-0,0427	-0,0473	-0,0548	-0,0453	-0,0486	-0,0423	-0,0427
Year = 1997	-0,0396	-0,0397	-0,0639*	-0,0637*	-0,0549	-0,0691	-0,0700*	-0,0752	-0,0613	-0,0754*
	-0,04	-0,0421	-0,0355	-0,0369	-0,0363	-0,0424	-0,036	-0,0477	-0,0378	-0,0393
Year = 1998	0,0152	0,0145	-0,0223	-0,0218	0,00757	-0,012	0,00599	0,0171	-0,0176	0,0577
	-0,0336	-0,037	-0,0338	-0,034	-0,0357	-0,0402	-0,0537	-0,0534	-0,0351	-0,044
Year = 1999	-0,000579	-0,00119	-0,0456	-0,0451	-0,00441	-0,0274	-0,0348	-0,0162	-0,0403	-0,00954
	-0,033	-0,0343	-0,0311	-0,0337	-0,0307	-0,0343	-0,0375	-0,0396	-0,0324	-0,0318
Year = 2000	-0,0441	-0,0447	-0,104***	-0,103***	-0,0548*	-0,0936**	-0,145***	-0,136***	-0,0968***	-0,198***
	-0,034	-0,0305	-0,0309	-0,0336	-0,0314	-0,037	-0,0534	-0,0437	-0,0339	-0,0543
Year = 2001	-0,0136	-0,0147	-0,0870**	-0,0861**	-0,021	-0,0765**	-0,121**	-0,111**	-0,0781**	-0,160***
	-0,0326	-0,0331	-0,0346	-0,0381	-0,0321	-0,0385	-0,0488	-0,0449	-0,0345	-0,0493
Year = 2002	-0,0104	-0,0115	-0,0954**	-0,0944**	-0,0183	-0,0832*	-0,126**	-0,115***	-0,0853*	-0,159***
	-0,0357	-0,0317	-0,0401	-0,0447	-0,0361	-0,0439	-0,0497	-0,0429	-0,0438	-0,0491
Year = 2003	0,0229	0,0218	-0,0731	-0,072	0,00784	-0,0697	-0,125*	-0,123**	-0,0619	-0,189***
	-0,0377	-0,039	-0,0469	-0,0453	-0,0415	-0,051	-0,0711	-0,056	-0,049	-0,0661
Year = 2004	-0,0756**	-0,0941***	-0,184***	-0,183***	-0,0864**	-0,183***	-0,254***	-0,256***	-0,176***	-0,352***
	-0,0352	-0,033	-0,0411	-0,0434	-0,036	-0,0515	-0,0856	-0,0644	-0,0446	-0,0797
Year = 2005	-0,0368	-0,0559	-0,160***	-0,159***	-0,0479	-0,159***	-0,265**	-0,267***	-0,150***	-0,413***
	-0,038	-0,0384	-0,0461	-0,0462	-0,0351	-0,0525	-0,119	-0,088	-0,0504	-0,117
Year = 2006	-0,0166	-0,0358	-0,155***	-0,154***	-0,0256	-0,155***	-0,283*	-0,287***	0,148	0,0789
	-0,0352	-0,0366	-0,0537	-0,0512	-0,0346	-0,053	-0,145	-0,104	-0,24	-0,212
Year = 2007	-0,0236	-0,0462	-0,177***	-0,176***	-0,0351	-0,178***	-0,314**	-0,320***	-0,150**	-0,483***
	-0,0322	-0,0312	-0,0513	-0,0533	-0,0364	-0,0604	-0,157	-0,117	-0,0584	-0,141
Year = 2008	-0,0840**	-0,107***	-0,246***	-0,245***	-0,0971***	-0,250***	-0,412**	-0,422***	-0,233***	-0,652***
	-0,034	-0,0297	-0,0531	-0,0574	-0,0322	-0,0625	-0,188	-0,137	-0,0587	-0,17
Year = 2009	-0,0934***	-0,116***	-0,245***	-0,244***	-0,108***	-0,242***	-0,361***	-0,362***	-0,0448	-0,173
	-0,0332	-0,0299	-0,0516	-0,0582	-0,0334	-0,0622	-0,132	-0,0977	-0,155	-0,153
Year = 2010	-0,0198	-0,0433	-0,179***	-0,178***	-0,0352	-0,176***	-0,306*	-0,307***	0,0547	-0,0722
	-0,0684	-0,0577	-0,0557	-0,0562	-0,0567	-0,0608	-0,162	-0,118	-0,216	-0,198
Year = 2011	-0,0556	-0,0788**	-0,223***	-0,222***	-0,0718*	-0,218***	-0,383**	-0,383***	-0,00882	-0,238
	-0,0372	-0,0325	-0,059	-0,0658	-0,0403	-0,0662	-0,184	-0,131	-0,172	-0,19
Year = 2012	-0,0991**	-0,122***	-0,272***	-0,271***	-0,116***	-0,265***	-0,429**	-0,427***	-0,148	-0,449***
	-0,0439	-0,0444	-0,0694	-0,0716	-0,0426	-0,0709	-0,178	-0,136	-0,103	-0,166
Year = 2013	-0,131***	-0,157***	-0,310***	-0,308***	-0,150***	-0,301***	-0,456***	-0,453***	-0,229***	-0,542***
	-0,0408	-0,0355	-0,0579	-0,0656	-0,0428	-0,075	-0,167	-0,123	-0,0768	-0,148
Year = 2014	-0,154***	-0,180***	-0,340***	-0,339***	-0,174***	-0,329***	-0,468***	-0,461***	-0,242***	-0,490***
	-0,0387	-0,0386	-0,0674	-0,0741	-0,0445	-0,0834	-0,146	-0,108	-0,0927	-0,139
Year = 2015	-0,113**	-0,139***	-0,308***	-0,307***	-0,135***	-0,297***	-0,379***	-0,369***	-0,184*	-0,263**
	-0,0449	-0,0443	-0,0713	-0,0782	-0,0457	-0,0852	-0,0931	-0,0847	-0,109	-0,117
R^2	0,223	0,231	0,244	0,244	0,227	0,257	0,247	0,260	0,251	0,266
Adjusted R^2	0,154	0,161	0,175	0,173	0,153	0,182	0,175	0,184	0,180	0,195
Countries	28	28	28	28	28	28	28	28	28	28
N	588	588	588	588	558	558	588	558	588	588

Note: Bootstrapped standard errors in parentheses: *** $p < 0,01$, ** $p < 0,05$, * $p < 0,1$. The dependent variable being estimated is the lagged carbon intensity. The reference group is the United Kingdom in 1995.