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<u>Thesis Title</u>

Assessing the Spillovers of Energy Prices & Growth: Evidence from EU

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Abstract: The aim of this thesis is to examine the long-run relationship among the energy prices and the economic growth within the EU framework using time series analysis. On the basis of cointegration and Error-Correction Mechanisms the prickly issue of causality among the real GDP and the energy prices is assessed. Furthermore, the model includes as explanatory variables the energy consumption and the intensity. Analytically, the study develops the Engle-Granger 2-step procedure as well as the Johansen's methodology for the purpose of a Vector-Error Correction Model. Delving into the causal effects Wald tests and Impulse-Response Functions are employed. Finally, the thesis proceeds to a Cholesky Forecast-Variance Decomposition Analysis for the sake of estimating the impact of energy prices, of energy consumption and that one of intensity on the real GDP. Evidence on conservation hypothesis is observed on the case of real European GDP and residential electricity prices, whereas growth hypothesis is entailed with respect to industrial electricity prices and real output. In fact, household electricity sector exhibits the highest level of influence; industrial electricity price and crude oil price can also *"Granger cause"* residential electricity prices in the EU. Signs of feedback hypothesis concern the final energy consumption and the residential electricity price. Though their significance at 10% level poses limits over the findings' accuracy. Finally, the European GDP is strongly endogenous in the short-run whereas shocks from the other aggregates are permanent and expand their leverage over the course of time.

Keywords: Economic growth, electricity prices, European Union, cointegration, causality, long-run equilibrium

Abbreviations

CI (d,b) : Cointegrated of order

ECM: Error-Correction Model

ECT: Error-Correction Term

EU: European Union

FEVD: Forecast-Error Variance Decomposition

FMOLS: Fully Modified Ordinary Least Squares

GDP: Gross Domestic Product

I (1), I (0): Integration of order one, Integration of order zero

IEA: International Energy Agency

IRF: Impulse-Response Function

OLS: Ordinary Least Squares

VECM: Vector Error Correction Model

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1. Introduction

The impetus of the field of energy economics and the profound changes in power relations in the international arena imply the need of re-examination over the energy-growth nexus. The increasing energy demand, the serious efforts to abate the devastating carbon dioxide emissions and concerns over scarcity events and energy security in conjunction with the implementation of energy and environmental policy measures revitalized the scientific interest over the involvement of energy into shaping the conditions of macroeconomic prosperity. Considering that energy is intertwined with economic development, offering to states with abundant resources an undeniable comparative advantage vis-à-vis to energy dependent economies the recent scientific attempts aplenty emphasize to potential dynamics between the economic growth and the energy demand.

Given that the interest on energy-growth relation gains momentum and the European Union has orchestrated a long-run energy strategy alongside the establishment of the internal energy market, to determine the magnitude of energy prices upon the real output is of a paramount importance. Nevertheless, the current literature attends to the probable dimensions of energy demand upon the real output, underestimating the aspects of energy prices as a principal factor in the production process.

Under the umbrella of the neoclassical school of thought, many theorists assess the energy-growth relation via extended models of factors of production including the energy use among the key inputs (Huntington & Smith, 1977). Other empirical studies investigate the issue with respect to causality originated namely from energy consumption to GDP growth and vice versa (Kraft & Kraft, 1978, Stern, 2000, Shabaz et al., 2013). Recently, in the bibliography attempts have been appeared that recognize the role of energy prices (Osigwe & Arawomo, 2015, Polemis & Dagoumas, 2013, Bretschger, 2009).

Nonetheless, the lack in bibliography together with the EU‟s ambitions to become a global leader in the energy field fosters the study of European economic activity with respect to energy prices. The purpose of this study is to bring the energy prices in the foreground; providing a reciprocal probe on the interrelations among the real economic growth and the energy prices, emphasizing on the energy prices‟ leverage on the real output.

Therefore the desideratum in this thesis is the ex-ante investigation of the potential dynamics among the energy prices and the European prosperity vis-à-vis to causal and effect relations for the period 1990-2018. Hence, this thesis aspires to shed light on the assumptions of *"conservation hypothesis"*, *"neutrality hypothesis"*, *"growth hypothesis"* and *"feedback hypothesis"* within the European framework. The evidence on a unidirectional causality arising from the real GDP to energy prices would favour the *"conservation hypothesis"*, whereas the inference of energy prices into the output's makeup would signal the existence of *"growth hypothesis"*. In contrast a bi-directional causality supports the *"feedback hypothesis"* and finally the absence of causality will entail the independence among the macroeconomic aggregates. Thus, it evinces the *"neutrality hypothesis"*.

The inkling of causal effects involves the seminal Granger's approach at the centre of the empirical analysis. Hence, the thesis intends to present the probable interdependence via the development of an extensive model that permits the thorough examination of the issue.

For that purpose the real European GDP, the real electricity prices for domestic use as well as that for industry and the crude oil prices synthesized a priori the model under examination. Furthermore, the model is enriched with two key macroeconomic indicators; the total final energy consumption and the level of intensity on the grounds of the current scientific attempts and in accordance with the EU's suggestions for macroeconomic modelling.

The year 1990 is considered the starting point for combating the climate change with the ratification of international treaties like the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol. Hence, seeking also to examine the effects from the implemented energy policies as well as from the adoption of international agreements the reference period is determined from 1990 to 2018.

Analytically, based on the cointegration theory in order to evade the risk of *"spurious regression"*, the long-run relations among the real GDP, the electricity prices, the crude oil prices, the total final energy consumption and the carbon dioxide emission intensity were defined. Thus, the thesis follows the Engle-Granger 2-Step Procedure in order to obtain the short-run and long-run dynamics. For the sake of robustness the model is also estimated via the Fully Modified Ordinary Least Squares and the Canonical Cointegration Regression. Afterwards, the direction of causality is assessed through the mechanism of Vector Autoregressive Error-Correction Model and Wald tests are employed.

In the case of the European economy finally signs of unidirectional causality originated from real GDP in residential electricity price have been found. Additionally, evidence on *"growth hypothesis"* concerns the case of industrial electricity price and the real GDP. Furthermore, the aforementioned findings are confirmed by a Variance Decomposition Analysis and the Impulse-Response Functions graphs.

The study is divided into six different parts. The ensuing section strives to capture the theoretical background over the energy and the economic growth nexus providing in detailed the most important approaches; then the European energy market as well as the parameters that determine the regime of prices in the EU. After understanding the EU reality the study proceeds to the core analysis presenting the methods that synthesize the empirical analysis. Afterwards, the empirical estimates upon the thorny issue of energy prices and economic growth and are analyzed, whilst the following section provides the main inferences. Finally, the chapter 7 embodies purposes for further research and some policy remarks over the European economy and the implemented energy policies.

2. Literature Review

The prickly subject of energy prices and economic growth has been a breeding ground for academic research over the last decades. Energy is commonly admitted as the engine of economic growth, offering to states with abundant resources a comparative advantage for further economic development. Considering growth as a spillover of energy use, the interdependence between them has been an issue of paramount importance, affecting directly or indirectly the tradable and the non-tradable sectors of an open economy. Especially, for an energy-dependent country –where the domestic production is heavily relied on imports of raw materials and fuels (coal, oil, gas) that are subject to global trends in energy markets- the fluctuations in international energy prices may easily lead to serious macroeconomic imbalances.

According to the aforementioned, many theorists attempt to investigate the potential tradeoff between energy prices and real output. Under the umbrella of the neoclassical approach, a plethora of extended models of factors of production is presented in which the energy use is illustrated as a key input (Huntington & Smith, 1977). Nonetheless, the majority of current empirical studies examine the dynamic relationship between energy and economic development with an emphasis on causality among energy consumption, energy prices and GDP growth (e.g. Kraft & Kraft, 1978, Stern, 2000, Shabaz et al., 2013, Polemis & Dagoumas, 2013). Notwithstanding in most of those scientific attempts the attention has revolved around the interrelation among the energy consumption and several macroeconomic indicators, like that of real GDP or real GDP growth, real income and unemployment rate. So, the main interest is structured around the energy consumption and the economic development rather than around the energy prices; that if they are embodied they used as explanatory variables.

Except of the twofold orientation of the academic research that is mentioned above, the uninterrupted interest in this modern field of energy economics would be well explained through the prism of increasing environmental awareness, the need for urgent solutions concerning the climate change followed by international agreements, as well as the implementation of up-to-day energy policies i.e. energy security, energy efficiency, RES penetration and innovative energy mix. For that purpose, some researchers employ the breakthrough in behavioral economics, using the principle of rational expectations in order to shape the interaction among economic growth, energy, firms and consumers' expectations[1] as well. However, other researchers reinforce the interdependence between energy and growth with regard to «energy's environmental costs and energy security issues[2]», while others suggest the energy intensity as a basic factor of measuring the level of a country's economic performance and energy use[3].

As it is mentioned in the previous section, this thesis attempts to investigate the relation between the energy prices and the real economic activity in the EU context. Considering that EU has established the Energy Union that encompasses an unambiguous common energy policy for its member-states. Notwithstanding, the EU has shaped a long-term energy strategy (2020 Energy Strategy, 2030 Energy Strategy, 2050 Energy Strategy) that incorporates certain environmental policy targets[4], originated from intergovernmental agreements, like the Paris Agreement. Theoretically, the common Energy Market plays the role of a safeguard with a view to protecting EU consumers from anti-competitive pricing behaviours, promoting the

[1]Sanstad, A.H., & Greening, L.A. (1996). Economic models for climate policy analysis: A critical discussion. *Environmental Modeling & Assessment*, 3(1-2), 3-18. [Online].
Available at: https://link.springer.com/article/10.1023/A:1019002620369 . Retrieved from 10th January 2019

[2] Liddle, B. (2006). How Linked are Energy and GDP: Reconsidering Energy-GDP Cointegration and Causality for Disaggregated OECD Country Data. *International Journal of Energy, Environment and Economics, 13(2), 97-113.* [Online]. Available at: http://mpra.ub.uni-muenchen.de/52334 Retrieved from 24th March 2019

[3]Kaufmann, R.K., & Kuhl, B. (2009). *Energy and the Macroeconomy. Economics Interactions with other Disciplines*, (Vol. II). [Online]. Available at: https://www.eolss.net/Sample-Chapters/C13/E6-29-03-06.pdf Retrieved from 15th January 2019

[4]European Commission, (2018). *Energy-Topics-Energy and Strategy and Energy Union*. [Online]. Available at: https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union Retrieved from 22nd January 2019

conditions of perfect competition, and enhancing the overall welfare in the EU region. Consequently the potential positive outcome of such policy measures in the real output has to be examined.

It is therefore of critical importance to demonstrate the basic economic principles and a model that have linked the economic growth with energy, taking into consideration the absence of an explicit theory between energy prices and output in the current bibliography. The ensuing sub-sections seek to present the different views over the issue. In order to understand the advancements in the latest energy and economic growth approaches, it is necessary to recognize the juncture of natural resources and energy as a key input to production phase.

Hence, the next sub-sections intend to bridge this gap providing theories related to energy and economic growth with respect to the role of energy in promoting economic prosperity. In particular, the following sub-section illustrates the resource-based concepts, like the well-known resource-curse theory. Afterwards, the classical and neo-classical fundamentals over the economic activity and the energy input in the production function are demonstrated. Finally, the most recent scientific attempts -including the ecological and behavioural economics rationale- are presented, as well.

2.1Economic Growth and Energy arising from natural resources: Theoretical Background

The classical and the neoclassical school of thought do not incorporate an entirely economic theory of energy and economic growth. In fact, as Stern mentioned the impact of energy and other natural resources on economic process has been underestimated[5], even though the firms and financial economists point out the energy importance to economic progress. However, the relationship between the energy and the economic performance has been a matter of serious scientific concern notably under the crucial energy crises and the significant technological breakthroughs over the last decades. Various empirical studies intensify the research; though the majority of them focus more on energy consumption and GDP growth rather on the impact of energy prices on real output expansion.

Whilst the conventional economic literature related to energy and environmental issues is restricted, there are four different views exploring the causality in energy consumption and growth[6]. Some studies argue that the energy use derives from the economic growth, as the energy is an important factor of production along with capital, labor and land (Navaz, Sadaqat, Awan, & Qureshi, 2012). The second view sustains that economic growth influences energy use, whereas a third group of researches supports the interdependence between them (Barney, 1995). Alternatively, the energy consumption would enhance economic growth and vice versa[7]. Finally, a last group of studies based on *"neutrality hypothesis*", estimates that

[5]Stern, D.I. (2003). *Energy and Economic Growth.* Rensselaer Working Papers in Economics. Rensselaer Polytechnic Institute.

[6] Nayan, S., Kadir, N., Ahmad M., & Abdullah, M.S. (2013). *Revisiting Energy Consumption and GDP: Evidence from Dynamic Panel Data Analysis.* MPRA. [Online]. Available at: http://mpra.ub.uni-muenchen.de/48714/ Retrieved from 23rd January 2019

[7] Nayan, S., Kadir, N., Ahmad M., & Abdullah, M.S. (2013). *Revisiting Energy Consumption and GDP: Evidence from Dynamic Panel Data Analysis*. MPRA. [Online]. Available at: http://mpra.ub.uni-muenchen.de/48714/ Retrieved from 1st February 2019

there is no actual causality between energy consumption and economic growth. Therefore, ″they are neutral with respect to each other". (Nayan, Kadir, Ahmad, & Abdulah, 2013). In the aftermath of the serious oil crisis in 1973, many economists tried to explain the decline in real output relatively to the peak in energy prices, mainly in oil prices. So, the energy-driven GDP slowness has been examined both through the prism of supply shocks- i.e. oil shocks with significant price fluctuations that affect the energy importing countries- and under the surprising phenomenon of GDP sluggishness for energy exporting countries. The famous ″resource curse theory″ (Sachs & Warner, 1999, Auty, 2001) sustains that resource rich countries are prone to several macroeconomic distortions in relation to that non-endowed naturally.

A premature attempt to explain the resource curse can be found in the seminal Prebisch-Singer hypothesis, which named from the homonym authors (Prebisch & H. Singer, 1950). The Prebisch-Singer hypothesis suggests that states depending excessively on primary goods sector will experience slower growth than countries depending on manufactured sector (Polterovich, Popov, & Tonis, 2008). However, the most decisive step to formulate a theory of economic flourishing arisen from abundant resources was the ″Staple theory of economic development" created by Innis, in 1954. Innis[8] suggests that a country's integration phase is incident to the exports of primary goods. His work was a stimulus for further research, giving birth to studies that examined many developed and emerging economies, arguing that *″the primary resource sector influences positively or negatively their economic growth*"[9] depending on the relevance with the other sectors and especially with that of extraction technology. New industries emerged from the advancements of resource sector and the economy risks to be entrapped. In order to evade from this danger the economy needs to diversify. If the diversification does not take place, *″the country falls into a staple trap"*. (Polterovich, Popov, & Tonis, 2008).

However, in the absence of significant macroeconomic indicators, the theory lacks of explanatory value (Findlay & Lundahl, 2001) in relation to resource curse theory, while the Dutch Disease, a possible outcome of resource curse (Roukanas, 2015) offers compelling explanations. Short-term rise in oil prices or other natural resource discoveries lead to higher growth rates or economic booms. The rapid increase in mineral sector's exports stimulates the currency appreciation, due to the influx of foreign currency. As a consequence, the other sectors become less competitive, while the increased domestic demand for non-tradable products and services provokes inflation[10]. Finally, the paradox of high capital outflows accelerates the unemployment rate, restricts the investments and finally inflation and low long-run growth manifest in the economy (Krugman, 1987, Auty, 2001, Roukanas 2015).

The Dutch Disease as a mechanism of Resource Curse stipulates the negative effects of a resource-driven boom. However, another effort to explain the decline in GDP growth in

[8] Innis, H.A. (1940). *The Cod Fisheries: The History of an International Economy.* New Haven: Yale University Press; Toronto: Ryerson Press.

[9] Polterovich, V., Popov, V., & Tonis, A. (2008). *Mechanisms of Resource Curse, Economic Policy and Growth*. MPRA. [Online]. Available at: http://mpra.ub.uni-muenchen.de/20570/ Retrieved from 20th January 2019

[10] Roukanas, S. (2015). *Russia's Resource Curse: Internal and External Political and Economic Impacts. Energy & Environmental Transformations in a Globalizing World.* Nomiki Bibliothiki. [Online]. Available at: https://www.nb.org/greek/energy-environmental-transformations-in-a-globalizing-world.html Retrieved from 22nd January 2019

resource rich countries is the *"Overshooting Model"*[11] that shaped by Rodriguez and Sacks in 1999. The model links the GDP deterioration with market failure, amplifying the assumption of inefficient adjustment to resource discoveries shocks[12].

2.2 From Classical to Neoclassical Approach

The importance of energy is not anchored in the classical growth theory. Thus, the energy per se is not a principal factor of production in Ricardian Model of Economic Growth that recognizes three basic factors of production: land, labor and capital. Nevertheless, according to Alam, the classical economists like Adam Smith and David Ricardo admit the crucial role of energy-resources in the economic development[13], as the aspect of natural resources-soil, minerals, water, air, climate and everything that can be used in order to produce goods and exists naturally are included into the factor of land.

In the neoclassical framework neither natural resources nor land is presented as a key factor of production. To the contrary, land is involved within the umbrella of capital, whereas energy is considered as *"an intermediate input"* (Razzaqi, Bilquees, & Sherbaz, 2011). Indeed in the Solow's long-run economic growth model[14] the resources are absent in the production function. On the other hand many neoclassical models incorporate the technological progress in the production function. The technological change is depicted by shifts in production function. As an outcome the desired level of output can be achieved without increases in inputs (Sanstaad & Greening, 1996). So, Kaufmann and Kuhl[15] refer to energy as a necessary part of production and consumption cycle, depending on the technological progress and the relative prices of the factors of production, while any fluctuations in the latter would lead to substitutes of factors of production.

The aforementioned reinforce the linkage in energy and economy with respect to technological advancements and energy use. These extensions of neoclassical perspective sustain the relative prices exogenous[16] resulting in lower energy prices in comparison to other input prices. Another significant step following this logic is the *"Hick's neutrality"*, which determines that for a specified capital-labor rate the technological change does not harm the marginal rate of substitution between capital and labor (Sanstaad & Greening, 1996).

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[11] Rodriguez, F., & Sachs, J.D. (1999). Why do resource abundant economies grow more slowly? A new explanation and an application to Venezuela. *Journal of Economic Growth,* 4(3), 277-303.

[12] Polterovich V., Popov V., & Tonis A.(2008). *Mechanisms of Resource Curse, Economic Policy and Growth.* MPRA. [Online]. Available at: http://mpra.ub.uni-muenchen.de/20570/ Retrieved from 19th December 2018

[13] Alam, M.S. (2006). *Economic Growth with Energy*. MPRA. Paper, (No1260). [Online]. Available at: https://mpra.ub.uni-muenchen.de/1260/ Retrieved from 5th January 2019

[14] Solow, R.M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal Economics, 70* (1), 65-94. [Online]. Available at: https://www.econ.nyu.edu/user/debraj/Courses/Readings/Solow.pdf Retrieved from 29th January 2019

[15] Kaufmann, R.K., & Kuhl, B. (2009). *Energy and the Macroeconomy*. *Economics Interactions with other Disciplines* (Vol. II). [Online]. Available at: https://www.eolss.net/Sample-Chapters/C13/E6-29-03-06.pdf Retrieved from 28th December 2018

[16] Sanstad, A.H., & Greening, L.A. (1996). Economic models for climate policy analysis: A critical discussion. *Environmental Modeling & Assessment*, 3(1-2), 3-18. [Online].
Available at: https://link.springer.com/article/10.1023/A:1019002620369 . Retrieved from 10th January 2019

An important endeavour under the neoclassical perspective was the Huntington- Smith's analysis over *"Energy prices, Factor reallocation and Regional Growth*", who emphasized the effects of relative energy prices on economic growth, employment and capital returns. Their findings were consistent to assumption that *"high payments for energy result in lower growth of capital and labour, which finally harms the output*". Therefore, an increase in energy prices may cause a decline in GDP rate, while a reduction in energy prices favours GDP expansion[17].

However, the energy as a pillar of the economic development coincides with the emergence of the field of ecological economics. The seminal study "Energy and Resource Quality: The Ecology of the Economic Process" written by Hall, Cutler, Cleveland and Kaufmann in 1986 is the first attempt to examine the "energy-resource interaction with economics and ecology". They argue that it is impossible to produce or recycle energy from the other factors of production, i.e. labor and land. Their reasoning is dictated upon the first and second law of thermodynamics; any type of energy can be modified into another type of energy, maintaining the entire quantity, but with lower quality[18] which is violated in the neoclassical context. The authors argue that *"a flow of low-entropy energy is necessary to maintain any organized structure*" and that is applied also in the economic system. The natural resources are converted into economic outputs, which are named *"economic work*", as far as the energies that can be controlled by humans are called "economic energies".

Thus, natural resources can be used with the aim of economic energies and finally transformed into goods and services. Furthermore, the interdependence between natural resources and factors of production does not considered as a new trend, but as the energy poses limits to the production process its significance is recognized. The *"EROI*", the energy return on investment has also been developed in order to measure the quality of natural resources. EROI reflects *"the gross amount of fuel extracted in the energy transformation process to the economic energy required to make that fuel available to society*" (Hall, Cutler, Cleveland & Kaufmann, 1986). Finally, the quality of natural resources determines the output, ceteris paribus countries with access to natural resources enjoy higher EROI and economic work too, whereas countries with limited access are subject to thermodynamic constrains. Therefore, energy is a priori the essential factor, whereas labor and land are considered as intermediate[19].

Further advancements in the field link thermodynamics to energy efficiency and decline in energy demand. An example is the recent study of Cullen, Allwood and Borgstein, which sustains that the energy demand would approximately be reduced by 15% providing that the efficiency trends would be applied to energy use[20]. Allwood and Cullen also claim that a

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[17] Huntington, H., & Smith, D.M. (1977). *Energy Prices, Factor Reallocation and Regional Growth. Energy Modeling Forum.* MPRA. (Paper No. 69066).[Online]. Available at: https://mpra.ub.uni-muenchen.de/69066 Retrieved from 8th January 2019

[18] Hall, C., Cleveland, C.J., & Kaufmann, R.K. (1986). *Energy and Resources Quality: The Ecology of Economic Process.* New York: Wiley Inter-science.

[19] Kaufmann, R.K., & Kuhl, B. (2009). *Energy and the Macroeconomy. Economics Interactions with other Disciplines* (Vol. II). [Online]. Available at: https://www.eolss.net/Sample-Chapters/C13/E6-29-03-06.pdf Retrieved from 26th January 2019

[20] Cullen, J.M., Allwood, J.M., & Borgstein, E.H. (2011). Reducing energy demand: What are the practical limits? *Environmental Science and Technology.* 45 (4), 1711-1718.

further reduction by 11% would be feasible, if the heavy industrial sector is adapted to more energy efficient technologies, i.e. the use of energy conversion devices[21]

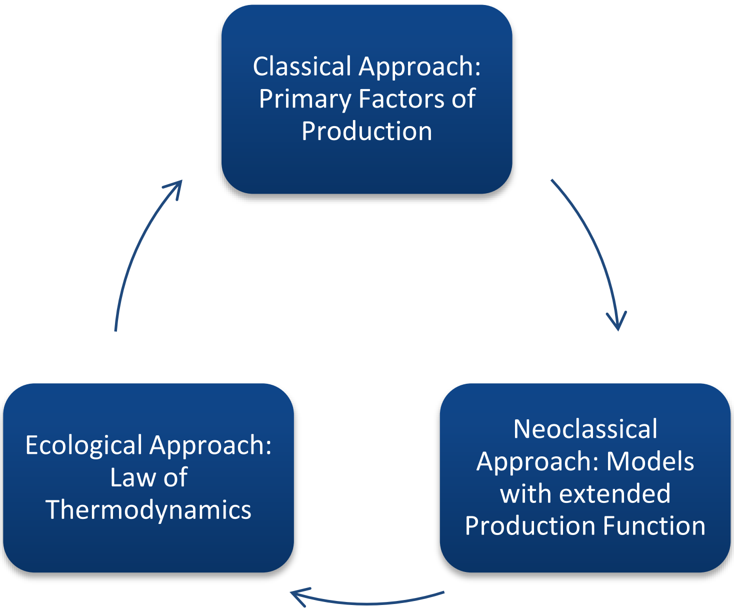

Figure 1 Evolution of Energy and Economic Growth Theories

2.3 Energy Intensity & Energy Efficiency

During the late 90s, further improvements appeared in the bibliography over the delicate issue of energy and economic activity with regard to mitigating climate change. Thus, energy intensity and energy efficiency has been used as an alternative to measure the energy-growth interdependence.

The long-run growth has to be met under the application of environmental policies, given that global growth would be at risk due to the potential negative effects of climate change (Burke et al., 2015).

High energy demand is typically correlated to high growth rates and simultaneously to greenhouse gas emissions. For that reason improvements in technology used would lessen the energy intensity and meet the targets over energy poverty[22], otherwise support the "*green growth hypothesis*". The idea is based on expansions of "*embodied technical change*" (Solow, 1960) which means that productivity growth accelerates from fresh capital (investments) coincides to increase in energy efficiency (Jin & Zhang 2016). The green growth hypothesis

[21] Cullen, J.M., & Allwood, J.M. (2010). Theoretical efficiency limits for energy conversion devices. *Energy* 45 (4), 1711-1718.
[22] Semieniuk, G. (2018). *Energy in Economic Growth: Is Faster Growth Greener*? (Paper No.208). SOAS Department of Economics Working. London: SOAS University of London.

assumes that faster economic growth is accompanied by capital accumulation, technological change and decrease in energy intensity. The international Panel for Climate Change in the latest report supports that higher factor productivity coexists with greater reduction in energy intensity[23]. Energy intensity is equivalent to the quotient of the total output divided by the aggregate energy use –energy that derives from different fuels and is used in different sectors- for a period of one year[24]. So, the models which follow the path of green growth hypothesis examine to a great extent the output elasticity of energy[25]. However, the empirical findings over the green growth hypothesis are limited and most of the studies investigate the relevance of energy intensity and output per capita or energy per capita due to the environmental Kuznets curves (Semieniuk, 2018).

The energy intensity also states an economy's energy efficiency; low intensity declares greater energy efficiency and vice versa (Kaufmann & Kuhnl, 2009). Otherwise a rise in a county's energy efficiency entails a decrease in energy-fuel use by maintaining the same level of output. Furthermore, the adoption of the "*autonomous energy efficiency improvement"* (AEEI) in many energy and environmental estimation models supports that higher energy efficiency occurs as an outcome of exogenous technological change (Sanstad & Greening, 1996). Thus, a greater AEEI means more anodyne adjustments in environmental goals like lessening the carbon emissions.

However, the AEEI has coped with lots of criticism, because it downgrades the segregation among sectors, the type of technological change and the significance of capital investment, which are crucial in understanding the growth process and the energy needs[26] in each sector. Another important parameter that is devaluated is the *"factor price biases*"[27] which reveals that abatement in energy intensity may be due to relative prices fluctuations, rather than in increasing energy efficiency, as Jorgenson and Hogan[28] pointed out in the US postwar case. Furthermore, doubts arise over the dimensions and the rebound effect of energy efficiency measures (Polemis & Dagoumas, 2013). Under these circumstances, it remains obscure if the decline in energy consumption results from the rise in demand for energy efficient services or if the energy efficiency spills over a reduction in energy services' real price[29].

The aforementioned explain clearly why the current empirical studies pay more attention to aggregate energy demand and consumption in certain sectors or in certain energy commodities (Polemis & Dagoumas, 2013).

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[23] Clarke, L. et al. & O. Edenhofer et al. (2014). *Assessing transformation pathways. In: Climate Change 2014: Mitigating of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. (pp. 413-510). Cambridge, UK and New York. Cambridge University Press.

[24] Kaufmann, R.K., & Kuhl, B. (2009). *Energy and the Macroeconomy.* Economics Interactions with other Disciplines (Vol. II). [Online]. Available at: https://www.eolss.net/Sample-Chapters/C13/E6-29-03-06.pdf Retrieved from 1st February 2019

[25] Marangoni, G. et al. (2017). Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways*. Nature Climate Change,* 7(2), 113-117.

[26] Sanstad, A.H., & Greening, L.A. (1996). Economic Models for Climate Policy analysis: A Critical Discussion. *Environmental Modeling and Assessment, 3(1-2),* 3-18.

[27] Sanstad, A.H., & Greening, L.A. (1996). Economic Models for Climate Policy analysis: A Critical Discussion. *Environmental Modeling and Assessment, 3(1-2),* 3-18.

[28] Hogan, W.W., & Jorgenson, D.W. (1991). Productivity Trends and the Costs of Reducing Carbon Dioxide Emissions. *Energy Journal,* 12(1), 67-85.

[29] Barker T., Dagoumas A., & Rubin, J. (2009). The *macroeconomic rebound effect and the world economy. Energy Efficiency (2)* (pp. 411-427).

Moreover, both the increasing environmental awareness and the need to mitigate the energy intensity have rotated the energy-growth research towards governmental interventions. Hence, the implementation of environmental policies urges governments to utilize all the instruments under their disposition like taxes. The question here is if greening the economy constrains the output growth. Thus, the scientific concern focuses on government's optimal choice vis-à-vis to adoption of policies that restrict the negative externality of pollution which is considered a spinoff of output growth. Economides and Philippopoulos (2007) examining *"the Ramsey second-best optimal economic policy"* with regard to environmental taxes, develop an extended growth model that includes renewable natural resources. The authors claim that in the long-run any tradeoff between economic growth and environmental quality is absent. Consequently, long-term growth can be achieved without environmental deterioration. Furthermore, policy makers are more prone to choose *"growth-enhancing policies[30]"* when citizens are aware of/acknowledge the environmental costs.

2.4 Volatility & Uncertainty over energy prices

Crude oil, natural gas, coal and oil derivates suffer the mostly from price volatility among the other commodities (Hasan, Akhter & Rabbi, 2013). On the other hand, as it is mentioned above, they are indispensable inputs in the production pace, since energy creates a spillover for output growth. The observed sharp fluctuations would be transmitted rapidly, via multiple channels under the globalized energy markets. Finally, the negative supply shocks, escalating the status of uncertainty would create serious macroeconomic imbalances, even recessions. Providing that price volatility affects seriously the GDP growth via investments lag[31] some analysts use the uncertainty in order to examine the link between energy and economic growth.

The sudden lurches in energy prices influence investments' decision and finally, the uncertainty and the delay lead to inadequate long-term resource allocation[32]. Volatility in energy prices coincides with asymmetry, i.e. the nature of shock-positive or negative one-harms differently the state of economy. Asymmetry means different degrees of latitude and magnitude over economy's adjustment. The mechanism of volatility in energy prices shows an anti-clockwise operation. Thus, volatility in energy returns augments when the energy prices increase[33].

Even though, volatility in energy prices may influence the macro-economy to a great extend, the vast majority of studies focuses on volatility persistence in oil prices. However, some

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[30] Economides G., & Philippopoulos, A. (2007). Growth enhancing policy is the means to sustain the environment. Review of Economic Dynamics. *Elsevier for the Society for Economic Dynamics* 11(1) 207-219 (doi: 10.1016/j.red.2007.05.001).

[31] Bernanke, B.S. (1983). Irreversibility, uncertainty and cyclical investment. *Quarterly Journal of Economics*, *97*(1), 85-106.

[32] Hasan, M.Z., Akhter, S., & Rabbi F. (2013). Asymmetry and Persistence of Energy Price Volatility. *International Journal of Finance and Accounting,* 2(7), 373-378. [Online].
Available at: https://researchonline.nd.edu.au/bus_article/ Retrieved from 2nd February 2019

[33] Hasan, M.Z., Akhter, S., & Rabbi, F. (2013). Asymmetry and Persistence of Energy Price Volatility. *International Journal of Finance and Accounting,* 2(7), 373-378. [Online].
Available at: https://researchonline.nd.edu.au/bus_article/ Retrieved from 2nd February 2019

researchers tend to incorporate more energy commodities in their estimations like Pindyck[34], who found evidence on volatility persistence in both crude oil and natural gas prices, while Andreadis and Serletis in 2014 include in their study gasoline, propane and heating. Finally, the work of Hasan, Akhter and Rabbi[35] in 2013 suggests that asymmetry in volatility of crude oil and natural gas is observed, while the coal does not follow the same path[36].

As far as the other issue of uncertainty, that is also mentioned above the scientific concern spins over the uncertainties arising from the adoption of climate policies. Moving in this direction Nordhaus has examined uncertainty through the spectrum of hedging and security on climate policy's implementation[37].

2.5 The latest empirical studies

The magnitude of energy use as a stimulus for accelerating welfare was analyzed in depth in the previous sub-sections while the main energy-related theories were illustrated to grasp the importance of the issue. Now, the focus is on the empirical approaches and the estimation methods with respect to principal energy-growth theories. A plethora of models based on appropriate econometric tools and techniques seeks to investigate the energy-growth causal-effect with regard to energy consumption, energy prices and GDP growth. However, the findings are miscellaneous or contradictory. For instance, Kraft and Kraft[38] conclude that the output-Gross National Product (GNP) in this case- influences the energy consumption. Whilst Yu and Hwang[39], Erol and Yu[40] suggest that there is no actual relationship between the energy consumption and the GNP, and likewise for the case of employment. Hence, the absence of causation in their findings favors the neutrality hypothesis.

Indeed, the thorough research of Janda and Torkhani (2016), Ozturk (2010) and Payne (2010) in the subject area of energy-growth fosters the ambiguity of findings[41]. Each one synthesizes a synopsis of the disposable bibliography indicating that the results are separated almost equally among the "*neutrality hypothesis, the growth hypothesis, the conservation hypothesis and the feedback hypothesis". Neutrality hypothesis* postulates that the economic growth does

[34] Pindyck, R.S. (2004). Volatility in Natural Gas and Oil Markets. *Journal of Energy and Development*, *30*(1), 1-19.

[35] Serletis, A., & Andreadis, I. (2004). Random fractal structures in North American energy markets. *Energy Economics,* 26 (3), 389-399.

[36] Hasan, M.Z., Akhter, S., & Rabbi F. (2013*).* Asymmetry and Persistence of Energy Price Volatility. *International Journal of Finance and Accounting,* 2(7), 373-378. [Online].
Available at: https://researchonline.nd.edu.au/bus_article/ Retrieved from 2nd February 2019

[37] Nordhaus, W.D. (1994). *Managing the Global Commons: The Economics of Climate Change.* Cambridge, MA: The MIT Press.

[38] Kraft, J., & Kraft, A. (1978). On the relationship between energy and GNP. *Journal of Energy and Development*. *93,* 401-403

[39] Yu, E.S.H., & Hwang, B.K. (1984). The relation between energy and GNP: Further Results. *Energy Economics*, 6, 186-190

[40] Erol, U., & Yu, E.S.H. (1989). Spectral analysis of the relationship between energy and income for industrialized countries. *Journal of Energy and Development, 13,*113 -122

[41] Lechthaler, F. (2016). Economic growth and energy use during different stages of development: an empirical analysis. *Environment and Development Economics 22(1),* 26–50. [Online].
Available at: https://doi.org/10.1017/S1355770X16000243 Retrieved from 9th December 2018

not emerge from energy and vice versa[42]. Nevertheless, the *growth hypothesis* entails a unidirectional causality from energy to growth underling that the energy use amplifies the economic growth. By contrast, the *conservation hypothesis* considers the GDP growth as a stimulus for accelerating energy consumption and finally the *feedback hypothesis* suggests a bidirectional relationship between growth and energy.

However, it is critical to mention that various empirical studies are based on VAR Granger causality tests as well as on Error Correction Mechanisms (ECM) in order to capture the short and long-term dynamics between energy and real growth. The decisive step is the stationarity or the presence of unit roots among the time series. Considering that the vast majority of economic time series are subject to fluctuations, the existence of a cointegration relationship allows the safe conduct of econometric results. Thus, the Engle-Granger[43] 2-step procedure or the Johansen cointegration[44] approach followed by Vector Autoregressive Error Correction Model (VECM) comprises the foundations of most scientific attempts (Stern, 2010, Chang, 2010, Menegaki, 2011, Shaari, Hussain & Ismail, 2012, etc). Though, the literature offers many surveys using different specification methods like the Modified Least Squares or the Three Stage Least Squares.

For instance, Soytas, *et al*[45] and Sarwat R. *et al*[46] seek to examine the potential trade-off between the energy and growth rates developing a Vector Autoregressive Error Correction Model (VECM) through the prism of potential long-run linkages between the variables of interest. Moreover, in both studies Granger causality tests are held in order to assess the direction of this dynamic relationship. Chang[47]attempts to define the interdependence among economic growth and principal energy variables such as the oil consumption, the CO2 gas emissions, the electricity consumption, the natural gas consumption and coal consumption in China from 1991 to 2006, applying an ECM since the cointegration among the variables of interest are defined. Similarly, Menegaki (2011)[48] examining the potential causal effect among renewable energies and real GDP in European countries for a time period between 1997 and 2007 employs the Engle-Granger 2-step method and provides evidence of the neutrality hypothesis of renewable energy and growth.

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[42] Shahateet, M. I. (2014). Modelling Economic Growth and Energy Consumption in Arab Countries: Co- Integration and Causality Analysis. *International Journal of Energy Economics and Policy*. *4*(3), 349 -359. [Online]. Available at: http://dergipark.gov.tr/download/article-file/361316 Retrieved from 8th December 2018

[43]Engle, R.F., & Granger, C.W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Journal Article, 55* (2), 251-276. [Online].
Available at: https://www.jstor.org/stable/1913236?seq=1#page_scan_tab_contents Retrieved from 7th January 2019

[44] Johansen, S. (1988). Statistical Analysis of Cointegrating Vectors. *Journal of Economic Dynamics and Control,*12, 231-254 [Online]. Available at: http://dx.doi.org/10.1016/0165-1889(88)90041-3 Retrieved from 14th December 2018

[45] *Soytas, U., Sari, R., & Ozdemir O. (2001). Energy Consumption and GDP Relation in Turkey: A Cointegration and Vector Error Correction Analysis. Economies and Business in Transition: Facilitating Competiveness and Change in the Global Environment Proceedings.* (pp.838-844). Global Business and Technology Association

[46]Razzaqi, S., Bilquees, F., & Sherbaz, S. (2011). Dynamic Relationship between Energy and Economic Growth: Evidence from D8 Countries. *The Pakistan Development Review*. 50(4), Part II, 437-458

[47]Chang, C.C. (2010). A multivariate causality tests of carbon dioxide emissions, energy consumption and economic growth in China. *Elsevier, Applied Energy,* 87, 3533 - 3537.

[48]Menegaki, A.N. (2011). Growth and renewable energy in Europe: A random effect model with evidence for neutrality hypothesis. *Energy Economics, 33* (2), pp. 257-263.

A further advancement in energy and economic growth nexus comes from J. Asafu-Adjaye[49], who creates a *"trivariate model"* including energy prices, GDP and energy consumption for Asian countries. Using the Engle-Granger 2-step procedure finds evidence on *"bidirectional Granger causality between energy consumption and income"*. Furthermore, Polemis and Dagoumas (2013) assess the spillover dynamics of electricity consumption in the case of Greece proceed to Engle-Granger 2-step Mechanism, to Granger causality tests, and finally employ a Vector Autoregressive Error Correction Model. Examining the causal link between economic growth and electricity consumption, they also incorporate into their model among the explanatory variables the low voltage residential electricity price[50].

Shifting the interest on energy prices, Breetschger (2009) estimates a system of equations with the aim of Three-Stage Least Squares for 37 developed countries. In his research *"Energy Prices, Growth and Channels in Between: Theory and Evidence"*(2009) he finds that moderate energy use results from higher energy prices, while higher energy prices do not affect the economy's long-run equilibrium[51]. The Engle-Granger method is also used in B. Liddle's[52] research for OECD countries where time series data for GDP per capita, road and residential energy consumption, total GDP from industry and total energy consumption by industry compose the author's core variables.

Fei, Li et al.(2011) in their attempt to investigate the economic growth and the energy consumption in a sample from 1960 to 2000 for China, they use the Dynamic Ordinary Least Squares(DOLS) and find evidence of co-movement and bidirectional relationship between the variables of interest[53]. In the recent attempts, another form of error correction mechanism based on Autoregressive Lag Distributed Models (ARDL) has appeared according to Perasan and Shin (1999) and Perasan et al., (2001*)* that allows the estimation of time series data regardless of their order of integration. Many attempts count on ARDL methodology, such as the Berk's and Yetkiner's ″Energy Prices and Economic Growth: Theory and Evidence in the Long-run″, who trace the negative effects of energy prices on both energy consumption and GDP per capita in the long-term. Another study on the grounds of ARDL methodology comes from Shahateet (2014), who examines the cointegration and causality in Arab economies.

Moreover, Shahbaz, Zakaria et al., (2018) following the path of Quantile-on-Quantile (QQ) approach proposed by Sim and Zhou[54] (2015) launched a ″specification model on the basis of

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[49] Asafu-Adjaye, J. (1999). *The relationship between energy consumption, energy prices and economic growth: Time series evidence from Asian developing countries*. [Online].
Available at: https://econpapers.repec.org/paper/agsaare99/123754.htm Retrieved from 2nd March 2019

[50] Polemis, M.L., & Dagoumas, A.S. (2013).The electricity consumption and economic growth nexus: evidence from Greece. *Energy Policy 62,* 798-808. [Online]. Available at: https://www.journals.elsevier.com/energy-policy Retrieved from 12th January 2019

[51] Bretschger, L. (2009). *Energy Prices, Growth and the Channels In Between:Theory and Evidence.* Oxford Center for the Analysis of Resource Rich Economies. Department of Economics OxCarre.

[52] Liddle, B. (2006). How Linked are Energy and GDP: Reconsidering Energy-GDP Cointegration and Causality for Disaggregated OECD Country Data. *International Journal of Energy, Environment and Economics, 13(2), 97-113.* [Online]. Available at: http://mpra.ub.uni-muenchen.de/52334 Retrieved from 24th March 2019

[53] Fei, Li, et al. (2011). Energy consumption-economic growth relationship and carbon dioxide emissions in China. *Energy Policy,* 39(2), 568 - 574.

[54] Sim, N., & Zhou, H. (2015). Oil prices US stock return, and the dependence between their quantiles. *Journal of Banking and Finance,* 55, 1-8. [Online]. Available at: https://doi.org/10.1016/j.jbankfin.2015.01.013 Retrieved from 16th January 2019

QQ technique″[55] in order to assess the relationship between energy consumption and economic growth for the ten most heavy energy consumer countries.

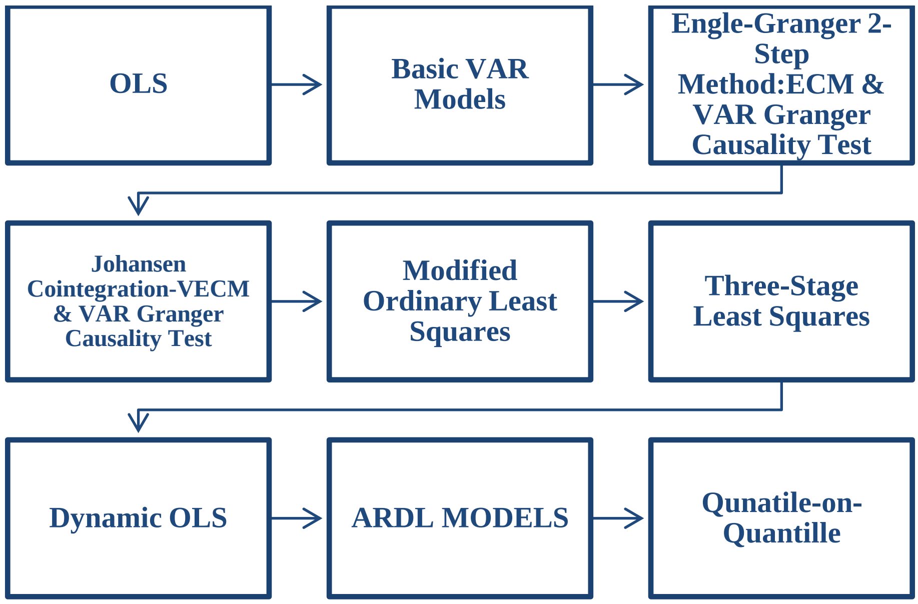

Figure 2. Evolution of Empirical Methods in Energy & Growth Nexus

QQ is a broad version of quantile regression which aims to specify if the quantiles that originated from one variable have an impact on the quantiles of another variable, i.e. in this case the quantiles of economic growth whether they influence the quantiles of energy consumption. The authors conclude that a positive effect concerns the majority of countries under investigation. However, differences regarding the quantiles of economic growth and energy consumption depend on the weight of energy as an input for accelerating the output; also arise from the phase of each economy's business cycle.

Finally, Mohamad Z.H., Selim Akhter and Fazle Rabbi shift the interest on energy prices fluctuations and their expected negative implications on the macroeconomic environment. Therefore, willing to examine the ″Asymmetry and persistence of energy price volatility″ (2013) they use the extensions of a GARCH model that prevails over other techniques when the desideratum depends on volatility. They suggest that coal presents low levels of volatility, while natural gas and crude oil are subject to relatively high asymmetric volatility[56].

Nowadays, issues of a great magnitude that could potentially jeopardize the welfare are examined in detail. So, the latest empirical attempts include more specialized indicators in their models, seeking to overcome previous weaknesses or willing to investigate the outcomes of significant parameters on energy prices, energy consumption and prosperity. Therefore, the economic growth theory develops under a broader spectrum incorporating recent environmental and energy policies and trends, like the European Emissions Trading Scheme

[55] Muhammad, S., Muhammad, Z., Jawad, S., & Mantu, K. (2018). *The Energy Consumption and Economic Growth Nexus in Top Ten Energy-Consuming Countries: Fresh Evidence from Using the Quantile-on-Quantile Approach.* MPRA. (Paper No. 84920) [Online]. Available at: https://mpra.ub.uni-muenchen.de/84920/ Retrieved from 18th January 2019

[56] Mohamad, Z.H., Selim, A., & Fazle, R. (2013). Asymmetry and Persistence of Energy Price Volatility. *International Journal of Finance and Accounting. 2*(7), 373-378.

in the European case or the renewable energy penetration. One recent paradigm is that of Shabaz et al., (2013), which examine the relation between carbon emissions, GDP growth and energy consumption from 1980 to 2010 in Romania[57]. A more stylized model on the long-run growth and energy prices is used by Berk and Yetkiner (2014), showing that increases in energy prices -whether are renewable or not- restrict the rates of GDP per capita[58]. In contrast, Bretschger (2009) claims that increasing energy prices do not put the growth mechanism at risk, but downgrade the energy use. In addition, he observes that energy taxes pressure the energy use and push up energy prices[59].

To sum up, some researchers claim that the overall energy use to economy serves as a valuable tool for examining the relationship between the energy and the economic growth. This framework favors the ambiguous role of energy prices in macroeconomic prosperity. However, many empirical studies have failed to prove the relevance of energy demand to growth. Hence, from the opponents' perspective, growth will happen ad hoc, whereas the variations in relative prices and the technological innovations are persuasive explanations.

Table 1
Indicative Results from previous studies/Evidence from previous studies

Author(s)	Research	Methodology	Variables	Findings
Kraft J. and Kraft A. (1978)	On the relationship between energy and GNP	VAR Model-Sims Causality	Gross National Product (GNP) &Gross Energy Consumption (GEC)	Conservation Hypothesis-Unidirectional Causality Y→ E
Asafu-Adjaye J. (1999)	The relationship between energy consumption, energy prices and economic growth: Time series evidence from Asian developing countries	Engle-Granger 2-Step Method	Commercial Energy Use (en), GDP (y) & Energy Prices (p)	Feedback Hypothesis Bidirectional Causality E↔Y
Soytas U., Sari R. and O. Ozdemir (2001)	Energy Consumption and GDP Relation in Turkey: A Cointegration and Vector Error Correction Analysis. Economies and Business in Transition: Facilitating	Johansen Cointegration VECM Model	GDP (LNGDP) Energy Consumption (LNEC)	Growth Hypothesis Unidierectional Causality E →Y

[57] Nayan, S., Kadir, N., Ahmad, M., & Abdullah, M.S. (2013). *Revisiting Energy Consumption and GDP: Evidence from Dynamic Panel Data Analysis.* MPRA. Available at: http://mpra.ub.uni-muenchen.de/48714/ Retrieved from15th January 2019

[58] Berk, I., & Yetkiner, H. (2013). *Energy Prices and Economic Growth: Theory and Evidence in the Long-Run*. Working Papers in Economics, Department of Economics, Izmir University of Economics. Available at: https://www.econstor.eu/handle/10419/175927 Retrieved from 14th January 2019

[59] Bretschger, L. (2009). *Energy Prices, Growth and the Channels in Between: Theory and Evidence.* Oxford Centre for the Analysis of Resource Rich Economies. Department of Economics OxCarre

	Competiveness and Change in the Global Environment Proceedings			
L. Bretschger (2006)	Energy Prices, Growth and Channels in Between: Theory and Evidence	Three-Stage Least Squares	Energy Prices, GDP, Energy Use, Capital Accumulation	Neutral Hypothesis No Causality in the long-run EP ↕ Y
Zachariadis T. (2007)	Exploring the relationship between energy use and economic growth with bivariate models: new evidence from G-7 countries	VECM, ARDL, Toda Yamamoto Causality tests	Energy Use, Economic Growth	Conservation Hypothesis Unidirectional Causality Y→ EC
Hou Qiang, (2009)	The Relationship between Energy Consumption Growths and Economic Growth in China	Johansen Cointegration test, Hsiao Granger Causality & Hsiao ECM	Real GDP, Energy Consumption	Feedback Hypothesis Bi-directional Causality EC ↔Y
Ansgar Belke, Frauke Dobnik, Christian Dreger	Energy consumption and economic growth: New insights into the cointegration relationship	Modified Johansen Cointegration test (proposed by Reinsel, Ahn and Reimers), DOLS, ECM	GDP per Capita, Energy Consumption per capita, Energy Price	Feedback Hypothesis Bi-directional Causality EC ↔ Y
Menegaki, A.N.(2011)	Growth and renewable energy in Europe: A random effect model with evidence for neutrality hypothesis	Engle-Granger 2-Step Method	Renewable Energy Consumption, Final Energy Consumption, Greenhouse Gas Emissions, Employment	Neutrality Hypothesis No Causality RES ↕ Y
Nicolas Apergis, Dan Constantin Danuletiu, 2014	Renewable Energy and Economic Growth: Evidence from the Sign of Panel Long-Run Causality	Unit Roots tests, ECM, Perasan & Yamagate 2-Step Procedure, Granger Causality	GDP, Renewable Energy Consumption, Real Gross Fixed Capital Formation, Total Labor Force	Feedback Hypothesis Unidirectional Causality RES ↔ GDP
Istemi Berk, Hakan Yetkiner, 2013	Energy Prices and Economic Growth: Theory and Evidence in the Long Run	2-sector growth model according to Rebelo, Persyn-Westerlund error-correction based cointegration test, ARDL	Energy prices, Energy Consumption per capita, GDP per capita	Energy Prices negatively affect both EC and Y EP → EC EP → Y
Mohammed Issa Shahateet 2014	. Modelling Economic Growth and Energy Consumption in	ARDL Model	GDP per unit of energy use, Energy use in kg of oil	Neutrality Hypothesis- No causality EC ↕Y

	Arab Countries: Cointegration and Causality Analysis		equivalent per $1000 GDP	
Augustine C. Osigwe, Damilola Felix Arawomo, 2015	Energy Consumption, Energy Prices and Economic Growth: Causal Relationships Based on Error Correction Model	Engle-Granger 2-Step Method	Growth rate of GDP (grgdp), Commercial Energy Use (enrcon), Price of barrel of crude oil (oil), Litters of kerosene (kercon), Price of kerosene per litter (kerpr) Electricity Consumption kWh (elecon), Electricity Price kWh (elepri)	Feedback Hypothesis Bidirectional causality between energy consumption & GDP growth except the case of kerosene. Also, bidirectional causality between electricity consumption and electricity price Y↔ EC ELC ↔ ELP
Bismark Ameyaw, Amos Oppong, Lucille Aba Abruquah, Eric Ashalley, 2016	Causality Nexus of Electricity Consumption and Economic Growth: An Empirical Evidence from Ghana	Johansen Cointegration test, VECM, Granger Causality test	GDP, Fixed Capital (k), Labor force (L), Electricity Consumption (E)	Conservation Hypothesis Unidirectional Causality Y→ ELC K→GDP L→GDP
Faisal Faisal, Turgut Tursoy, Ozlem Ercantan (2017)	The relationship between energy consumption and economic growth: Evidence from non-Granger causality test	ARDL. Bounds test Toda-Yamamoto approach for causality	GDP per capita, Energy Consumption	Conservation Hypothesis Unidirectional Causality Y → EC
Stephan B. Bruns, Johannes König, David I. Stern, 2018	Replication and Robustness Analysis of 'Energy and Economic Growth in the USA: a Multivariate Approach	Bivariate VAR Models, Multivariate VAR Models Modified Granger Causality tests (Toda & Yamamoto), Granger Causality tests,	GDP, Capital without residential, Capital with residential, Capital without residential (adjusted by utilization rate), capital with residential (adjusted by utilization rate), Full-time equivalent employment, Hours-worked, Primary energy use, Final energy use, Quality adjusted final	Growth Hypothesis under constraints Causality runs from energy use to GDP growth by nesting Quality-adjusted energy use, labor & capital EC → Y

		energy use, Quality adjusted primary energy use, Primary energy prices, Final energy prices, Quality adjusted primary energy prices,Quality adjusted final energy prices

Note: Y denotes GDP or GNP. EC denotes Energy Use or Energy Consumption. EP denotes energy prices, ELP electricity prices and ELC electricity consumption respectively. RES, K and L denote renewable energy, capital and labor force.

2.6 Applied Behavioural Economics to Energy & Growth

An alternative approach to energy-growth nexus comes from the field of behavioural economics, where consumer and producer behaviour is analyzed with regard to energy demand and climate policies. Providing that the structure of market economies dominate the contemporary societies and the energy commodities are tradable goods in those markets the aggregate energy demand may be subject to orthodox economics. More explicitly, the energy demand adapts to changes in energy prices over different periods of time in different markets[60], due to the law of supply and demand. So, energy suppliers might face increasing marginal costs and users decreasing marginal utility, while state or regulatory authorities may intervene in order to return to initial state of equilibrium (Sorrell, 2015). The aforementioned require well-informed rational participants as well as the conditions of well-functioning markets.

Thus, the starting point is the neoclassical framework of utility maximization. The core hypothesis denotes that both consumers and firms have rational expectations, or they are perfect foresight[61]. Acting rationally and using all the available information they can make the optimal decisions. However, the model underestimates the individual incentives and preferences as well as the issue of imperfect or asymmetric information[62]. Indeed the empirical results have implied a controversial pattern between the neoclassical suggestions and the effective reactions on both consumers and firms' side.

In particular, the expected discount rates over energy efficiency investments surpass significantly the borrowing and saving interest rates. This trend of somehow fulsome future

[60] Sorrell, S. (2015). Reducing energy demand: A review of issues, challenges and approaches. *Renewable and Sustainable Energy Reviews*, 47, 74-82. [Online]. Available at: www.elsevier.com/locate/rser Retrieved from 2nd February 2019

[61] Sanstad, A.H., & Greening, L.A. (1996). Economic Models for Climate Policy analysis: A Critical Discussion. *Environmental Modeling and Assessment,* 3(1-2), 3-18.

[62] Sorrell, S. (2015). Reducing energy demand: A review of issues, challenges and approaches. *Renewable and Sustainable Energy Reviews*, 47, 74-82. [Online]. Available at: www.elsevier.com/locate/rser Retrieved from 2nd February 2019

returns has been laid on market barriers or failure[63]. Another attempt to solve this problem arises from the idea of ″energy efficiency gap", which can be surpassed through remedial policies[64]. For instance, Sanstad and Howard in 1995 appeal for ″substantive rationality"[65] over consumers' decisions, consider political interference necessary to maximizing energy efficiency. Likewise, Gillingham and his colleagues in 2009 call on the energy efficiency gap argued that divergences from the economically optimal outcome provoked due to market and behavioural failures[66].

Other theorists, such as Gowdy denote that the application of rational choice theory in energy related issues is unsustainable due to ″the complexity of human decision-making"[67]. However, Allcott furnishes satisfying explanations for the divergence from the rational agent-based model[68], explaining in his work that consumers are ″myopic and inattentive" with respect to their future expectations over energy prices. On the other hand, the concept of bounded rationality offers a deeper understanding of human attitudes.[69] The initial model's scarcity to capture the complexity of human decision-making is surpassed as new variables enter into the model[70]. The model reflects the problem of time inconsistency; the incapacity of certain critical variables -i.e. discount rates, etc- to adjust rapidly to surprising changes, which in return explains sufficiently why decision-makers are feeble when predicting properly the real market movements.

The principles of behavioural economics link energy efficiency, uncertainty and volatility in the energy markets. For that purpose some researchers focus not only on consumers' behaviours but also on investors' behaviours with respect to psychological and social aspects. For instance, Pavan and Iacoviello found that increase in savings rate may justify the smoothness in the household energy consumption, as the uncertainty over the real estate market augments and the investment rate drops due to the end users' intention to hedge against future wealth shocks by increasing their savings[71]. Other scientists examine the financial cost associated to shifts in energy consumption behaviour, verifying that reduction

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[63] Howarth R.B., & Sanstad A.H. (1995). Discount rates and energy efficiency. *Contemporary Economic Policy*, 13(3), 101-109

[64] Hasset, G.E., & Metcalf, K.H. (1993). Energy conservation investment: Do consumers discount the future correctly? *Energy Policy*, *21*(6), 710 – 716

[65] Sanstad, A., & Howard, R. (1994). *Consumer Rationality and Energy Efficiency.* [Online].Available at: http://enduse.lbl.gov/Info/ACEEE-Efficiency.pdf Retrieved from 4th January 2019

[66] Gillingham, K., Newell, G. R., & Palmer, K. (2009). Energy Efficiency Economics and Policy. *Annual Review of Resource Economics, Annual Reviews,* 1(1), 597-620. [Online].
Available at: https://www.nber.org/papers/w15031 Retrieved from 18th March 2019

[67] Gowdy, J.M. (2008). Behavioural Economics and Climate Change Policy. *Journal of Economic Behavior & Organization,* 68 (3-4), 632-644. [Online].
Available at: https://econpapers.repec.org/article/eeejeborg/v_3a68_3ay_3a2008_3ai_3a3-4_3ap_3a632-644.htm Retrieved from 22nd March 2019

[68] Allcott, H., (2009). *Rethinking Real Time Electricity Pricing*. [Online].
Available at: http://web.mit.edu/ceepr/www/publications/workingpapers/2009-015.pdf Retrieved from 5th February 2019

[69] EIA, (2014). *Behavioral Economics Applied to Energy Demand Analysis: A Foundation.* U.S. Energy Information Administration. Independent Statistics & Analysis. [Online]. Available at: www.eia.gov. Retrieved from 22nd January 2019

[70] Gabaix, X. (2011). A Sparsity-Based Model of Bounded Rationality. *Quarterly Journal of Economics*. [Online]. Available at: http://pages.stern.nyu.edu/~xgabaix/papers/sparsebr.pdf Retrieved from 29 December 2018

[71] Iacoviello, M., Pavan, M., (2009). Housing and Debt over the Life Cycle and over the Business Cycle. [Online]. Available at : https://www.federalreserve.gov/pubs/ifdp/2011/1032/ifdp1032.htm Retrieved from 20th January 2019

in energy use is linked to higher energy prices and low consumers' willingness to pay[72]. Furthermore, some scientific work embodied significant issues of social psychology like societal norms, beliefs, inclination and tendencies that affects economic and energy decisions[73].

Finally, the urge for reduction in energy demand has been met since the severe oil crisis in 1970s with regard to energy security concerns, while later in the 1980s the market liberalisation underlined the need of lessening energy demand due to climate change. Ambitious policies evangelized the energy efficiency by promoting for example new cost-effective technologies and imposed limits to traditional carbon usage, but simultaneously risked the competiveness and the income distribution. It is commonly admitted that a rise in energy prices would restrict energy use and consequently governments via imposing new taxes in energy prices would influence the energy demand. Therefore, taxes and other related measures would influence the consumer behaviour.

Behavioural economics explains why end-users insist on using more the conventional technologies than energy efficient and low-cost technologies. One reason is that customers are more likely prompted to energy efficiency measures when the latter is presented as a means to prevent them from a potential loss rather than a window of profit[74].

In the latest attempts behavioural economists tend to associate the energy issue with herd behaviour. Herding is primarily applied to finance clarifying the fact that a group of investors purposefully or not would act in the same manner simultaneously, influencing other investor's decisions in the financial markets. The proneness to imitate others behavior is similar to that one observed in a herd. Herding refers to mass irrational behaviour of investors which is associated to exclusive private sources of information[75] or the information aggregation.

Herding is divided into two main categories "*rational or spurious herding"* and "*irrational or intentional herding"*. Rational herding may be caused due to new available information or to investors' response to certain conditions. The second type arises from the inclination of investors to follow the same decision path with others. That mimesis may lead to market destabilization due to growing volatility[76] and uncertainty arising from widely sells and buys. Therefore, it is possible to create bubbles and crashes in financial markets. Fernando Palao Sánchez (2016) in *"Behavioural Aspects of European Carbon Market*" found evidence on herding behaviour under the European Emissions Trading Scheme (ETS). In particular, by examining the European Futures Carbon market, herding patterns are observed *"due to the lack of randomness in sequences of positive or negative changes in European Emission*

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[72]Spence, A., Leygue, C., Bedwel, I.B., O'Malley C., (2013). Engaging with energy reduction: Does a climate change frame have the potential for achieving broader sustainable behaviour? *Journal of Environmental Phychology*, *38,* 17-18. [Online]. Available at: https://www.elsevier.com/ Retrieved 1st February 2019

[73] Sorrell, S. (2015). Reducing energy demand: A review of issues, challenges and approaches. *Renewable and Sustainable Energy Reviews*, 47, 74-82. [Online]. Available at: www.elsevier.com/locate/rser Retrieved from 2nd February 2019

[74]Sorrell, S. (2015). Reducing energy demand: A review of issues, challenges and approaches. *Renewable and Sustainable Energy Reviews*, 47, 74-82. [Online]. Available at: www.elsevier.com/locate/rser Retrieved from 2nd February 2019

[75] Banerjee, A. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics,107(* 3), 797-817 The MIT Press. [Online]. Available at: https://economics.mit.edu/files/8869 Retrieved from 12th December 2018

[76] Sánchez, F.P. (2016). *Behavioural Aspects of the European Carbon Market.* Department of Financial Economics, University of Valencia. [Online]. Available at: https://www.uv.es/bfc/Doctorat/Tesis%20Fernando%20Palao.pdf Retrieved from 18th December 2018

Allowances prices" in the secondary market. Sánchez noticed that herding expands along with the speculation motives and the carbon price volatility, while breaking news serves also as a signal of herd behaviour. Finally, his research supports that the access to complete information is prevented by herding phenomenon.

3 The European Union Context

The European Union aspires to become an ad hoc global leader in transition to a low-carbon economy with respect to energy efficiency, renewable energy penetration and fair deal for end-users[77]. The EU's vision for a wiser energy use is closely linked to reductions in CO2 intensity through the ratification of international agreements (Kyoto Protocol, Paris Agreement, etc) and the recognition of new opportunities for further economic development.

In fact, energy was an issue of great concern since the infant stages of the European Union. Energy is a pillar of macroeconomic stability and that was obvious on the minds of European leaders since their initial attempts to create the European Union. The establishment of the European Coal and Steel Community in 1951 was a real milestone for the awakening of joint actions in the energy sector.

Afterwards, the creation of the European Atomic Energy Community (EURATOM) in 1961 brought again the energy to the fore. However, the energy has been referred explicitly as a priority of action in the Maastricht Treaty, whereas the Lisbon Treaty that came into force in 2009 and settled a clear base for the energy policies. Specifically, the treaty legalized the institution and the functioning of the internal energy market, the interconnection of energy networks, the security of supply and measures promoting energy efficiency and energy savings. The EU advanced its energy decisions with the adoption of four energy packages that would be analyzed later in this sub-section.

On these grounds, the EU has launched the establishment of a single energy market as a part of its long-term energy security strategy and environmental action[78]. The EU’s energy policies have prioritized certain goals and objectives with the view to ensuring the security of supply and promote the competitiveness within the limits of a fully-integrated internal energy market. According to the official European Commission’s statement, the Energy Union intends to *"making energy more secure, affordable and sustainable*". It also aims to cross boundaries flow of energy safeguarding energy demand for each member-state. In addition the Energy Union stimulates employment and further economic growth.

[77]European Commission, (2017). *European Commission, Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank.* Third Report on the State of the Energy Union- COM (2017)688 final. [Online]. Available at: https://ec.europa.eu/commission/sites/beta-political/files/third-report-state-energy-union_en.pdf. Retrieved from 17 December 2018

[78] European Commission, (2018). *Energy Strategy and Energy Union; secure, competitive and sustainable energy. European Commission, Energy, Topics, Energy Strategy and Energy Union*. [Online]. Available at: https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union Retrieved from 16th December 2918

The Energy Union meets both the targets of "European Energy Security Strategy" and "2030 Framework for Climate Change and Energy". The official Commission's website[79] regarding the internal energy market refers to the sequent fie aspects :

- *"security, solidarity and trust: diversifying Europe's sources of energy and ensuring energy security through solidarity and cooperation between EU countries*
- *a fully integrated internal energy market: enabling the free flow of energy through the EU through adequate infrastructure and without technical or regulatory barriers*
- *energy efficiency: improved energy efficiency will reduce dependence on energy imports, lower emissions, and drive jobs and growth*
- *decarbonising the economy: the EU is committed to a quick ratification of the Paris Agreement and to retaining its leadership in the area of renewable energy*
- *research, innovation and competitiveness: supporting breakthroughs in low-carbon and clean energy technologies by prioritizing research and innovation to drive the energy transition and improve competitiveness."*

Figure 3.2030 Framework for Energy and Climate-Agreed headline targets
Source: European Commission

Furthermore, a renewed market design with regard to electricity and gas system has been adopted, enabling rivalry among suppliers and offering more competitive prices to EU consumers. The required enactment on the grounds of effective market liberalization led to the implementation of four energy packages (Directive 1996-92, Directive 2003/54 and Directive 2009/72 & Regulation 2009/714 and the Clean Energy for all European package) that embodied the necessary structural reforms.

In particular, the 1st legislative package includes the subsidiary principle, the gradual liberalization of the national energy markets, the creation of regulatory authorities and the division among supply, generation and transmission with an emphasis on the third party access into the networks. The 2nd energy package contains rules that guarantee the consumer's ability to choose any provider and further steps for a more competitive market, alongside with the emergence of the first energy exchanges. As far as the provisions of the 3rd Energy

[79]European Commission, (2018). *Building the Energy Union. European Commission, Energy, Topics, Energy Strategy and Energy Union, Building the Energy Union.* [Online].
Available at: https://ec.europa.eu/energy/en/topics/energy-strategy-and-energy-union/building-energy-union
Retrieved from 16th December 2018

Package[80] , they foresee the complete unbundling of energy supply and generation from the transmission networks (legal and ownership unbundling) with the founding of independent transmission operators and independent system operators. Furthermore, it strengthens the independence of regulatory authorities, the establishment of the Authority of Cooperation of Energy Regulators (ACER) and the harmonisation of retail markets. Moreover, the EU customers enjoy special treatment as far as the reliability of their information, which means the guarantee of consistent information over their electricity and gas consumption which would lead on reduction of their energy use. The "Winter Package" contains further regulations for the wholesale and retail markets, guidance for the governance of the Energy Union, risk preparedness plans for electricity crises, improved energy efficiency targets and accomplished global leadership in renewable energy sector[81].

The state of the renewed market structure remains at a preliminary stage, instead of the recent years' advancement. Whilst, significant issues risks the well-functioning and the integration of the European energy market, like market's segmentation, conditions of imperfect competition and inadequate investments[82]. Taking the aforementioned into consideration, joint efforts and further political willing are critical for the fulfilment of the internal energy union.

3.1 Energy prices in the European Union

Before energy reaches the mains of end-users, a challenging process takes place including the energy production of a large number of power plants, numerous sales, purchases and bids in the wholesale and retail market and finally the distribution and transmission through the grid. It is estimated that more than 10.000 transactions[83] are realized in EU wholesale electricity and gas market on a daily basis. However, as the energy prices are negotiated it is possible to be subject of certain changes. These variations in energy prices may influence the final energy consumption. Moreover, they may cause additional charges to suppliers affecting finally the end-users price.

So, the quest for a dynamic relation between the economic growth and the energy prices demands the examination of various factors affecting the state of the macroeconomy in the European Union. First of all, the EU is idiosyncratic by nature; it consists of 28 member states, whereas among them only the 19 belongs to the euro area. According to the theory of the Optimum Currency Areas[84], the European monetary union does not form an optimal currency area, while the macroeconomic imbalances originate from the monetary union also agonize the other European Union member states through various transmission channels. The

[80]European Commission, (2018). *Energy-Markets and Consumers: Integrated energy markets for European households and businesses. European Commission, Energy, Topics, Markets and consumers*. [Online]. Available at: https://ec.europa.eu/energy/en/topics/markets-and-consumers Retrieved from 13th December 2018

[81] Hancher, L., & Winters, B.M. (2017). The EU Winter Package Briefing Paper Allen & Overy. [Online] Available at: http://fsr.eui.eu/wp-content/uploads/The-EU-Winter-Package.pdf Retrieved from 28th December 2018

[82]European Commission, (2018). *Priority Policy Area; A fully-integrated internal energy market. European Commission, Priorities, Energy Union and climate, A fully-integrated energy market.* [Online}. Available at: https://ec.europa.eu/commission/priorities/energy-union-and-climate/fully-integrated-internal-energy-market_en Retrieved from 13th December 2018

[83]European Commission, (2018). *Wholesale market. European Commission, Energy, Topics, Markets and consumers, Wholesale market.* [Online]. Available at: https://ec.europa.eu/energy/en/topics/markets-and-consumers/wholesale-market Retrieved from 13th December 2018

[84]Mundell, R.I. (1961). A Theory of Optimum Currency Areas. *The American Economic Review,* 51, (4), 657-665. [Online]. Available at: http://www.jstor.org/stable/1812792 Retrieved from 1st April 2019

uniqueness of the European Union in conjunction with the regional and global economic conditions has to be analyzed profoundly. Thus, it is critical to take into consideration the global supply-side shocks, such as the oil shocks, as well as the degree of asymmetry or symmetry of macroeconomic shocks affecting a monetary union through the deepening of economic integration and simultaneously their impact on final consumer prices.

The high degree of sensitivity and uncertainty in energy markets due to asymmetric information problems as well as the missing money problem provoke serious fluctuations in energy prices. The information problems arise from unreliable and fake information over the disposable energy produced or decreasing generation[85]. Price manipulations due to asymmetric or false information-which can be found typically at financial markets-, are also observed in energy markets. Thus, that kind of price control would happen especially in the EU framework, where cross borders trading and network interconnection takes place. In order to evade this danger, the European institutions have adopted certain measures against market abuse, for instance diffusion of fake information, use of inside information, deliberate sells and purchases are forbidden. In parallel, the role of ACER has been amplified; ACER is responsible for the market monitoring with the right to demand direct intervention of national regulators when abusive behaviors are observed. Moreover, for transparency reasons the energy market actors are obliged to communicate their data over transactions to ACER.

The missing money problem that is mentioned previously is linked to alternative sources penetration in the power markets. Electricity generated from renewables stresses prices due to downsized or zero operational costs and null variable production costs[86], that forces the other power plants (gas power plants, conventional power plants etc.) to offer electricity at very low prices or prices which equal to the marginal cost, if they want to remain competitive. On the other hand variable generation i.e. solar panels and wind plants produce energy under particular circumstances during the day, which result in overloading at specific time periods, creating the conditions of oversupply and reducing the power prices. Moreover, it creates concerns over the design and the forecast of energy demand. Opportunities for additional profits exist through the prism of scarcity events or abuse of dominant position; thus, if a participant with significant market power follows a strategic behaviour. Nevertheless, in a regulated energy market where the independent authority poses price caps and may intervene for the purpose of security of supply and conditions of perfect competitions, shortages are limited. In order to safeguard the security of supply and ensure the availability of energy demand, the European Energy Exchanges foresee mechanisms of capacity and ancillary services (Allocation and Congestion Management, Forward Capacity Allocation and Balancing Market[87]). Furthermore, given that the EU is an energy dependent economy, the European institutions emphasize on the strategic reserves.

[85] European Commission, (2018). *Wholesale market. European Commission, Energy, Topics, Markets and consumers, Wholesale market*. [Online]. Available at: https://ec.europa.eu/energy/en/topics/markets-and-consumers/wholesale-market Retrieved from 16th December 2018

[86] Ela, E., Milligan, M., Bloom, A., Botterud, A., Townsend, A., & Levin, T. (2014). Evolution of Wholesale Electricity Market Design with Increasing Levels of Renewable Generation. *NREL,* 139. [Online]. Available at: http://www.nrel.gov/docs/fy14osti/61765.pdf Retrieved from 29th March 2019

[87] European Commission, (2018). *Electricity network codes and guidelines. European Commission, Energy, Topics, Markets and Consumers, Wholesale market, Electricity network codes and guidelines.* [Online]. Available at: https://ec.europa.eu/energy/en/topics/markets-and-consumers/wholesale-market/electricity-network-codes Retrieved from 19th December 2018

Supposing that prices for energy products and their derivatives are traded in energy markets, their prices are influenced by various factors, as it is already mentioned above. Except for the international trends which affect the supply of mineral products and raw materials, the asymmetries in information and the missing money problem, another problem that influences end-users are the additional fees such as levies and taxes incorporated into the energy prices. In fact, the average electricity prices for household consumption has risen by 3, 2% from 2008 to 2017, despite the drop in wholesale electricity prices. According to European Commission's data the burdens in final prices have augmented by 10% in the member-states because of taxes and levies (VAT, social tariffs, compensation, and employment). The decrease in wholesale electricity prices lays on internal energy market and price coupling. However, neither industries nor households have already benefited. Nevertheless, the electricity prices in the industrial sector have risen more smoothly; the price range of increase in electricity prices varies from 0, 8% to 3, 1% per annum for the period 2008 to 2015.

Despite the current progress in the internal energy market and the entry of renewable resources into the energy mix, the EU's net imports of electricity originated from fossil fuels have presented an upward trend[88]. As far as the gas, Europe finds itself dependent on imports by approximately 69%. Gas consumption in the European Union accounts for 23% of the aggregate energy consumption[89] and it also constitutes a significant fuel for electricity provided both to households and industries. The EU's dependence on gas means that fuel's prices fluctuate with respect to tendencies in international energy markets. Wholesale prices have fallen significantly reaching to a reduction of 50% in 2017 in comparison to those of 2013. This trend is rendered to international financial crisis unpleasant outcomes whilst the forthcoming recession decelerates the global demand. Even if the downward phase of global business cycle is not mirrored into household consumer prices that have increased by 2% yearly since the outbreak of the international crisis, the taxes and levies have risen again sharply. However, the retail prices for industries have decreased.

Concerning the crude oil price, it had been reduced sharply between 2014 and 2016 according to European Commission's estimations but it returns to 2014 level since then. Nevertheless, the decrease in retail price slightly subtracted inflationary pressures due to euro's devaluation as well as the large portion of taxes in the petroleum final price. Furthermore, petroleum is highly sensitive to inflationary pressures, so the oil prices rely to a great extent to the state of the international economy. Thus, the EU's competitiveness and the exchange rate influence the ability of importing oil.

To sum up, energy prices in the European Union continue to vary due to several externalities like the geographical characteristics, a more sophisticated energy use, the domestic political will or the different national approaches, as member-states still enjoy a certain degree of freedom under the absence of a central government. For this reason the energy expenses vary

[88] European Commission, (2017). Opinion of the European Economic and Social Committee on the 'Report from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Energy prices and costs in Europe. *Official Journal of the European Union*. [Online]. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1544084744452&uri=CELEX:52016AE6928 Retrieved from 18th January 2019

[89] European Commission, (2017). Opinion of the European Economic and Social Committee on the 'Report from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Energy prices and costs in Europe. *Official Journal of the European Union.* [Online]. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1544084744452&uri=CELEX:52016AE6928 Retrieved from 18th January 2019

significantly among member states. In some cases for example, consumers are charged excessively with taxes, like the residential Swedish gas price, which is the highest one in the European territory. Even though the residential energy expenditure has increased, the overall household energy consumption has maintained in a stable level since 2008. Energy prices affect directly the overall economy, as fuels and minerals are indispensable for the production of goods and services. Therefore, energy prices influence the EU's macroeconomic conditions such as global competitiveness, the terms of trade and the GDP growth.

3.2 Key Energy & Macroeconomic Indicators

The aforementioned theories, in conjunction with the policy goals prioritized by the EU's institutions indicate the existence of the most adequate indicators in the quest of inherent relation between energy prices and economic growth. These indicators typically concern the output, the output growth, the level of energy used, the energy consumption, the energy intensity, the energy imports as well as the technological advancements and resource allocation in Research & Development (R&D).

The European Commission suggests that some ″key energy drivers" can be used for macro-energy modelling[90] analyzing the energy dynamics and the domestic performance. Among them the primary energy consumption and the final energy consumption are of paramount importance. As far as the primary energy consumption in EU-28 in the last decades, it shows a downward trend compared to 1970s levels. Indeed, the EU-28 primary energy consumption in combination with US primary energy consumption has accounted for 50% of global energy demand since 1970 (European Commission, 2016). However, this trend changed due to structural reforms, persistent fluctuations in energy prices and adoption of more energy efficient technologies. Similarly, the increase in final energy consumption over the last decades originates from households electricity consumption and transportation sector, as well. The electricity final consumption reaches approximately 20% of the aggregate final energy consumption.

The energy intensity is also a significant indicator for energy demand and economic performance. When the economy is in an expansion phase the energy demand and the energy consumption rise; consequently, the levels of intensity tend to rise. However, both technological innovations and increasing energy efficiency pressured the intensity in EU, which has fallen by 30% during 1990 - 2013[91]. The lower intensity rates that are observed from 2010 correspond to modest growth rates and GDP slowness due to recession. However,

[90] European Commission, (2016). *EU energy trends and macroeconomic performance -Understanding the drivers of EU energy trends. Deliverable D1 Study on the Macroeconomics of Energy and Climate Policies.* [Online]. Available at:https://ec.europa.eu/energy/sites/ener/files/documents/ENER%20Macro-Energy_Trends-Macroeconomic-Performance_D1%20Final%20%28Ares%20registered%29.pdf Retrieved from 17th December 2018

[91]European Commission, (2016). *EU energy trends and macroeconomic performance -Understanding the drivers of EU energy trends. Deliverable D1 Study on the Macroeconomics of Energy and Climate Policies.* [Online]. Available at:https://ec.europa.eu/energy/sites/ener/files/documents/ENER%20Macro-Energy_Trends-Macroeconomic-Performance_D1%20Final%20%28Ares%20registered%29.pdf Retrieved from 28th December 2018

the European Commission's data support that growth in energy consumption is steadily lower than GDP growth, which favours the view of reduced intensity in EU over the last decades. The newly entered member-states show different levels of intensity, though the EU's commitment to achieve specific targets over the energy and environmental policies resulted in a steady decline in energy intensity in those member-states too. Furthermore, the carbon intensity in European economy follows the same pattern in recent decades, indicating the significant cut of greenhouse gas emissions. In fact, as the European Commission's survey points out ″the greenhouse gas intensity of EU energy consumption fell by some 19% over the period 1990-2013", this particular trend contributes to a decline in energy-related greenhouse gas emissions per unit of GDP. The reduction in greenhouse gas emissions is related to adaption of new energy mix and improvements in energy efficiency. In parallel, the decline in gas emissions serves the dimensions of energy security and gradual decrease in energy dependence. The other indicators refer to energy dependence, energy investments and energy innovation. First of all, the EU is heavily dependent on fuel and mineral imports and simultaneously exposed to serious fluctuations in international prices. The high levels of exposure create several macroeconomic distortions. Therefore, measuring the energy dependency, which is depicted via the energy imports as well, plays a crucial role for EU. Especially after the severe oil shocks in 1970s and 1980s that gave a clear reminder of how GDP sluggishness could be provoked. Finally, energy investment is related to expansions in installed capacity and new renewable installations, while the innovation concerns more the R&D in energy sector and notably the nuclear energy.

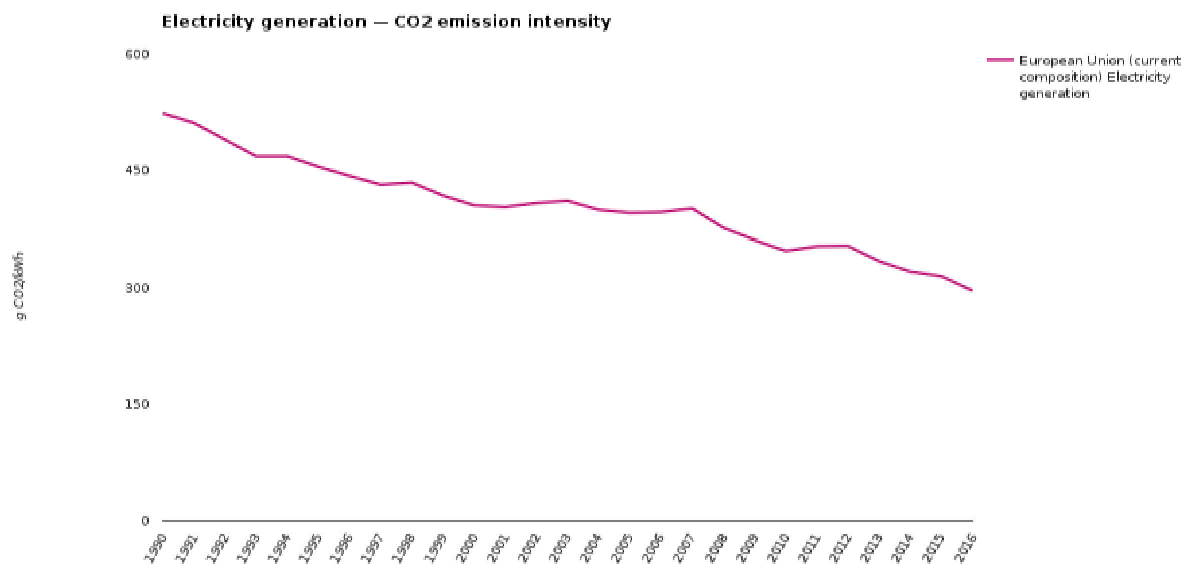

Figure 4. Electricity Generation -CO_2 emissions Intensity.
Note: The CO_2 emission intensity (kg CO_2/kWh) is calculated as the ratio of CO_2 emissions from public electricity production (as a share of CO_2 emissions from public electricity and heat production related to electricity production), and gross electricity production.
Source: European Environmental Agency. [Online]. Available at: https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity-5#tab-googlechartid_chart_11_filters=%7B"rowFilters"%3A%7B%7D%3B"columnFilters"%3A%7B Retrieved from 10th December 2018

4. Methodology

As it is mentioned in the previous section, a cornerstone for a country's economic prosperity is the energy used in the production process. Providing that the current economic orthodoxy is oriented toward an energy-centric path with respect to economic activity, examining the hypothesis of an expected powerful link between the energy prices and the real growth is of a paramount importance. The impetus of the field of energy economics and the findings of the current literature foster that kind of research.

The empirical surveys emphasize the role of energy consumption aplenty, whilst studies that nest energy prices inside their core models have proved that the trends in energy prices seem to influence the state of the macroeconomy drastically and equally in the global and domestic context. For that purpose the energy-economic growth nexus will be re-examined and the energy prices be taken into consideration as a major driver for promoting economic growth.

Therefore, the scientific focus here is oriented towards the interdependence of energy prices and economic growth in the EU framework. More precisely, the main scope of this thesis is to highlight the potential dynamics of energy prices on the real output and vice versa. Thus, the investigation of a cause and effect relationship synthesizes the core assumption. To define the driving forces between the former aggregates together with the direction of causality, the study follows the *"general-to-specific-technique"*[92] providing a model that allows the thorough probe of the issue.

The starting point is the construction of a generic model that encompasses the variables of interest together with the main macroeconomic indicators proposed by the EU's energy-macroeconomic modelling. Therefore, the initial model regarding the estimate of the energy prices and the economic growth is enriched with two aggregates; the total final energy consumption and the intensity level. The latter is well-explained under the spectrum of the significant energy-related measures and the environmental policies implemented by the EU.

More precisely, the real GDP is used as a proxy for the real economic growth, whereas the energy prices concern the final residential electricity prices, the final electricity prices for industry and the crude oil prices. The natural gas prices are not contained into the model due to the data absence. Whilst, the absence of observations on the final energy consumption indicator previous to 1990 -that is used as the base year- requires the model's re-examination through alternative estimation methods in order to verify the empirical findings. Hence, the estimates of CCR and FMOLS methods function like a sensitivity analysis, considering that the reference period from 1990 to 2018 offers a relatively small sample.

Afterwards, willing to study the direction of the expected causality a restricted VAR, i.e. a VECM model is employed in the second part of the empirical analysis.

To sum up, this study seeks to examine the meaningful role of energy prices for shaping the European prosperity via an extensive empirical analysis with the aim of two different models which will be presented broadly in the next sub-section. The examined period refers to the European electricity prices, the spot oil prices and the real output from 1990 to 2018. The

[92] Vamvoukas, G.A. (2016). *Contemporary Econometrics: Analysis and Applications*. Athens: University of Business and Economics

year 1990 is considered the starting point for giving the initial pivot to combat the climate change with the ratification of United Nations Framework Convention on Climate Change[93] (UNFCCC) and the adoption of Kyoto Protocol in 1997. At the centre of this research is the assumption of a vigorous linkage between the energy prices and the GDP growth, whereas the findings control for changes in final consumption behavior and the level of intensity under the spectrum of EU's official guidelines for mitigating climate change and the establishment of the European energy market.

The chapter is divided into two sub-sections that illustrate the econometric method and the data collected for the prosecution of the empirical analysis. In particular, the following sub-section outlines the boundaries and the parameters that have been taken into account for the construction of the estimation model and finally depicts the ultimate model's structure. Afterwards, there is an extensive presentation of the principal macroeconomic indicators that serve the purpose of an accurate model.

4.1 Estimation Methods

The scope of this empirical study is the examination of imminent interdependence between energy prices and economic growth in the EU. Hence, a multiple linear regression model would be a precise tool on observing the impact of one variable on another. The macroeconomic aggregates that depict such a probable interrelationship have already been specified. This section presents in detail the core model, which embodies GDP, electricity prices, crude oil spot price, final energy consumption andCO_2 emissions intensity

Thus, for the sake of a well-fitting and economic reasonable model, the GDP growth rate, the electricity prices, the crude oil spot prices, the total final energy consumption and the intensity level anchor the regression function; whereas the mathematical expression of variables is used to deal with the issues of high correlation and multicollinearity which are expected in the model. Therefore, the variables are transformed into the form of the natural logarithms to detect the aforementioned problems. Given the size and the number of the observations the time series linear regression model (1) would be represented by the following response function:

$$lnGDP_t = b_0 + b_1 lnREP + b_2 lnIEP + b_3 lnCOP + b_4 lnC02INTENS + b_5 lnFEC + u_t \qquad (1)$$

One of the most commonly accepted estimation methods for linear regression models is the Ordinary Least Squares (OLS). This estimation method assumes that the estimators satisfy the conditions of Best Linear Unbiased Estimators (BLUE)[94] in accordance with Gauss-Markov theorem. Furthermore, homoscedasticity and normality of residuals are also presumed. However, OLS are very sensitive with respect to time series analysis, which is the case. The prerequisite to perform OLS with time series data and avoid the wrong estimations is the stationarity of time series; although the nature of the macroeconomic data suggests the

[93] United Nations, (1992). United Nations Framework Convention on Climate Change. [Online]. Available at: https://unfccc.int/resource/docs/convkp/conveng.pdf Retrieved from 9th April 2019

[94] Wooldridge, M.J. (2013). Introduction to Econometrics; A modern Approach. 5th Edition. Cengage Learning, (pp.352-354).

contrary[95]. The majority of economic time series are not covariance-stationary; It faces the problem of autocorrelation and rarely appears to be stationary processes, i.e. integrated of order zero I(0).

The integrated process must be examined using the d differences in order to modify the stochastic processes from non-stationary to stationary, thus, integrated of order d, I(d). Therefore, the OLS poor interpretation ability and their controversial outcomes or *nonsense correlations*[96] as Yule G.U. mentioned, create certain weaknesses regarding the results' accuracy, whereas the likelihood of *spurious regression*[97] is high indeed. The spurious regression concerns a relatively high R^2 and statistically significant t-statics, which in fact are forged. The previous shortcoming could be surpassed if the time series expressed in their first differences become covariance-stationary processes, which appear in most of the macroeconomic data. The hypothesis of time series stationary via an integrated process permits the application of OLS through the channel of cointegration.

Engle-Granger (1987) in their seminal cointegration analysis proved that variables that are not stationary at level but are integrated of order one I(1) could be estimated through the OLS, if there is evidence on a linear combination of I(0) among them[98] (Polemis & Dagoumas, 2013). In other words, if the time series are cointegrated, then the residuals obtained from the cointegration regression must be stationary or integrated of I(0). The concept of cointegration underlines the existence of one or more long-run equilibrium among two or more variables. More explicitly, considering that the model contains X_k variables (X_1, X_2,…, X_k) are cointegrated of order d,b -where d represents the order of integration and b represents the cointegrating vector respectively- then the variables X_k are cointegrated of order d,b, namely CI(d,b). If the variables are stationary I(1) and one cointegrating relationship exists among them, then *"the Granger representation theorem"* is satisfied and an Error Correction Model (ECM) is shaped.

So, the dissertation adjusted to the up-to day methodology follows the Engle-Granger 2-Step procedure[99] via performing an Error Correction Model, supposing that the cointegration relationship is proved. By applying this procedure the sort-run and long-run elasticities could be obtained outlining the potential interrelationships among the variables of interest. In the second stage of this empirical analysis and given that cointegration is found, a Vector Error Correction Model (VECM) will be applied in order to define the direction of causality and indentify the long-run and short-run equilibria among the variables. Additionally, in order to verify the direction of the causality we proceed to Wald tests. While delving into the potential

[95] Vamvoukas, G.A. (2016). *Contemporary Econometrics: Analysis and Applications*. Athens: University of Business and Economics.

[96] Yule, G.U. (1926). Why Do We Sometimes Get Nonsense Correlations Between Time Series; A Study in Sampling and the Nature of Time Series. *Journal of the Royal Statistical Society* 89, 1-64

[97] Yule, G.U. (1926). Why Do We Sometimes Get Nonsense Correlations Between Time Series; A Study in Sampling and the Nature of Time Series. *Journal of the Royal Statistical Society* 89, 1-64

[98] Polemis, M.L., & Dagoumas, A.S. (2013).The electricity consumption and economic growth nexus: evidence from Greece. *Energy Policy,* 62, 798-808. [Online]. Available at: https://www.journals.elsevier.com/energy-policy Retrieved from 12th January 2019

[99] Engle, R.F., & Granger, C.W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Journal Article, 55* (2), 251-276. [Online].
Available at: https://www.jstor.org/stable/1913236?seq=1#page_scan_tab_contents Retrieved from 7th January 2019

interactions among the energy prices and the real GDP, the Impulse-Response Functions (IRF) and a Cholesky's Forecast-Error Variance Decomposition Analysis (FEVD) take place.

Computing the IRF provides evidence on the effects of a shock arising from one endogenous variable in the VECM system on the current and future values of the other endogenous variables. Furthermore, the FEVD shows to what extent an endogenous variable influences the other endogenous variables. Here the examination concerns the shocks derive from the residential electricity prices, industrial electricity prices, spot oil prices, total final energy consumption and CO_2 intensity on the GDP, which would be the response-variable. Hence, it will be examined whether or not the innovations of the other endogenous variables affect the real output. Finally, we investigate the effects of impulses arising from the GDP on to the others system's variables. Hence, proceed to IRFs and FEVD analysis as well.

4.2 Econometric Models' Decomposition

First of all, the time series analysis indicates the examination of stationarity; for instance, it is critical to investigate if the time series are stationary, following a white noise process or non stationary with the inking of stochastic trends. The econometric literature supports the examination of stationarity via the appropriate unit roots tests. So, the existence or not of unit roots has to be defined via performing the Phillips-Perron, Dickey-Fuller, KPSS and DF-GLS tests. If the existence of unit roots is confirmed and the variables are non-stationary integrated of order one I(1), then the obstacle of spurious regression can be surpassed based on the cointegration technique.

The Engle-Granger 2-step procedure will be applied in order to derive an ECM, assuming only one cointegration relationship among the examined variables. Initially, the multivariate model in equation (1) is used to obtain the following function:

$$u_{t=}\ lnGDP_t - b_0 - b_1\ lnREP_t - b_2\ lnIEP_t - b_3\ lnCOP_t - b_4 lnCO2INTENS_t - b_5\ lnFEC_t \qquad (2)$$

The stochastic term u_t - the disequilibrium error - denotes the range of changes on GDP, residential electricity prices, industrial electricity prices, spot oil prices, final energy consumption and intensity in the short-run. If the variables are stationary I(1) and u_t stationary, i.e. integrated of order zero I(0), this will lead to the existence of a linear combination among them. If the variables are indeed CI(1,1) then the following ECM would be developed:

$$\Delta \ln GDP_t = b_0 + \sum_{i=1}^{j} b_1 \Delta lnREP_{t-i} + \sum_{i=0}^{k} b_2 \Delta lnIEP_{t-i} + \sum_{i=0}^{l} b_3 \Delta lnCOP_{t-1} + \sum_{i=0}^{m} b_4 \Delta lnCO2INTENS_{t-1} + \sum_{i=0}^{n} b_5 \Delta lnFEC_{t-1} + \gamma U_{t-1} + \delta e_{t-1} \qquad (3)$$

Where Δ represents the first difference operator u_{t-1} which is the disequilibrium error and is considered a stationary time series I(0), γ is the adjustment coefficient that *measures the speed of adjustment towards the long-run equilibrium*[100] and γU_{t-1} is the error correction term that shows the short-term and long-term relation between the energy prices and GDP.

[100] Shrestha, M.B. & Bhatta, G.R. (2017). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, 4(2), 71-89. [Online]. Available at: www.sciencedirect.com/science/article/pii/S2405918817300405?via%3Dihub Retrieved from 12th February 2019

Moreover, the j,k,m…s, t represent the lag orders in order to obtain stationary white noise e_t for the number of lags j,k,m…s,t. To sum up, the ECM's coefficients depict how deviations from the long-run equilibrium -long-run equilibrium is estimated from equation (1), the cointegration regression- influence their changes in the next period[101].

The long-run and short-run equilibria enlighten the potential interdependence among energy prices and GDP growth. However, deepening the investigation on energy prices and economic growth nexus demands the determination of the direction of causal effects. Hence, the next step is to perform Granger causality tests according to Granger and Sims[102]. The reasoning of causality tests is to determine whether changes in energy prices are due to GDP growth or vice versa[103]. Granger causality tests are based on bivariate VAR models in which the variables are considered endogenous. Controlling for cause and effect among the variables will lead to four different outcomes according to Granger's rationale that has four different dimensions:

- GDP provokes changes in energy prices i.e. **Y→X**
- Energy prices affect GDP, i.e. **X →Y**
- Energy prices and GDP affect each other, hence, bidirectional causality, i.e. **Y↔ X**
- GDP and energy prices are independent **Y ↕ X**

Otherwise, if GDP does *"Granger-cause"* energy prices, then the past GDP values have an impact on energy prices. Hence, GDP Growth would be useful to predict the future energy prices. On the other hand, if it is proved that energy prices cause GDP, then the histories of energy prices would be used to obtain the future values of GDP. As the main objective is the investigation of Granger-cause relationships, Vector Autoregressive Models, VAR (m) might be expressed that represent the *"unrestricted model"* for its combination among the variables under investigation:

$$Y_t = \Sigma_{i=1}^{m} \alpha_i Y_{t-1} + \Sigma_{i-1}^{m} \beta_1 X_{t-1} + e_{1t} \qquad (4)$$

$$X_t = \Sigma_{i=1}^{m} \alpha_i Y_{t-1} + \Sigma_{i-1}^{m} \beta_1 X_{t-1} + e_{2t} \qquad (5)$$

Both a_i and β_i are parameters, whereas e_{1t} and e_{2t} are stochastic terms that are expected to be uncorrelated. Then, the *"restricted model"* will be as follows:

$$Y_t = \Sigma_{i=1}^{m} a_i Y_{t-1} + u_{t-1} \qquad (6)$$

$$X_t = \Sigma_{i-1}^{m} \beta_1 X_{t-1} + u_{t-1} \qquad (7)$$

Using the OLS estimation technique the regressions for unrestricted and restricted models are performed. Then Wald or F-tests are carried out under the null hypothesis of non-causality and the alternative of causality respectively:

$$H_0: \ \beta_1 = \beta_2 = ... = \beta_m = 0$$

101 Vamvoukas, G.A. (2016). *Contemporary Econometrics: Analysis and Applications.* Athens: University of Business and Economics.
102 Sims, C.A. (1972). Money, Income and Causality. *The American Economic Review*, 62(4), 540-552. [Online]. Available at: https://www.jstor.org/stable/1806097 Retrieved from 12th March 2019
103 Granger, C.W.J. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica.* 37(3), 424-438

H_1: $\beta_1 = \beta_2 = \ldots. = \beta_m \neq 0$ *for (4) and (6) and*

H_0: $a_1 = a_2 = \ldots. = a_m = 0$

H_1: $a_1 = a_2 = \ldots. = a_m \neq 0$ *for (5) and (7)*

More explicitly, willing to observe that GDP's history has an impact on energy prices the unrestricted regression (4) will carried out. Afterwards the restricted model, equation (6) will be regressed supposing that the coefficients of GDP's lagged values are equal to zero and the Wald test for its coefficients will be employed in order to compare the results and conclude if GDP Growth rate has indeed a causal effect on energy prices. The lag length is based on the selection order criteria like AIC, SBIC, LR and SBIC. The Wald test is obtained using the following formula:

$$F = \frac{RRSS - URSS}{URSS}\left(\frac{T-k}{q}\right) \quad (8)$$

Where RRSS represents the residual sum of squares of the restricted model and URSS the residual sum of squares of unrestricted model, T is the sample size, k the number of lags and q the restrictions. Comparing the obtained F-statistic to the critical values F_c, finally it will be ascertained whether or not the null hypothesis is rejected and causal effects of GDP are present or not. Similarly, the above steps must be applied in order to investigate if causality runs from energy prices to GDP Growth, i.e. if current and lagged values of electricity and crude oil prices aid to the prediction of the future values of GDP Growth.

Granger causality could also be indentified from an ECM. In that case, a Vector Error Correction Model (VECM) will be shaped according to Johansen methodology for cointegration[104]. This study moves toward this approach. Hence, Granger Causality tests are applied via adapting a VECM and after performing Wald tests.

The VECM is a VAR system with p lags in which one or more cointegrated relations exist based on Johansen's maximum likelihood[105]. A VAR model is a system of simultaneous equations, in fact *"a combination of several autoregressive models"*[106]. So, the VAR model for the selected variables is illustrated as:

General form of VAR model: $Y_t = v + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + \ldots A_p Y_{t-p} + e_t$ (9)

Where Y_t is a K ×1 vector of variables, v is a K × 1 vector of parameters, A_1, A_2, A_p are K × K matrices of parameters and e_t is a K × 1 vector of disturbances, with mean zero[107]. More analytically, the vector representation of the model is:

[104] Johansen, S. (1988). Statistical Analysis of Cointegrating Vectors. *Journal of Economic Dynamics and Control,* 12(2-3), 231-254 [Online].
Available at: http://dx.doi.org/10.1016/0165-1889(88)90041-3 Retrieved from 5th April 2019

[105] Johansen, S. (1995). *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models.* Oxford: Oxford University Press.

[106] Suharsono A., Aziza A., & Pramesti, W. (2017). *Comparison of Vector Autoregressive (VAR) and Vector Error Correction Models (VECM) for Index of ASEAN Stock Price*. [Online]. Available at: https://doi.org/10.1063/1.5016666 Retrieved from 23rd February 2019

[107] Stata Corporation. (2019). *Introduction to Vector Error-Correction Models.* [Online]. Available at: https://www.stata.com/manuals13/tsvecintro.pdf Retrieved from 11th February 2019

$$Y_t = \begin{bmatrix} lnGDP \\ lnRESID \\ lnINDP \\ lnCSOP \\ lnCO2INTENS \\ lnTFC \end{bmatrix}, \quad e_t = \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \\ e_{5t} \\ e_{6t} \end{bmatrix}, \qquad A_1 = \begin{bmatrix} a_{11} a_{12} a_{13} a_{14} a_{15} a_{16} \\ a_{21} a_{22} a_{23} a_{24} a_{25} a_{26} \\ a_{31} a_{32} a_{33} a_{34} a_{35} a_{36} \\ a_{41} a_{42} a_{43} a_{44} a_{45} a_{46} \\ a_{51} a_{52} a_{53} a_{54} a_{55} a_{56} \\ a_{61} a_{62} a_{63} a_{64} a_{65} a_{66} \end{bmatrix},$$

$$A_2 = \begin{bmatrix} \beta_{11}\beta_{12}\beta_{13}\beta_{14}\beta_{15}\beta_{16} \\ \beta_{21}\beta_{22}\beta_{23}\beta_{24}\beta_{25}\beta_{26} \\ \beta_{31}\beta_{32}\beta_{33}\beta_{34}\beta_{35}\beta_{36} \\ \beta_{41}\beta_{42}\beta_{43}\beta_{44}\beta_{45}\beta_{46} \\ \beta_{51}\beta_{52}\beta_{53}\beta_{54}\beta_{55}\beta_{56} \\ \beta_{61}\beta_{62}\beta_{63}\beta_{64}\beta_{65}\beta_{66} \end{bmatrix}, \ldots\ldots, \qquad A_p = \begin{bmatrix} \zeta_{11}\zeta_{12}\zeta_{13}\zeta_{14}\zeta_{15}\zeta_{16} \\ \zeta_{21}\zeta_{22}\zeta_{23}\zeta_{24}\zeta_{25}\zeta_{26} \\ \zeta_{31}\zeta_{32}\zeta_{33}\zeta_{34}\zeta_{35}\zeta_{36} \\ \zeta_{41}\zeta_{42}\zeta_{43}\zeta_{44}\zeta_{45}\zeta_{46} \\ \zeta_{51}\zeta_{52}\zeta_{53}\zeta_{54}\zeta_{55}\zeta_{56} \\ \zeta_{61}\zeta_{62}\zeta_{63}\zeta_{64}\zeta_{65}\zeta_{66} \end{bmatrix}$$

Whereas each equation of the VAR system has the ensuing form:

$$lnGDP_{t=} \quad a_{11}\ lnGDP_{t-1}+a_{13}\ lnREP_{t-1}+a_{13}lnIEP_{t-1}+a_{14}lnCOP_{t-1}+a_{15}lnCO2INTENS_{t-1}+ a_{16}lnFEC_{t-1}+\beta_{11}\ lnGDP_{t-1} + \beta_{12}lnREP_{t-2}+\beta_{13}lnIEP_{t-2}+\beta_{14}lnCOP_{t-2}+\beta_{15}lnCO2INTENS_{t-2}+\beta_{16}lnFEC_{t-2}+\ldots\ldots+ \zeta_{11}lnGDP_{t-p} + \zeta_{12}\ lnREP_{t-p}+\zeta_{13}lnIEP_{t-p}+\zeta_{14}lnCOP_{t-p}+\zeta_{15}lnCO2INTENS_{t-p}+\zeta_{16}lnFEC_{t-p} +e_{1t} \tag{10}$$

$$lnREP_t= a_{21}lnGDP_{t-1}+a_{22}lnREP_{t-1}+a_{23}lnIEP_{t-1}+ a_{24}lnCOP_{t-1}+a_{25}lnCO2INTENS_{t-1}+a_{26}lnFEC_{t-1}+\beta_{21}\ lnGDP_{t-1}+ \beta_{22}lnREP_{t-2}+\beta_{23}lnIEP_{t-2}+\beta_{24}lnCOP_{t-2}+\beta_{25}lnCO2INTENS_{t-2}+\beta_{26}lnFEC_{t-2}+\ldots+ \zeta_{21}lnGDP_{t-p}+\zeta_{22}lnREP_{t-p} +\zeta_{23}lnIEP_{t-p}+ \zeta_{24}lnCOP_{t-p}+ \zeta_{25}lnCO2INTENS_{t-p}+\zeta_{26}lnFEC_{t-p} +e_{2t} \tag{11}$$

$$lnIEP_t= a_{31}lnGDP_{t-1}+a_{32}lnREP_{t-1}+a_{33}lnIEP_{t-1}+a_{34}lnCOP_{t-1}+ a_{35}lnCO2INTENS_{t-1}+a_{36}lnFEC_{t-1}+\beta_{31}\ lnGDP_{t-1}+\beta_{32}lnREP_{t-2}+ \beta_{33}lnIEP_{t-2}+\beta_{34}lnCOP_{t-2}+\beta_{35}lnCO2INTENS_{t-2}+\beta_{36}lnFEC_{t-2}+\ldots+ \zeta_{31}lnGDP_{t-p}+\zeta_{32}lnREP_{t-p}+\zeta_{33}lnIEP_{t-p}+\zeta_{34}lnCOP_{t-p}+ \zeta_{35}lnCO2INTENS_{t-p} + \zeta_{36}lnFEC_{t-p} + e_{3t} \tag{12}$$

$$lnCOP_t= a_{41}lnGDP_{t-1}+a_{42}lnREP_{t-1}+a_{43}lnIEP_{t-1}+a_{44}lnCOP_{t-1}+ a_{45}lnCO2INTENS_{t-1}+a_{46}lnFEC_{t-1}+\beta_{41}\ lnGDP_{t-1}+\beta_{42}lnREP_{t-2}+ \beta_{43}lnIEP_{t-2}+\beta_{44}lnCOP_{t-2}+\beta_{45}lnCO2INTENS_{t-2}+\beta_{46}lnFEC_{t-2} +\ldots+ \zeta_{41}lnGDP_{t-p}+\zeta_{42}lnREP_{t-p}+\zeta_{43}lnIEP_{t-p}+\zeta_{44}lnCOP_{t-p}+ \zeta_{45}lnCO2INTENS_{t-p}+ \zeta_{46}lnFEC_{t-p} + e_{4t} \tag{13}$$

$$lnCO2INTENS_t= a_{51}lnGDP_{t-1}+a_{52}lnREP_{t-1}+a_{53}lnIEP_{t-1}+a_{54}lnCOP_{t-1} +a_{55}lnCO2INTENS_{t-1}+a_{56}lnFEC_{t-1}+\beta_{51}\ lnGDP_{t-1}+\beta_{52}lnREP_{t-2}+ \beta_{53}lnIEP_{t-2}+\beta_{54}lnCOP_{t-2}+\beta_{55}lnCO2INTENS_{t-2}+\beta_{56}lnFEC_{t-2} +\ldots+\zeta_{51}lnGDP_{t-p}+\zeta_{52}lnREP_{t-p}+ \zeta_{53}lnIEP_{t-p} + \zeta_{54}lnCOP_{t-p} + \zeta_{55}lnCO2INTENS_{t-p} + \zeta_{56}lnFEC_{t-p} +e_{5t} \tag{14}$$

$lnFEC_t$= $a_{61}\,lnGDP_{t-1}$+$a_{62}\,lnREP_{t-1}$+$a_{63}\,lnIEP_{t-1}$+$a_{64}\,lnCOP_{t-1}$+
$a_{65}\,lnCO2INTENS_{t-1}$+$a_{66}\,lnFEC_{t-1}$+$\beta_{51}\ lnGDP_{t-1}$+$\beta_{52}\,lnREP_{t-2}$+
$\beta_{53}\,lnIEP_{t-2}$+$\beta_{54}\,lnCOP_{t-2}$+$\beta_{55}\,lnCO2INTENS_{t-2}$+$\beta_{66}\,lnFEC_{t-2}$+…+
$\zeta_{61}\,lnGDP_{t-p}$+$\zeta_{62}\,lnREP_{t-p}$+$\zeta_{63}\,lnIEP_{t-p}$+$\zeta_{64}\,lnCOP_{t-p}$ + $\zeta_{65}\,lnCO2INTENS_{t-p}$+ $\zeta_{66}\,lnFEC_{t-p}$ + e_{6t}

(15)

However, the existence of a cointegrated relationship -that it will be identified through the Johansens's test for cointegration- leads to the application of a Vector Error Correction Model. On the grounds of a VECM the short-run and long-run causality would be also defined. So, the next step is the implementation of a VECM in order to verify the previous findings and examine more closely the cause and effect link between the variables. Assume that the unit roots tests and the Johansen test for cointegration on the dependent and the independent variables have been employed so, as the variables are first-difference stationary processes, I(1) and cointegrated, then the equations in the VECM context are written:

$$\Delta Y_t = v + \Pi\, Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i\, \Delta\, Y_{t-1} + e_t \tag{16}$$

Where $\Pi = \sum_{j=1}^{j=p} A_j - I_k$ and $\Gamma_i - \sum_{j=i+1}^{j=p} A_j$. The v is a K × 1 vector and e_t is a K × 1 vector of disturbances or innovations. In this case Π is (6 × 6) matrices holding information *"on the long-run adjustment of the variables in Y"*(Polemis, Dagoumas, 2013), while Y is a (6 × 1) vector of the model's endogenous variables, i.e. lnGDP, lnREP, lnIEP, lnCOP, lnCO2INTENS and lnFEC. Furthermore, If the variables in Y_t are integrated of order one processes I(1), then according to Engle-Granger (1987) the number of cointegrating vectors, r in matrix Π will have a rank 0 ≤ r < K. In case of cointegration, i.e. r > 0, a VAR in first-differences excludes the error-correction term and is considered inconsistent, whereas if Π equals zero there are not cointegrating relationships and the estimates of a VAR in first-differences give sufficient results. If the rank of Π=K then all the variables in Y_t are I(0).

Suppose that Π has a rank 0 < r < K, so that Π can be expressed as Π=$\alpha\beta'$, in which α and β are both r × K matrices of rank r. Adapting the latter to the model under consideration, we obtain r × 6 matrices of rank r. In addition, β denotes the matrix of cointegrating vector or cointegrating vectors if there is more than one cointegrating relation. For the sake of simplicity it is assumed that the model contains only one cointegrating relation. Therefore, $\beta\, Y_{\tau-1}$ corresponds to the Error Correction Term, while α becomes the speed of adjustment vector.

Finally, the initial equations within the VECM model and without taking into account **v** would appear:

$\Delta lnGDP_{\ t}$ $=\alpha_{11}(\beta_{11}\,lnGDP_{t-1}\beta_{12}\,lnREP_{t-1}\beta_{13}\,lnIEP_{t-1}\beta_{14}\,lnCOP_{t-1}$+$\beta_{15}\,lnCO2INTENS_{t-1}$+
$\beta_{16}\,lnFEC_{t-1})$+$\gamma_{11}\Delta lnGDP_{t-1} + \gamma_{12}\Delta lnREP_{t-1} + \gamma_{13}\Delta lnIEP_{t-1} + \gamma_{14}\Delta lnCOP_{t-1} +$
$\gamma_{15}\Delta lnCO2INTENS_{\ t-1} + \gamma_{16}\Delta lnFEC_{t-1}$

(17)

$\Delta lnREP_{\ t}\ =\ a_{21}\ (\beta_{11}\,lnGDP_{t-1} +\ \beta_{12}\,lnREP_{t-1} + \beta_{13}\,lnIEP_{t-1} +\ \beta_{14}\,lnCOP_{t-1}\ +$
$\beta_{15}\,lnCO2INTENS_{t-1}$+$\beta_{16}\,lnFEC_{t-1\_}$) +$\gamma_{11}\,\Delta lnGDP_{t-1}$+$\gamma_{12}\Delta lnREP_{t-1}$+$\gamma_{13}\Delta lnIEP_{t-1}$+

$\gamma_{14}\Delta lnCOP_{t-1}+\gamma_{15}\Delta lnCO2INTENS_{\ t-1}+\gamma_{16}\Delta lnFEC_{t-1}$
(18)

$\Delta lnIEP_{\ t} = a_{31}(\beta_{11}lnGDP_{t-1} + \beta_{12}lnREP_{t-1} + \beta_{13}lnIEP_{t-1}+\beta_{14}lnCOP_{t-1} + \beta_{15}lnCO2INTENS_{t-1}+\beta_{16}lnFEC_{t-1}) +\gamma_{11}\Delta lnGDP_{t-1}+\gamma_{12}\Delta lnREP_{t-1}+ \gamma_{13}\Delta lnINDP_{t-1}+ \gamma_{14}\Delta lnCOP_{t-1}+ \gamma_{15}\Delta lnCO2INTENS_{\ t-1}+\gamma_{16}\Delta lnFEC_{t-1}$
(19)

$\Delta lnCOP_{\ t} = a_{41}(\beta_{11}lnGDP_{t-1} + \beta_{12}lnREP_{t-1} + \beta_{13}lnIEP_{t-1}+\beta_{14}lnCOP_{t-1} + \beta_{15}lnCO2INTENS_{t-1}+\beta_{16}lnFEC_{t-1}) +\gamma_{11}\Delta lnGDP_{t-1}+\gamma_{12}\Delta lnREP_{t-1}+\gamma_{13}\Delta lnIEP_{t-1}+\gamma_{14}\Delta lnCOP_{t-1} + \gamma_{15}\Delta lnCO2INTENS_{\ t-1}+\gamma_{16}\Delta lnFEC_{t-1}$

(20)

$\Delta lnCO2INTENS_{\ t} = a_{51}(\beta_{11}lnGDP_{t-1} + \beta_{12}lnREP_{t-1} + \beta_{13}lnIEP_{t-1}+ \beta_{14}lnCOP_{t-1} + \beta_{15}lnCO2INTENS_{t-1}+\beta_{16}lnFEC_{t-1}) +\gamma_{11}\Delta lnGDP_{t-1}+\gamma_{12}\Delta lnREP_{t-1}+\gamma_{13}\Delta lnIEP_{t-1}+\gamma_{14}\Delta lnCOP_{t-1}+ \gamma_{15}\Delta lnCO2INTENS_{\ t-1}+\gamma_{16}\Delta lnFEC_{t-1}$

(21)

$\Delta lnFEC_{\ t} = a_{61}(\beta_{11}lnGDP_{t-1} + \beta_{12}lnREP_{t-1} + \beta_{13}lnIEP_{t-1}+\beta_{14}lnCOP_{t-1} + \beta_{15}lnCO2INTENS_{t-1}+\beta_{16}lnFEC_{t-1}) +\gamma_{11}\Delta lnGDP_{t-1}+\gamma_{12}\Delta lnREP_{t-1}+\gamma_{13}\Delta lnIEP_{t-1}+\gamma_{14}\Delta lnCOP_{t-1}+ \gamma_{15}\Delta lnCO2INTENS_{\ t-1}+\gamma_{16}\Delta lnFEC_{t-1}$

(22)

Or following the Holtz-Eakin et al. approach (1988) the VECM can be written**:**

$\Delta lnGDP_t=\Sigma_{i=1}^{m}\theta_{11}\Delta lnGDP_{t-k}+\Sigma_{i-1}^{m}\theta_{12}\Delta REP_{t-k}+\Sigma_{i-1}^{m}\theta_{13}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{14}\Delta COP_{t-k}+\Sigma_{i-1}^{m}\theta_{15}\Delta IEP_{t-k} +\Sigma_{i-1}^{m}\theta_{16}\Delta FEC_{t-k}+\lambda_1 ECT_{1t-1}+ e_{1t}$

(23)

$\Delta lnREP_t=\Sigma_{i=1}^{m}\theta_{21}\Delta lnGDP_{t-k}+\Sigma_{i-1}^{m}\theta_{22}\Delta REP_{t-k}+\Sigma_{i-1}^{m}\theta_{23}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{24}\Delta COP_{t-k}+\Sigma_{i-1}^{m}\theta_{25}\Delta IEP_{t-k} +\Sigma_{i-1}^{m}\theta_{26}\Delta FEC_{t-k}+\lambda_2 ECT_{2t-1}+ e_{2t}$

(24)

$\Delta lnIEP_t=\Sigma_{i=1}^{m}\theta_{31}\Delta lnGDP_{t-k}+\Sigma_{i-1}^{m}\theta_{32}\Delta REP_{t-k}+\Sigma_{i-1}^{m}\theta_{33}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{34}\Delta COP_{t-k}+\Sigma_{i-1}^{m}\theta_{35}\Delta IEP_{t-k} +\Sigma_{i-1}^{m}\theta_{36}\Delta FEC_{t-k}+\lambda_3 ECT_{t-1}+ e_{3t}$

(25)

$\Delta lnCOP_t=\Sigma_{i=1}^{m}\theta_{41}\Delta lnGDP_{t-k}+\Sigma_{i-1}^{m}\theta_{42}\Delta REP_{t-k}+ \Sigma_{i-1}^{m}\theta_{43}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{44}\Delta COP_{t-k}+\Sigma_{i-1}^{m}\theta_{45}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{46}\Delta FEC_{t-k}+\lambda_4 ECT_{t-1}+e_{4t}$ (26)

$\Delta lnCO2INTENS_t=\Sigma_{i=1}^{m}\theta_{51}\Delta lnGDP_{t-k}+\Sigma_{i-1}^{m}\theta_{52}\Delta REP_{t-k}+ \Sigma_{i-1}^{m}\theta_{53}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{54}\Delta COP_{t-k}+\Sigma_{i-1}^{m}\theta_{55}\Delta IEP_{t-k}+\Sigma_{i-1}^{m}\theta_{56}\Delta FEC_{t-k}+\lambda_5 ECT_{t-1}+ e_{5t}$ (27)

$$\Delta lnFEC_t = \Sigma_{i=1}^{m}\theta_{61}\Delta lnGDP_{t-k} + \Sigma_{i-1}^{m}\theta_{62}\Delta REP_{t-k} + \Sigma_{i-1}^{m}\theta_{63}\Delta IEP_{t-k} + \Sigma_{i-1}^{m}\theta_{64}\Delta COP_{t-k} + \Sigma_{i-1}^{m}\theta_{65}\Delta IEP_{t-k} + \Sigma_{i-1}^{m}\theta_{66}\Delta FEC_{t-k} + \lambda_6 ECT_{6t-1} + e_{6t} \quad (28)$$

Where **Δ** indicates the first differences, ECT_{t-1} is the error correction term, λ_ι illustrates the speed of adjustment[108], k denotes the lag length and e_{it} depicts the stochastic error term or the innovations (residuals) and is expected to be serially uncorrelated with mean zero (Belke, Dobnik, Dreger, 2014). Finally, θ_i are the short-run coefficients; denoting the model's short-run adjustment towards its long-run equilibrium.

Once the VECM is employed and the long-run and short-run dynamics are defined, willing to verify the direction of causality, Granger causality tests will be performed, namely Wald tests based on the estimations from the VECM and according to theory discussed previously in this section.

The F-statistic will be produced from the above (8) formula for each case. For instance, examining the case of Granger causality from GDP to residential electricity price entails one of the next outcomes:

- F* > F_c and $\hat{\lambda}$**,** the speed of adjustment, is statistical significant, then real GDP affects residential electricity price both in the short and the long-run.
- F* < F_c and $\hat{\lambda}$ is statistically insignificant, then real GDP does not Granger cause residential electricity price neither in the short nor in the long-run.

Likewise, examining if causality runs from residential electricity prices to GDP will result to:

F* > F_c and $\hat{\lambda}$ is statistically significant, so residential electricity price Granger causes GDP Growth in the short and long-run.

F* < F_c and $\hat{\lambda}$ is statistically insignificant, then residential electricity price does not Granger cause GDP Growth in the short and the long-run.

The same procedure is developed for every pair of variables that finally leads to one of the following outcomes: unidirectional causality **Y→X** or **X→Y**, bidirectional causality **X↔Y** and/or no causality **X↕Y**, that correspond to conservation, growth, feedback and neutrality hypothesis respectively. Granger causality is also tested via a joint Wald-F test among the dependent variables and the sum of lags of each explanatory variable[109].

Finally, the study proceeds to further investigation of the possible interrelation among the variables of interest via the interpretation of Impulse Response Functions (IRF) and a Forecast-Error Variance Decomposition Analysis (FEVD) as well. Whilst, all the necessary post-estimation tests are available in Appendices (See p.p.).

[108] Vamvoukas G.A. (2016). *Contemporary Econometrics: Analysis and Applications*. Athens: University of Business and Economics

[109] Osigwe A.C., & Arawomo, D.F. (2015). Energy Consumption, Energy Prices and Economic Growth: Causal Relationships Based on Error Correction Model. *International Journal of Energy Economics and Policy*, 5(2), 408-414. Available at: http: www.econjournals.com Retrieved from 20th March 2019

4.3 Data Analysis

The main scope of this thesis is to mirror the potential interdependence between the economic activity and the energy prices under the European Union's spectrum. The period under examination originates from 1990 to 2018. Hence, the desideratum is to delineate if growth rates in EU are energy-driven.

The described model seeks to highlight the hypothesis of an active junction among the electricity and oil prices and the main energy macroeconomic aggregates. Hence, the model incorporates annual observations for the European Union entirely -i.e. EU-28 and not for each member-state separately- for the following key-indicators: household electricity prices, industrial electricity prices, real GDP, CO_2intensity and total final energy consumption.

Concerns vis-a-vis the findings' credibility can be surpassed through the use of reliable data sources, whereas issues over the data's availability may create bias. To cope with these issues the study uses four different databanks; the World Bank, the International Energy Agency (IEA), the European statistical office, Eurostat and the BP Energy Outlook.

Analytically, the data used for households and industry end-use electricity prices- under the denomination lnREP and lnIEP respectively- is obtained from the IEA's World Energy Prices Database and specifically from the World Energy Prices Electricity dataset[110] (*http://wds.iea.org/WDS/TableViewer/tableView.aspx*, source IEA). The electricity prices for both the residential and the industrial sector are expressed in 2010 USD (PPP)/unit per MWh of electricity. Hence, household electricity prices are deflated with respect to Consumer Price Indices (CPIs) whilst for the industrial sector the Producer Price Indices (PPIs) is used. Then, both are converted to 2010 USD (PPP)/unit including the power purchase parities.

Time series for real GDP is obtained from the World Bank's database, World Development Indicators and is expressed to constant 2010 US dollar, according to World Bank's deflation methodology[111], so the inflation again is taken into account. The World Development Indicators are also used for the selection of CO2 intensity from energy use, appeared in the above model as lnCO2INTENS and is measured in kg per kg of oil equivalent. Carbon dioxide intensity is defined as *"the ratio of carbon dioxide per unit of energy, or the amount of carbon dioxide emitted as a result of using one unit of energy in production"* and mostly refers to intensity from solid fuels, such as coal[112].

The data regarding the total final energy consumption (lnFEC) is obtained from Eurostat's Sustainable Development Indicators *"Goal 7 - Affordable and green energy"*. The indicator covers the energy consumed by end-users (households, industry, agriculture, transport and services), but excludes losses during the transformation and distribution processes, as well as

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[110] IEA (2018). [Online]. Available at: http://wds.iea.org/WDS/TableViewer/tableView.aspx Retrieved from 29th March 2019

[111]The World Bank, (2019). *What is your constant US dollar methodology.* [Online]. Available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/114943-what-is-your-constant-u-s-dollar-methodology Retrieved from 28th February 2019

[112]The World Bank, (2019). *World Development Indicators - Metadata*. [Online]. Available at: https://databank.worldbank.org/data/reports.aspx?source=2&series=EN.ATM.CO2E.EG.ZS&country Retrieved from 24th February 2019

the energy used by the energy sector. Final energy consumption is measured in million tons of oil equivalents.

Finally, the crude oil prices are given from the BP's 2018 Energy Outlook and are expressed to US $. Crude oil prices are also deflated using the US Consumer Price Index.

Table 2
Variables Description

Variable name	Macroeconomic aggregates	Unit	Indicator	Databank
lnGDP	Gross Domestic Product	Constant 2010 US $	World Bank Development Indicators	World Bank
lnREP	Residential end-user electricity price	Total price 2010 USD/Unit using PPP	World Energy Prices	IEA
lnIEP	Industry end-user electricity price	Total price 2010 USD/Unit using PPP	World Energy Prices	IEA
lnCOP	Crude oil spot price	US$ (deflated with US CPI)	BP 2018 World Energy Outlook	BP
lnCO2INTENS	Carbon dioxide intensity	Kg per kg of oil equivalent	World Bank Development Indicators	World Bank
lnFEC	Total final energy consumption	Million tones of oil equivalent	Sustainable Development Indicators Goal 7	Eurostat
lnENUSE	Total energy use	Kg of oil equivalent per capita	World Bank Development Indicators	World Bank

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5. Empirical Results

This section presents the empirical estimates of the model discussed in the previous section. As it was expected the macroeconomic time series face the phenomenon of non-stationarity and the presence of unit roots are identified. The following tables (Table 3) provide evidence over the existence of unit roots, according to the appropriate tests for time series stationarity.

The variables are controlled for unit roots both at levels and at first differences via employing Augmented Dickey-Fuller, Phillips-Perron, Kwiatkowski–Phillips–Schmidt–Shin (KPSS)[113] tests and the modified Dickey-Fuller test as proposed by Elliott, Rothenberg and Stock via applying the Generalized Least Squares technique. The latter, the well-know DF-GLS test is admitted that has more power over the alternatives in relatively small samples[114].The applied

[113] Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, 54, 159-178

[114] Elliott,G., Rothenberg,T. J., & Stock, J.H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica,* 64(4), 813-836.

tests take into consideration the existence of stochastic trends and intercepts for that purpose time series are examined both including trends and without trends in order to determine if the time series are random walks with drift or random walks without drift. Moreover, the lag length for each stochastic process is based on the optimal selection lag criteria. (See Appendix p.p.).

Table 3
Unit Root Testing Model 1

Variables	Augmented Dickey-Fuller		Phillips-Perron		KPSS		DF-GLS	Order of integration
Levels	τ_t	τ_μ	τ_t	τ_μ	$\hat{\eta}_\tau$	$\hat{\eta}_\mu$		
lnGDP	-1.529 (0.8188)	-1.534 (0.5168)	-1.030 (3) (0.9399)	-1.316 (3) (0.6283)	0.212* (3)	1.03 (3)	-1.300 (1)	I(1)
lnREP	-1.563 (0.8066)	-1.640 (0.4623)	-0.360 (3) (0.9880)	-0.299 (3) (0.9257)	0.234* (3)	0.28 (3)	-1.179 (2)	I(1)
lnIEP	-1.181 (0.9143)	0.093 (0.9656)	-1.182 (3) (0.9142)	-0.068 (3) (0.9526)	0.219(3)	0.693**(3)	-0.927 (1)	I(1)
lnCOP	-2.288 (0.4405)	-1.828 (0.3666)	-2.227 (3) (0.4745)	-1.929 (3) (0.3184)	0.625*(0)	0.513**(1)	-1.457(1)	I(1)
lnCO2INTENS	-3.197 (0.0849)	-1.541 (0.5129)	-3.517 (3) (0.0376)	-2.468 (3) (0.1234)	0.225* (2)	0.961* (3)	-1.166 (1)	I(1)
lnFEC	-1.216 (0.6666)	-2.314 (0.1676)	-1.462 (3) (0.8419)	-1.699 (3) (0.4314)	0.221* (2)	0.716* (0)	-1.832 (3)	I(1)
First Differences								
ΔlnGDP	-4.260* (0.0036)	- 3.834* (0.0026)	-4.235** (3) (0.0040)	-4.060* (3) (0.0011)	0.106(0)	0.335***(0)	-3.795* (0)	I(0)
ΔlnREP	-3.803** (0.0164)	- 4.233 * (0.0006)	-5.245* (3) (0.0001)	-4.329* (3) (0.0004)	0.175** (1)	0.72** (0)	-2.005 (1)	I(0)
ΔlnIEP	-5.668* (0.0000)	-5.495* (0.0000)	-5.677* (3) (0.0000)	-5.539* (3) (0.0000)	0.111***(0)	0.28 (0)	-2.131 (8)	I(0)
ΔlnCOP	-5.721* (0.0000)	-5.700* (0.0000)	-5.713* (3) (0.0000)	-5.692 (3) (0.0000)	0.134***(2)	0.223 (0)	-4.362*(1)	I(0)
ΔlnCO2INTENS	-3.414*** (0.0496)	-3.341** (0.0131)	-7.635*(3) (0.0376)	-7.290* (3) (0.0000)	0.181**(1)	0.372* (2)	-2.500 (1)	I(0)
ΔlnFEC	-3.546** (0.0347)	-3.149** (0.0231)	-7.127* (3) (0.0000)	-6.845* (3) (0.0000)	0.0525 (0)	0.216 (1)	-2.875 (1)	I(0)

Note: Dickey-Fuller tests are conducted according to optimal lag selection criteria AIC,SBIC,HIC. The optimal lag length is based on Schwarz information criterion (SBIC). Number in parenthesis in Phillips-Perron test indicates the Newey-West lags. MacKinnon approximate p-value are in paranthesis. In DF-GLS test the number in parenthesis denotes the optimal lag according to NG-Perron (Opt Lag (Ng-Perron seq t).
* denotes significance at 1% level
** denotes significance at 5% level
*** denotes significance at 10% level

The above results (Table 3) confirm that the variables are integrated processes of order one I(1), given that the majority of unit roots tests proves that they become stationary after first differencing. More analytically, the ADF and PP tests support mutually that the time series are non-stationary at levels, but the null hypothesis of non-stationarity is rejected reciprocally at 1% and 5% significance level after first differencing. The DF-GLS results are also consistent with respect to unit roots at levels, while KPSS results indicate that the variables are integrated of order one I(1) at 5% or 10% significance level. However, the aforementioned estimates provide strong evidence against the stationarity at levels and favour the assumption of cointegration among the variables, considering that they seem to be I(1) processes.

Providing that, the next step is the adoption of Engle-Granger 2-step procedure, as it was mentioned in the previous chapter in order to investigate if the variables are indeed cointegrated or random walks. Hence, the prerequisite of cointegration among the variables of interest has to be met. Remind that two variables are said to be cointegrated when both are I(1) processes and there is evidence of a linear combination which is I(0) process.

So, the cointegration theory sustains that non-stationary variables may "*reach the equilibrium point*"[115] in the long-run. The deviations from the state of the equilibrium could be surpassed through the error correction mechanism. Engle-Granger procedure (1987) suggests the estimation of cointegration regression, where the variables are estimated via OLS at levels, then the residuals are examined in order to observe if they are I(0) processes or I(1). If the assumption of stationarity is met, then the second step regression using the first differences is developed. Therefore, the short-run relationships would be derived through the second step regression while the error correction term measures the speed of adjustment towards the long-run equilibrium. Given that the variables are integrated of order one the next sub-sections present the results of the 1st step regression, the Engle-Granger test for cointegration as well as an Error Correction Model for the Models under consideration. The ECM creates *"an additional causality channel*[116]*"*, although it does not dictate the direction of causal relationships. Therefore, a VECM is derived for each model together with IRFs and VDC analysis that delineate the issue of causality among the variables of interest.

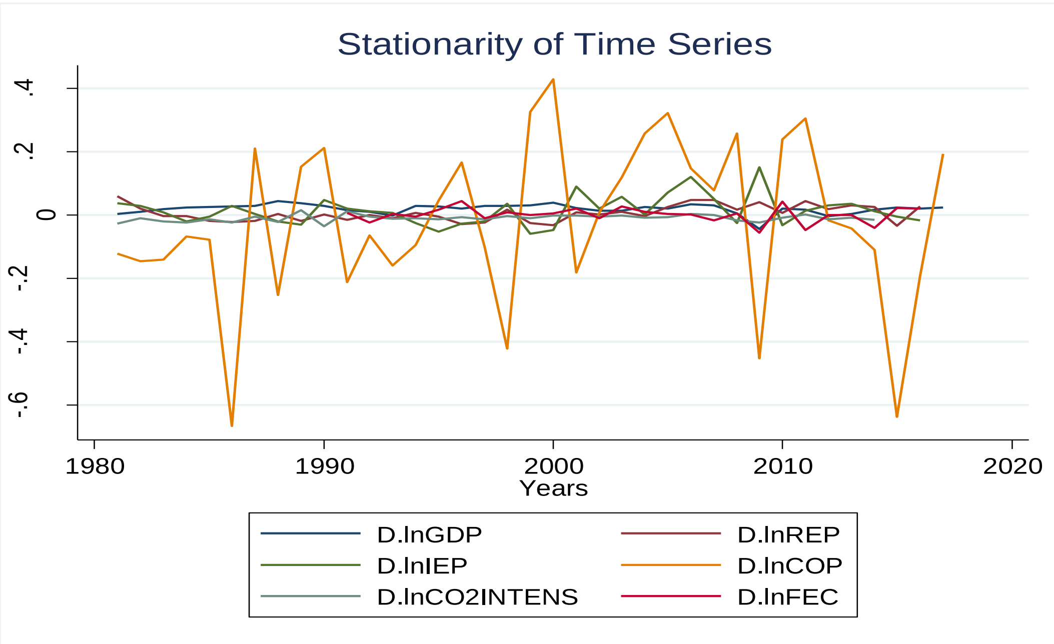

Figure 5. Time Series expressed in 1st differences Model 1.

[115]Suharsono A., Aziza A., & Pramesti, W. (2017). *Comparison of Vector Autoregressive (VAR) and Vector Error Correction Models (VECM) for Index of ASEAN Stock Price*. [Online]. Available at: https://doi.org/10.1063/1.5016666 Retrieved from 23rd February 2019

[116]Osigwe A.C., & Arawomo, D.F. (2015). Energy Consumption, Energy Prices and Economic Growth: Causal Relationships Based on Error Correction Model. *International Journal of Energy Economics and Policy*, 5(2), 408-414. Available at: http: www.econjournals.com Retrieved from 20th March 2019

5.1 Cointegration & Long-run Dynamics

Although, economic time series are not stationary, both economic theory and the concept of cointegration permit the existence of long-term relations among the economic variables. The macroeconomic aggregates may deviate from their long-run equilibrium; meanwhile the market forces will act in such a way that equilibrium is re-established. In the sense of cointegration a group of variables may not converge in the short-run, but a linear combination among them which is I(0) may exist in the long-run.

Following Engle-Granger's procedure the variables are found to be cointegrated. Thus, in the model there is evidence of at least one cointegrating relationship. Table 5 illustrates the results of the cointegration regression - that depicts the long-run relations among the variables under investigation - as well as these of the 2nd step regression - underlying the short-run dynamics - while Table 4 indicates the existence of cointegration by presenting the results of the residuals' ADF test based on the cointegration regression.

Once the variables are found to be cointegrated at 5% significance level, the long-run and short-run dynamics among the GDP, the examined energy prices, the CO2 emissions of final energy consumption -named C02 intensity- and the final energy consumption could be analyzed. To deal with robustness concerns arising from a relatively small sample size not only the OLS estimation method, as it is proposed by Engle-Granger is used, but also Fully-Modified Ordinary Least Squares and Canonical Cointegration Regression.

Table 4
Cointegration results for Model 1

Engle-Granger test for	**cointegration**		
Test statistic	1% critical value	5% critical value	10% critical value
-5.609**	-6.409	-5.438	-4.981

Note: The reporting t-statistics and the critical values are calculated by McKinnon (1990, 2010)[117].
** denotes significance at 5% level.

Table 5
Long-run & Short-run dynamics Model.

Long-run relationships	**Dependent variable**	**Independent variables**					
	lnGDP	**lnREP**	**lnIEP**	**lnCOP**	**LnCO2INTES**	**lnFEC**	
OLS		-0.6724846** (-2.36)	0.2498798** (2.13)	0.0557998* (2.18)	-1.920597* (-10.30)	0.4765385 (1.34)	
FMOLS		-0.580765 * (-2.66)	0.1945369** (2.13)	0.0622266* (3.13)	-1.927966* (-12.93)	.5059371** (1.91)	
CCR		-0.6231971** (-2.15)	0.2962164** (2.22)	0.0487596*** (1.80)	-1.886813* (-14.34)	0.6205941 (1.60)	
Short-run relationships	**ΔlnGDP**	**ΔlnREP**	**ΔlnIEP**	**ΔlnCOP**	**ΔLnCO2INTES**	**ΔlnFEC**	**ECT**
		-0.2596662 (-1.33)	0.1749058*** (1.78)	-0.0214163 (-1.41)	-0.5482922 (-1.11)	-0.1631966 (-1.11)	-0.4597502** (-2.70)

[117] MacKinnon, J. G. (1990). *Critical Values for Cointegration Tests*. (Working Paper No. 1227). Ontario: Economics Department; Queen's University. [Online]. Available at: http://ideas.repec.org/p/qed/wpaper/1227.html Retrieved from 6th April 2019

Note: The numbers in parenthesis denote the t-statistic & z-statistic with respect to OLS, FMOLS and CCR estimation methods. ECT indicates the error-correction term that is significant and negative with respect to Engle-Granger (1987) cointegration analysis.
* denotes significance at 1% level
** denotes significance at 5% level
*** denotes significance at 10% level

According to the findings of Table 6, the Residential Electricity Prices (lnREP) are inelastic and also have a negative impact on GDP growth rates; providing that 1% change in the lnREP is likely to lessen GDP by 0,67% at 5% significance level. Hence, an increase of 1% in the household final electricity price would affect negatively the economic growth in the EU context. Our findings are consistent with the European Commission's view as far as the increasing energy demand due to household's electricity consumption[118] that plays indeed an important role in GDP foundation. The negative sign on lnREP is expected from the economic theory; as shifts in the demand curve are justified due to increase in prices. The law of demand accounts for decreases in products or services as the price escalates. In this case if electricity price increases, then the consumers will restrict their consumption that will lead finally to a slight decline in GDP. Hence electricity prices are price insensitive due to low marginal rate of substitution. Furthermore, the OLS empirical findings are verified by FMOLS and CCR techniques which provide very close results (-0,59% and -0,62% at 1% and 5% significance level respectively).

As far as, the Industrial Electricity Prices (lnIEP), it appears that 1% increase in the end-use price does not provoke a decline in GDP. To the contrary a positive, but weak link is observed; an increase by approximately 0,25% - that is statistically significant at 95% confidence interval - suggests that EU's economic growth improves from a marginal uptick in the final electricity prices in the industry sector. Thus, as the industrial electricity price is inelastic to changes there is an open window for further implementation of energy-related measures; for instance, imposing a tax with regard to mitigate CO2 emissions from industry production without posing a risk to EU's economic activity. In addition, the FMOLS and CCR coefficients provide similar results with respect to long-term relations, both at 5% significance level.

A very interesting observation comes from the lnCOP elasticity. Crude oil prices seem to not harm EU's growth rates, given that a 1% rise in crude oil spot prices has a slightly positive effect on real GDP. The latter seems to increase by approximately 0,06% which is a very small amount, notwithstanding EU has achieved to oppose to oil prices high volatility. Likewise, the coefficient of FMOLS indicate that an increase by 1% in lnCOP results to an increase by 0,06% in lnGDP at 1% significance level. However, the CCR shows that lnCOP has a positive effect on lnGDP at 10% significance level. Thus, EU seems to succeed towards energy diversification and energy security targets.

Moreover, a decrease by -1,92% in economic growth is observed when the levels of carbon dioxide emissions rise by 1%. Hence, a trade-off characterizes the long-run relation between the real output and the gas emissions, so as a reduction close to 1% in the levels of intensity

[118] *European Commission, (2016). EU energy trends and macroeconomic performance -Understanding the drivers of EU energy trends. Deliverable D1 Study on the Macroeconomics of Energy and Climate Policies*. [Online]. Available at:https://ec.europa.eu/energy/sites/ener/files/documents/ENER%20Macro-Energy_Trends-Macroeconomic-Performance_D1%20Final%20%28Ares%20registered%29.pdf Retrieved from 17th December 2018

would accelerate economic development by approximately 2 percentage points. That favours the energy and the environmental policies adopted by EU's institutions during the recent decades. The FMOLS and CCR findings are identical to OLS estimation results, proving that the findings in long-run equation are robust.

Finally, the total final energy consumption, as it was expected improves the economic activity. However, this is confirmed from CCR and FMOLS estimations, while the coefficient of OLS is not statistically significant. More explicitly, an increase of 1% in lnFEC boosts real GDP by 0,5% according to FMOLS estimation and by 0,62% with respect to CCR findings.

Given that the long-run dynamics among the variables have already defined and the error correction term (ECT) satisfies the conditions of statistical significance and its value is negative (-0,459) the short-run relationships will be also revealed. The ECT shows that the variables interact in the short-term in order to restore the long-run equilibrium. Nevertheless, the speed of adjustment of -0,459 implies that GDP moves towards the long-run equilibrium at around 46% during the first year. So, if GDP is subject to a shock, then recovers moderately.

Furthermore, the coefficients on short-term relations appear insignificant, except ΔlnIEP's results. Though, the latter is statistically significant at a 10% level of significance, betraying that if industrial electricity price moves upwards by 10%, then it pushes up GDP at around 17,4 %. However, short-run causality is not identified, which entails a weak relationship among GDP, electricity prices, crude oil price, final consumption and gas emissions in the short-run. Thus, neither energy prices nor final consumption and gas emissions have a short-term effect on real economic growth.

To sum up, long-run equilibrium relationships are verified. To the contrary short-run relations are not observed excluding the case of lnIEP at the 10% level. As it was referred the ECM creates an alternative channel to causality, yet its direction remains obscure. The development of a VECM would lighten the sources of causality.

5.2 Johansen Cointegration Method

In this sub-section the interest is turned into the short-run interactions and the causal links among the variables. For that purpose, a Vector Autoregressive Error Correction Model is estimated. Recall that VECM is a restricted VAR model in differences. Based on Sims (1992) a VAR is a system of simultaneous equations that disregards the issues of endogeneity or exogeneity. In a VAR's environment all the variables are considered endogenous, so there is no need of imposing further restrictions, when a group of variables complies with the simultaneity condition[119]. In order to fit an adequate model and avoid spurious results, the assumption of white noise disturbance terms have to be met, which demands variables' stationarity. VAR models capture the short-run relations among the variables, while VECM

[119] Kazanas T. (2017). *A Vector Error Correction Forecasting Model of the Greek Economy. Hellenic Fiscal Council*. Hellenic Fiscal Council. Working Paper. [Online]. Available at: https://www.hfisc.gr/sites/default/files/dianysmatiko_ypodeigma_diorthosis_lathon_gia_tin_elliniki_oikonomia.pdf Retrieved from 30th March 2019

are necessary to capture the long-run equilibrium relationships as well as the short ones, especially when time series are cointegrated.

The presence of at least one cointegrating relationship has been already revealed from the Engle-Granger ECM approach. Hence, in this sub-section, the study adopts the Johansen's maximum likelihood method, examining the existence of one or more cointegration relationships among the variables. The obtained results of likelihood ratio tests (trace statistic) and maximum eigenvalue tests are reported in Table 6.

An issue of a great importance when Johansen cointegration test is performed is the adequate lag length. Hence, the selection-order criteria are taken into consideration. Based on the LL criterion we incorporate two lags. The cointegration tests are implemented including unrestricted and restricted trends and constant, in order to capture every possible case of deterministic trend and intercept in the VECM framework.

Johansen's cointegration method follows a stepwise procedure; starts with a Null Hypothesis (H_0) of no cointegration against the Alternative Hypothesis (H_a) of cointegration and then the Null of cointegration of equation(s) is examined against the Alternative one of no cointegration of equation(s). The results of Johansen's cointegration test would be obtained by trace test and/or eigenvalue test. For instance, per maximum rank zero (r=0) if trace statistic does not exceed critical values and/or max eingenvalues do not exceed critical values, then the H_0 of no cointegration is not rejected, otherwise the H_a is accepted. Per maximum rank one (r=1) if trace statistic is not greater than the critical values and/or max eigenvalue test does not surpass the critical value, then the H_0 of cointegration of equation 1 is not rejected, if this is not the case, the H_a of no cointegration is accepted and so on. To sum up, the number of cointegrated vectors is determined via the test's rejection.

So for Case 1 the trace test reveals full rank, whereas eingernvalue test indicates two cointegrating equations. In Case 2, the trace test shows the existence of three cointegrating equations at the 1% significance level and four at the 5% significance level respectively. By contrast, eingevalue test denotes the presence of two cointegrating relations at both 1% and 5% level. As far as, the Case 3 the trace statistic reveals two cointegrating equations at 1% level of significance, which is identical to eigenvalue's output of two cointegration relationships. On the other hand, four cointegrating equations are obtained from the trace test in Case 4 at the 1% significance level, while at the 5% level the trace test indicates a rank equal to five. Nevertheless, the eingevalues entail the existence of two cointegrating relations at the 1% significance level and three at the 5% significance level. As regards the Case 5, the trace test suggests that r = 4 at 1% level of significance and r = 5 with respect to 5% level of significance. Eingenvalue test denotes the existence of two cointegrating relations at 1% level of significance and four at 5% level of significance.

Table 6
Johansen maximum likelihood cointegration test

H_0 : no cointegration	**H_a : cointegration**		**5% Critical values**	**1% Critical values**
Case 1: Unrestricted trend				
Trace statistic				
r=0	r=1	230.7262*	104.94	114.36
r≤1	r=2	132.4384*	77.74	85.78
r≤2	r=3	74.0135*	54.64	61.21

r≤3	r=4	46.6496*	34.55	40.49
r≤4	r=5	23.7685*	18.17	23.46
r≤5	r=6	8.7848*	3.74	6.40
Maximum eigenvalues				
r=0	r=1	98.2878*	42.48	48.17
r≤1	r=2	58.4250*	36.41	41.58
r≤2	r=3	27.3638	30.33	35.68
r≤3	r=4	22.8811	23.78	28.83
r≤4	r=5	14.9838	16.87	21.47
r≤5	r=6	8.7848	3.74	6.40
Case 2: Restricted trend, $\boldsymbol{\tau} - 0$				
Trace statistic				
r=0	r=1	234.7568*	114.90	124.75
r≤1	r=2	135.0204*	87.31	96.58
r≤2	r=3	75.7103*	62.99	70.05
r≤3	r=4	48.2270 **	42.44	48.45
r≤4	r=5	25.2192	25.32	30.45
r≤5	r=6	10.1831	12.25	16.26
Maximum eigenvalues				
r=0	r=1	99.7363*	43.97	49.51
r≤1	r=2	59.3102*	37.52	42.36
r≤2	r=3	27.4832	31.46	36.65
r≤3	r=4	23.0078	25.54	30.34
r≤4	r=5	15.0361	18.96	23.65
r≤5	r=6	10.1831	12.52	16.26
Case 3: Unrestricted constant $\boldsymbol{\tau} - 0,\ \rho - 0$				
Trace statistic				
r=0	r=1	205.8754*	94.15	103.18
r≤1	r=2	111.3094*	68.52	76.07
r≤2	r=3	53.5106**	47.21	54.46
r≤3	r=4	27.9143**	29.68	35.65
r≤4	r=5	10.5812	15.41	20.04
r≤5	r=6	0.3792	3.76	6.65
Maximum eigenvalues				
r=0	r=1	94.5660*	39.37	45.10
r≤1	r=2	57.7987*	33.46	38.77
r≤2	r=3	25.5963	27.07	32.24
r≤3	r=4	17.3331	20.97	25.52
r≤4	r=5	10.2020	14.07	18.63
r≤5	r=6	0.3792	3.76	6.65
Case 4: Restricted constant $\boldsymbol{\tau} - 0, \rho - 0, \boldsymbol{\gamma} - 0$				
Trace statistic				
r=0	r=1	228.7970*	102.14	111.01
r≤1	r=2	133.9134*	76.07	84.45
r≤2	r=3	75.3148*	53.12	60.16
r≤3	r=4	44.5623*	34.91	41.07
r≤4	r=5	24.3527**	19.96	24.60
r≤5	r=6	7.0291	9.42	12.97
Maximum eigenvalues				
r=0	r=1	94.8836*	40.30	46.82
r≤1	r=2	58.5986*	34.40	39.79
r≤2	r=3	30.7525**	28.14	33.24
r≤3	r=4	20.2095	22.00	26.81
r≤4	r=5	17.3237	15.67	20.20
r≤5	r=6	7.0291	9.24	12.97
Case 5: No trend $\boldsymbol{\tau} - 0, \rho - 0,\ \boldsymbol{\gamma} - 0$ **and** $\boldsymbol{\mu} - 0$				
Trace statistic				
r=0	r=1	183.1368*	82.49	90.45
r≤1	r=2	109.9120*	59.46	66.52
r≤2	r=3	52.8279*	39.89	45.58
r≤3	r=4	26.6322**	24.31	29.75

r≤4	r=5	7.7871	12.53	16.31
r≤5	r=6	0.5055	3.84	6.51
Maximum eigenvalues				
r=0	r=1	73.2248*	36.36	41.00
r≤1	r=2	57.0841*	30.04	35.17
r≤2	r=3	26.1957**	23.80	28.82
r≤3	r=4	18.8451**	17.89	22.99
r≤4	r=5	7.2816	11.44	15.69
r≤5	r=6	0.5055	3.84	6.51

Note: Johansen cointegration test follows a stepwise procedure; H_0 :no cointegration is examined against the H_a :cointegration, then the H_0 of cointegration of equation(s) is examined against the H_a of no cointegration of equation(s). Thus, per maximum rank zero (r=0) if trace statistic < critical values and/or max eingenvalues < critical values, then the H_0 of no cointegration is not rejected, otherwise the H_a is accepted. Per maximum rank one (r=1) if trace statistic < critical values and/or max eigenvalues < critical values, then the H_0 of cointegration of equation 1 is not rejected, otherwise the H_a of no cointegration is accepted and so on.
r signifies the rank of cointegrating equations, i.e. the number of cointegrating equations.
* denotes the rank of cointegrating equations at 1% significance level.
** denotes the rank of cointegrating equations at 5% significance level.
case 1: allows quadratic trends in levels and entails that cointegrating equations are trend stationary[120]
case 2: $\tau - 0$ allows linear trends in levels and entails that cointegrating equations are trend stationary
case 3: $\tau - 0, \rho - 0$ assumes no quadratic trends in levels and entails that cointegrating equations are stationary around a constant mean.
case 4: $\tau - 0, \rho - 0, \gamma - 0$ assumes no linear trends in levels and entails that the cointegrating equations are stationary around a constant mean.
case 5: $\tau - 0, \rho - 0, \gamma - 0$ and $\mu - 0$ assumes that means or trends in levels and differences are equal to zero and entails that the cointegrating equations are stationary with zero means.

Therefore, the results of Johansen cointegration test are in accordance with the previous estimates from Engle-Granger's test, supporting the existence of long-run equilibrium relationships. Allowing for a constant term in the VECM we have to rely on Case 3 that excludes the existence of quadratic trends in the levels of the time series and accounts the cointegrating equations to be stationary around a constant mean. For the estimated VAR model with six endogenous variables and two lags, the trace statistic in Table 7, implies two cointegrated vectors, given that at r = 2 the trace statistic of 53,5106 does not exceed the critical value of 54,46 at the 1% significance level. So, two cointegrating equations are indentified, whilst the maximum eigenvalue test confirms the existence of two cointegrated vectors at both 1% and 5% level, Providing that both tests correspond to a rank greater than zero and less than K = 6, a VECM of r = 2 will be employed. However, for the sake of simplicity the VECM includes only one cointegrating equation.

5.3 Vector Error Correction Model

This sub-section seeks to define the direction of causality through the mechanism of VECM. The scope is to investigate if causality derives from economic growth to energy prices and/or vice versa. Furthermore, we search for causality running from total final energy consumption and C02 intensity. In other words, the scope is to trace out the existence of *"conservation, growth, feedback* and *neutrality hypotheses"* in the EU context. The estimated VECM embodies only one cointegrating relation for simplicity. The findings of VECM with two lags and rank 1 are presented in the Table below (Table 7).

[120]Stata Corporation. (2019). *Introduction to Vector Error-Correction Models.* [Online]. Available at: https://www.stata.com/manuals13/tsvecintro.pdf Retrieved from 11th February 2019

Table 7
Vector Error Correction Model Estimates

	Cointegrating Equation	**Cointegrating Eq1**					
	lnGDP	1					
	lnREP	6.017424* (21.44)					
	lnIEP	-1.763515* (-14.04)					
	lnCOP	-.590021* (-22.16)					
	LnCO2INTENS	1.787819* (11.58)					
	lnFEC	2.704432* (8.33)					
	constant	-72.06947					
Dependent Variables	ECT	ΔlnGDP	ΔlnREP	ΔlnIEP	ΔlnCOP	ΔlnCO2INTENS	ΔlnFEC
ΔlnGDP	0.0594782*** (1.73)	0.4390951 (1.35)	-0.4016555** (-1.93)	0.4200368* (3.10)	0.0406756 (1.25)	-0.7790739 (-1.37)	-.0206892 (-0.12)
ΔlnREP	-0.1685536* (-6.99)	0.4330332** (1.90)	0.190926 (1.31)	-0.3123415* (-3.29)	-0.0830584* (-3.63)	-0.1228218 (-0.31)	0.2060317*** (1.77)
ΔlnIEP	-0.2836592* (3.07)	0.7149443 (0.82)	-0.7477484 (-1.34)	-0.2969193 (-0.81)	-0.0504461 (-0.57)	-0.3451035 (-0.23)	0.0439273 (0.10)
ΔlnCOP	0.8211134 (1.43)	-0.1159906 (-0.02)	3.142066 (0.90)	2.99666 (1.32)	0.6442913 (1.18)	-2.787071 (-0.29)	1.499811 (0.54)
ΔLnCO2INTENS	-0.0047569 (-0.34)	0.1642259 (1.24)	-0.2153482** (-2.55)	0.1072689** (1.95)	0.0055031 (0.41)	-0.0878689 (-0.38)	-0.0041149 (-0.06)
ΔlnFEC	0.0650793 (1.28)	0.4936421 (1.03)	-0.5546528*** (-1.81)	0.4144269** (2.07)	0.0450611 (0.94)	-1.307944 (-1.56)	-0.688694* (-2.81)
R-squared	-	0.7468	0.8910	0.6743	0.2540	0.7803	0.4717
Log likelihood	409.9463						
AIC	-31.03881						
Schwarz criterion	-28.42224						

Note: Numbers in parentheses indicate t-statistic.
* Indicates significance at 1% level.
** Indicates significance ar 5% level.
*** Indicates significance at 10% level

The VECM clarifies that the examined macroeconomic aggregates may diverge substantially from their long-term equilibrium. Notwithstanding a linear combination of I(0) poses limits to this deviation and forces them to equilibrium. The long-run model extracted from the VECM is represented in equation (29):

Johansen Normalization & Long-run model

$$ECT_{t-1} = [1.000lnGDP_{t-1} + 6.017424lnREP_{t-1} - 1.763515lnIEP_{t-1} - 0.590021lnCOP_{t-1} + 1.787819lnCO2INTENS_{t-1} + 2.704432lnFEC_{t-1} - 72.06947 \quad (29)$$

The model's target variable is the lnGDP. In order to interpret the results the signs of the coefficients must be must reversed and the long-run elasticities would be obtained. Thus, lnREP has a negative impact on lnGDP, outlining that 1% increase in residential electricity prices would provoke a decrease by 6,017% at the 1% significance level. In the opposite direction the economic growth would be improved by approximately 6% if a decrease in residential electricity prices takes place. Therefore, residential electricity prices affect extremely the real output. It seems that household electricity price is elastic to changes in the EU. The economic principles of supply and demand explain explicitly this phenomenon. The *"law of demand"* and the *"law of supply"* state that as price rise the demand for a service or a product declines and vice versa. Given that the electricity consumption in EU relies broadly on residential consumption and consumers are not willing to pay more, an increase in final electricity price restrains the final consumption. Thus, fiscal policy measures such as levies and taxes would aim EU to accomplice targets related to environmental policies. The results from Johansen's normalization support the decline in lnGDP due to increases in lnREP, similarly to OLS, FMOLS and CCR estimates. However, it differentiates in relation to the magnitude of changes as it shows that the lnREP is elastic.

Regarding the industrial electricity prices -lnIEP- appear to have a positive effect on the real GDP, increasing real output by 1,76% at 1% significance level. Hence, industrial electricity prices appear to be inelastic to changes in price, which is in accordance with the previous inferences from OLS, CCR and FMOLS. Hence, imposing fiscal burdens on industry sector seems not to pose a risk neither to production nor to real GDP in the EU.

Similarly, to lnIEP crude oil prices are positively related to economic growth. A 1% change in lnCOP is associated with 0,59% increase in lnGDP on average, in the long-run ceteris paribus. Moreover, the increase in lnGDP due to lnCOP is statistically significant at the 1% level. This finding delineates that the energy security concerns in EU lead to succeeding diversification of energy resources.

The findings concerning the carbon dioxide emissions resulting from energy use, lnCO2INTENS, indicate a negative relation between the economic growth and the gas emissions. Namely, a 1% increase in lnCO2INTENS leads to a reduction in real GDP near to 1,8% which is statistically significant at the 1% level. The findings concerning the total final energy consumption imply also a negative relation with the economic growth that is also statistically significant at the 1% level of significance, outlining that 1% change in total energy final consumption would restrict real GDP by 2,7%.

Thus, lnREP, lnCO2INTENS and lnFEC are negatively associated with lnGDP, whereas lnIEP and lnCOP are positively associated with lnGDP. Therefore, the estimated aggregates have asymmetric effects on economic growth in the long-run on average, ceteris paribus. The estimates on long-run equilibrium relationships from the VECM output are in accordance with the previous carried out by OLS, CCR and FMOLS estimations, expect the case of lnFEC

Once the long-run equilibria are specified, the short-run dynamics and the direction of causality have to be analyzed. The equations below provide the short-run estimates extracted from the VECM in Table 8

VECM & Causality

Before providing evidence on the potential causal effects among the economic growth, the electricity prices, the $C0_2$ emission intensity and the total final consumption, the estimates from the VECM -also presented in Table 8- are expressed as:

$$\Delta lnGDP_t = 0.0030236 - 0.4390951\Delta lnGDP_{t-1} - 0.4016555\Delta lnREP_{t-1} + 0.4200368\Delta lnIEP_{t-1} + 0.0406756\Delta lnCOP_{t-1} - 0.7790739\Delta lnCO2INTENS_{t-1} - 0.0206892\Delta lnFEC_{t-1} + 0.0594782ECT_{t-1} \quad (30)$$

$$\Delta lnREP_t = -0.0065508 + 0.4330332\,\Delta lnGDP_{t-1} + 0.190926\Delta lnREP_{t-1} - 0.3123415\Delta lnIEP_{t-1} - 0.0830584\Delta lnCOP_{t-1} - 0.1228218\Delta lnCO2INTENS_{t-1} + 0.2060317\Delta lnFEC_{t-1} - 0.1685536ECT_{t-1} \quad (31)$$

$$\Delta lnIEP_t = -0.0089008 + 0.7149443\Delta lnGDP_{t-1} - 0.7477484\Delta lnREP_{t-1} - 0.2969193\Delta lnIEP_{t-1} - 0.0504461\Delta lnCOP_{t-1} - 0.3451035\Delta lnCO2INTENS_{t-1} + 0.0439273\,\Delta lnFEC_{t-1} - 0.2836592ECT_{t-1} \quad (32)$$

$$\Delta lnCOP_t = -0.0033652 - 0.1159906\,\Delta lnGDP_{t-1} + 3.142066\,\Delta lnREP_{t-1} + 2.99666\Delta lnIEP_{t-1} + 0.6442913\,\Delta lnCOP_{t-1} - 2.787071\,\Delta lnCO2INTENS_{t-1} + 1.499811\Delta lnFEC_{t-1} + 0.8211134.ECT_{t-1} \quad (33)$$

$$\Delta lnCO2INTENS_t = -0.0124024 + 0.1642259\Delta lnGDP_{t-1} - 0.2153482\Delta lnREP_{t-1} + 0.1072689\Delta lnIEP_{t-1} + 0.0055031\Delta lnCOP_{t-1} - 0.0878689\Delta lnCO2INTENS_{t-1} - 0.0041149\Delta lnFEC_{t-1} - 0.0047569ECT_{t-1} \quad (34)$$

$$\Delta lnFEC_t = -0.016973 + 0.4936421\Delta lnGDP_{t-1} - 0.5546528\Delta lnREP_{t-1} + 0.4144269\Delta lnIEP_{t-1} + 0.0450611\Delta lnCOP_{t-1} - 1.307944\Delta lnCO2INTENS_{t-1} - 0.688694\Delta lnFEC_{t-1} + 0.0650793ECT_{t-1} \quad (35)$$

Two conditions have to be met in order to obtain the long-run and short-run causal effects; the adjustment coefficient has to be statistically significant and negative.The error-correction term in lnGDP equation does not provide evidence on long-run causality, as the adjustment coefficient has a positive value and is significant at the 10% significance level. Thus, convergence to long-run equilibrium is not indentified. As far as the short-run causality both residential and industrial electricity prices seem to influence the economic growth. More precisely, lnREP has a negative short-run effect on lnGDP at the 10% significance level, whereas the lnIEP causes lnGDP in the short-run at the 1% significance level. According to our findings a 10% increase in lnREP would restrict lnGDP by 40,16 %. Whereas, lnIEP moves to the opposite direction indicating that an increase by 10% in the industry electricity price accelerates the economic growth by 42%.

Furthermore, long-run causality is observed with regard to residential electricity prices providing that the adjustment coefficient is -0,168 and statistically significant at the 1% level. The adjustment term (-0,168) illustrates that the deviation from the long-run equilibrium is corrected during the first year at around 17%. Hence, the rate of convergence is quite low. Likewise, short-run causal effects are evident in the ΔlnREP equation. The lnGDP coefficient traces out short-run causality from real GDP to lnREP at the 10% significance level, revealing that if lnGDP improves by 10% then lnREP will escalate, circa 43,30%.

By contrast, lnIEP and lnCOP have a negative short-run impact on lnREP both at the 1% level with p-values of 0.001 and 0.000 respectively. The decrease derived from a ten percentage points increase in lnIEP is about 31,23%, while the lnCOP’s negative effect restrains lnREP by 8,3%. Hence, energy prices entrain each other in the EU, while appreciations in crude oil prices that may affect directly the electricity price in industry sector are offset via reductions in household electricity price. Similarly, ascents in industry electricity price yield to significant reductions in the residential electricity sector. Additionally causality derived from lnCO2INTENS is not evident. Finally, lnFEC has a short-run causal effect on residential electricity prices. Namely, if lnFEC moves upwards, then lnREP will ascent at around 20,60%, though at the 10% significance level. The latter is expected from the economic theory; increasing consumption provokes shifts in the short-run demand curve resulting finally to higher prices before the recovery into the equilibrium. To sum up, in the case of residential prices strong causality is evident, taking into consideration the existence of log-run and short-run causality.

Proceeding to industrial electricity price our findings support that only long-run causality is existent, providing that the adjustment coefficient of -0,28 is statistically significant at the 1% level. The speed of adjustment in ΔlnIEP regression suggests that divergence from the long-run equilibrium is restored by 28% within the first year that is relatively low. Moreover, the coefficients of the independent variables are statistically insignificant at all the levels of significance. Signs of causality cannot also be extracted from the ΔlnCOP equation. Considering that EU belongs to energy dependent economies, while crude oil prices are subject to major fluctuations in the international markets, the fact that the European macroeconomic aggregates do not influence them is consistent.

As far as the error correction term on ΔlnCO2INTENS does not imply causality in the long-run. Hence, only short-run causal effects are present. In fact, intensity in the EU context arises from residential electricity prices (lnREP) at the 5% level of significance and from industry electricity prices (lnIEP) at the 10% level of significance respectively. The coefficient on lnREP denotes a negative interaction in the short-run, suggesting a reduction at around 21,53% in the carbon dioxide emissions if a ten percentage points increase in lnREP happens. By contrast, a 10% increase in lnIEP rises the lnCO2INTENS by approximately 10,7%. Thus, lnIEP is positively related to lnCO2INTENS in the EU countries.

Finally, the output on ΔlnFEC regression indicates the existent of short-run causal effect among lnFEC, lnREP and lnFEC. lnREP is negatively related to lnFEC in the short-run at the 10% level, while lnIEP has a positive causal link to lnIEP in the short-run at the 5% significance. Analytically, if lnREP increases by 10% the lnFEC would be reduced by 55,5% whilst an upward trend in lnIEP does not affect lnFEC. Moreover, lnFEC influences its level in the short-term.

To sum up, the short-run elasticities reveal that the European electricity prices are substantially inelastic. As regards the causal and effect relations among the economic growth and the energy prices under consideration, causality runs from real GDP to residential electricity prices and vice versa. Thus, there is evidence on bidirectional causality between household price and economic growth. Also, unidirectional causality arises from industrial electricity prices to real GDP. Furthermore, the aforementioned estimates support the existence of causality driving from industry electricity prices and crude oil prices to residential electricity prices. Whereas the causal effect from total final energy consumption to residential electricity prices are statistically significant at the 10% level. Unidirectional causality is also derived from residential and industrial electricity prices to lnCO2INTENS. A bidirectional causality is observed in the case of lnREP and lnFEC notwithstanding at 10% level. Additionally, unidirectional causality runs from lnIEP to lnFEC at 5% level, Notwithstanding, the phenomenon of strong causal effects is observed in the case of lnREP, given the existence of long-run and short-run causality. Seeking to trace out the type of causality; i.e. strong or weak short-run and long-run causal relationships our next step is to perform Wald tests and validate the above results.

5.4 Wald tests

The interpretation of Wald tests will signify if strong or weak causality occurs among the economic growth, the energy prices, the final energy consumption and the carbon dioxide emission intensity in the European Union. The presence of cointegrated relationships extracted from Engle-Granger 2-step procedure betrays the existence of Granger causality among the variables of at least one direction[121]. However, as the source of causality cannot be defined, the Johansen's maximum likelihood approach (Johansen 1991, Johansen & Juselius 1990) and a VECM are adapted in this study following in Pala's (2013), Apergis's (2014), Osigwe's and Aramovo's (2015) footsteps.

Notwithstanding that the VECM's interpretation has already furnished evidence on causality, seeking to confirm the above results and determine if strong or weak causal effects are existent Wald tests have been applied. The null hypothesis of no Granger causality is rejected providing that the probability chi-square is significant.

Regarding the ΔlnGDP, the histories of ΔlnREP seem to influence the value of lnGDP. Thus, ΔlnREP can be used to predict ΔlnGDP, though at the 10% significance level. The chi-square on ΔlnIEP, indicates significance at the 1% level of significance, so industrial electricity prices have a short-run causal effect on real GDP. The other variables do not influence GDP growth, given that chi-square is insignificant. While examining the short-run causal effects of all the explanatory variables the acquired chi-square is statistically significant at the 5% level.

As far as the ΔlnREP, the lagged values of lnGDP betray causality running from the real GDP to residential electricity prices at the 10% significance level. To the contrary, the industrial electricity prices have a short-run effect on lnREP at 1% significance level. Similarly, lnCOP could cause lnREP in the short-run, - chi-square is statistically significant at the 1% level - while lnFEC has a short-run impact on lnREP at the 10% significance level. Finally, all the variables appear to have a short-run effect on lnREP, taking into account the chi-square statistic of 17,94.

Table 8
Granger Causality Wald tests

Dependent variable	Excluded	x^2 statistic	df	p-value
ΔlnGDP	ΔlnREP	3.72***	1	0.0537

[121] Engle, R.F., & Granger, C.W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Journal Article, 55* (2), 251-276. [Online]. Available at: https://www.jstor.org/stable/1913236?seq=1#page_scan_tab_contents Retrieved from 7th January 2019

	ΔlnIEP	9.60*	1	0.0019
	ΔlnCOP	1.55	1	0.2129
	ΔlnCO2INTENS	1.89	1	0.1698
	ΔlnFEC	0.02	1	0.9008
	ALL	11.50**	5	0.0423
ΔlnREP	ΔlnGDP	3.60***	1	0.0577
	ΔlnIEP	10.81*	1	0.0010
	ΔlnCOP	13.17*	1	0.0003
	ΔlnCO2INTENS	0.10	1	0.7574
	ΔlnFEC	3.14***	1	0.0765
	ALL	17.94*	5	0.0030
ΔlnIEP	ΔlnGDP	0.67	1	0.4144
	ΔlnREP	1.78	1	0.1818
	ΔlnCOP	0.33	1	0.5658
	ΔlnCO2INTENS	0.05	1	0.8211
	ΔlnFEC	0.01	1	0.9216
	ALL	2.72	5	0.7424
ΔlnCOP	ΔlnGDP	0.00	1	0.9830
	ΔlnREP	0.82	1	0.3658
	ΔlnIEP	1.75	1	0.1854
	ΔlnCO2INTENS	0.09	1	0.7685
	ΔlnFEC	0.29	1	0.5882
	ALL	4.32	5	0.5042
ΔlnCO2INTENS	ΔlnGDP	1.54	2	0.2145
	ΔlnREP	6.48**	2	0.0109
	ΔlnIEP	3.79***	2	0.0515
	ΔlnCOP	0.17	2	0.6783
	ΔlnFEC	0.00	2	0.9513
	ALL	9.66***	5	0.0853
ΔlnFEC	ΔlnGDP	1.06	1	0.3040
	ΔlnREP	3.26***	1	0.0709
	ΔlnIEP	4.29**	1	0.0382
	ΔlnCOP	0.88	1	0.3495
	ΔlnCO2INTENS	2.44	1	0.1181
	ALL	6.59	5	0.2529

Note: Δ implies the first difference.
*   Indicates significance at 1% level.
** Indicates significance ar 5% level.
*** Indicates significance at 10% level

The Wald tests for ΔlnIEP reveal independence among the other variables and the lnIEP, which means that none of the macroeconomic aggregates influence the industrial electricity price in the short-run. As it was expected the same deduction comes from lnCOP's output. Conversely, the lagged values of lnCO2INTENS could be predicted from the lagged values of lnREP and lnIEP. Hence, residential electricity price would lead to lnCO2INTENS at the 5% significance level and industrial electricity price may lead to lnCO2INTENS at the 10% significance level. The interpretation of the sum of the variables supports that all have an effect on the levels of lnCO2INTENS. However, the chi-square statistic is statistically significant at the 10% level.

Examining the ΔlnFEC, short-run effects can be observed from lnREP, but at the 10% significance level. Also the chi-square statistic in lnIEP that is statistically significant at the 5% level implies short-run effects on lnFEC.

To conclude, Wald tests reveal that lnREP and lnIEP can Granger cause lnGDP in the EU context that is consistent with the previous findings of VECM. Moreover, strong causal effects are evident in the case of electricity prices and real GDP, providing that the ECT, the coefficient of lnGDP and the chi-square in Wald test are all statistically significant. Furthermore, the existence of bidirectional causality with respect to lnGDP and lnREP is confirmed. The lnREP also yields from lnIEP and lnCOP. The finding of unidirectional causality in VECM is tantamount to Wald tests. Wald tests also sustain the existence of bidirectional causality between lnFEC and lnREP, though at the 10% significance level like VECM's results. Thus, strong causal links can be deducted in the case of causality from lnFEC to lnREP as the ECT is statistically significant and both the coefficient of lnFEC and the Wald test are significant. As far as the lnCO2INTESN, it seems that both lnREP and lnIEP can Granger cause lnCO2INTENS. Finally, the unidirectional causality from lnIEP to lnFEC is also deduced from the Wald tests. Therefore, Wald tests furnish evidence on robustness of our previous conclusions as the estimates are equivalent in both cases.

Notwithstanding, deepening the examination of variables' interactions, the IRFs are computed and a Variance Decomposition analysis is presented in the following sub-section.

5.5 IRFs Analysis

The Impulse-Response Function is an econometric tool of a paramount importance allowing researchers come to a safe conclusion over the consequences of a shock to an endogenous variable on itself and upon the others (Lutkepohl, 2005, Hamilton, 1994) More explicitly, in a VAR environment the effects occurred from shocks in the error terms of the endogenous variables can be assessed as well as to what extent that shocks-call them innovations-may influence the other system's variables (Polemis & Dagoumas 2013).

Via the IRF computation the responses of the main dependent variable, the lnGDP due to impulses of lnREP, lnIEP, lnCOP, lnCO2INTENS and lnFEC will be analyzed. Thus, the outcomes of unexpected changes in energy prices and their symmetric or asymmetric effects on the other examined macroeconomic aggregates will be assessed. For, instance, a shock arising from the crude oil price, that is a supply side shock, is expected to provoke macroeconomic imbalances. In the EU context is considered as an external shock which might have symmetric negative effects on each member-state's real GDP and consequently to the aggregate European growth. Symmetrical effects are also observed when a shock to one macroeconomic aggregate stimulates changes to other. Based on the previous example, fluctuations in the oil price will prompt inflation expectations or provoke prices appreciations; where both will restrain real output. The increasing inflation will lead to increase in industrial and household electricity price, restricting the total final consumption, while the increasing inflation's expectations will influence investments' decisions and finally restrain the real GDP.

Hence, the IRF depicts *"the outcomes of a one-time shock to one of the innovations on present and future values of the endogenous variables"* (Polemis & Dagoumas, 2013) Before the Impulse-Response Functions and the Forecast Error Variance Decomposition are computed, is considered appropriate to perform the diagnostic tests for the serial autocorrelation, the normality of residuals and the stability of the VECM system. The diagnostic tests must be employed in order to avoid bias from misspecified lags' selection providing that the innovations must be uncorrelated. According to Gonzalo[122] a higher order of lagged values results to serial correlation, whereas fewer lags causes bias due to omitting information.

The post-estimation tests will finally elucidate if the VECM's results will be used to obtain the IRFs and the FEVD.

Diagnostics

The VECM discussed in the previous sub-sections uses two lags and one cointegrating equation. First of all, in order to know if our system is well-fitted the remaining eigenvalues have to be strictly less than unit according to the theory. Though, evidence on misspecification comes from the remaining eigenvalues of the companion matrix. If the remaining eigenvalues are close to unit circle, then the VECM does not satisfy the stability conditions. Otherwise it can be used.

The VECM for lnGDP, lnREP, lnIEP, lnCO2INTENS and lnFEC imposes 5 unit moduli, i.e. in the system there are five eigenvalues equal to 1 (See Appendix p.p). Proceeding to the graphical representation of the remaining eigenvalues none of them is so close to the unit circle. Hence, this is not a sign of misspecification. Moreover, the Lagrange Multiplier for serial correlation in the residuals indicates the absence of autocorrelation. With a p-value of 0,70 and 0,51 respectively, the null hypothesis of no autocorrelation cannot be rejected.

[122] Gonzalo, J. (1994). Five alternative methods of estimating long-run equilibrium relationships. *Journal of Econometrics,* 60, 203–233.

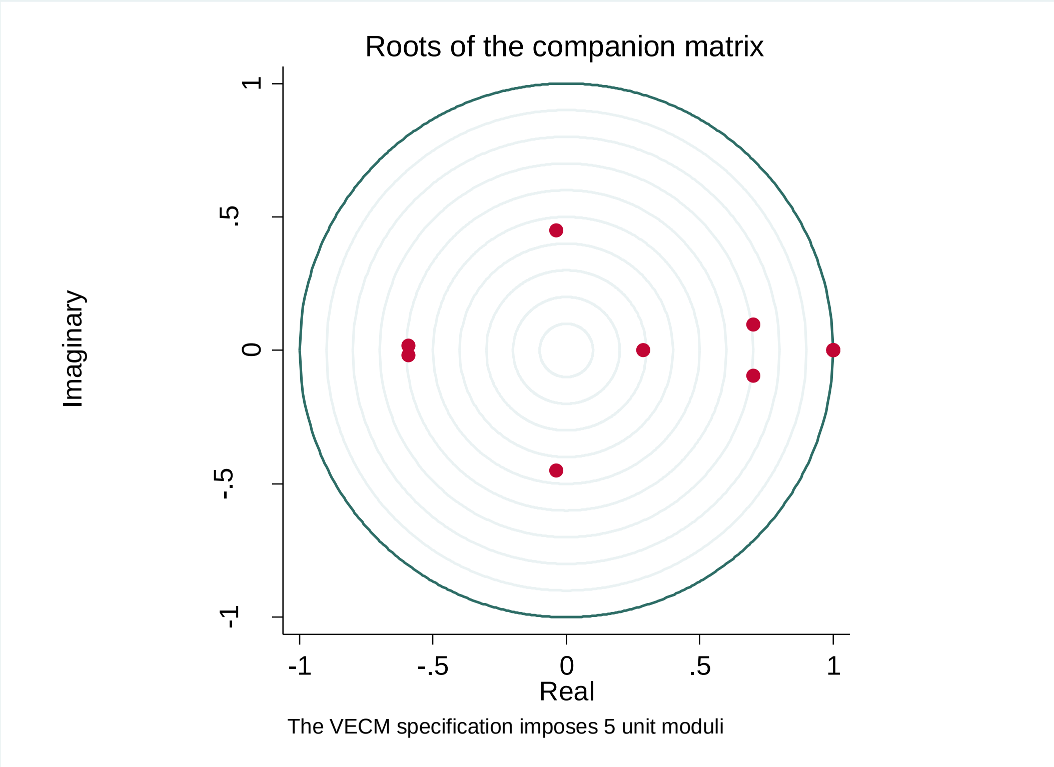

Figure 6. Representation of remaining eigenvalues in the VECM

Things differ in the case of normality. The Jarque-Bera test for normally distributed residuals shows that the residuals in ΔlnGDP and ΔlnFEC equations are not normally distributed. In order to avoid misspecification and bias in our results, a new VECM is employed with higher order of lags according to AIC and SBIC criteria. However, the results are worsened and we conclude that the initial VECM is the optimal, facing only the issue of non-normality of the residuals in two of the six equations of the VECM's system. Furthermore it accounts Toda's and Yamoto's view including more than one lag in levels[123]. Finally, the unit moduli in the companion matrix entails that the effects of some shocks will be persistent in the course of time.

IRFs

Understanding the responses of European GDP to shocks derived from the energy prices, the total final consumption and the gas emissions intensity is the primary goal. The next graph offers the responses of lnGDP to impulses from the other's system variables. The IRFs are adapted to a time horizon of 10 years, namely from 2019 to 2029. These long-term forecasts will render the potential VECM's dynamics.

In addition, the below graphs illustrate both IRFs and OIRFs, so they illustrate how an orthogonalized shock to one of the independent variables affect the real GDP. The horizontal axis shows the time period while the vertical one percentage points of change.

The response of lnGDP to its own innovation is mainly positively. lnGDP increases steadily from the period one until the period six, when reaches to its peak of 2,34%. Then it drops

[123] Toda, H.Y., & Yamamoto, T. (1995). Statistical Inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics,* 66, 225–250

imperceptibly. However, this subtle decrease does not harm the economic growth. It seems that lnGDP counterbalanced the effects of its own positive shock at the end of a five year period. From the period six until the period ten the lnGDP remains stable, which corresponds to the equilibrium state. Hence, the effects of lnGDP's own shock are positive and permanent, as they weaken slightly after a decade. The latter is explained through the *Business Cycle Theory* which suggests that the economic cycle experiences alternating periods of growth and decline, i.e. expansion or contraction phases respectively. Finally, an orthogonalized shock from lnGDP does not influence itself at all. To sum up, a change of one standard deviation in the error-terms of lnGDP's causes to itself a positive response both in the short-run and long-run.

In contrast, a shock of lnREP has a negative impact on lnGDP. The lnGDP's response at a one standard deviation impulse of lnREP is negatively for more than three years. GDP experiences its lowest value between the second and the third period. After a period of three years the negative implications from lnREP's shock tapper off and during the fourth year are neutralized. Then, lnGDP follows a steady upward trend. Thus, approaching to the long-run horizon the effects of the shock become positive. Even lnGDP reacts immediately to impulses from lnREP, fails to counterbalance them rapidly. Finally, shocks to lnREP harm in the short-run the lnGDP, but have a positive sign in the long-run, resulting finally to a steady increase. Again the response of lnGDP to an orthogonalized shock is negligible, providing that a marginal increase is observed. Notwithstanding, it has a long-term positive impact. To sum up. a shock of the household electricity price's side restricts the real GDP in the European Union for more than three years, indicating that unexpected changes in residential electricity price may impose limits to GDP's growth rates.

The graphs also support the magnitude of industrial electricity prices for the European economy. One standard deviation shock of lnIEP has indeed significant effects on real GDP. Analytically, a shock on lnIEP stimulates rapidly lnGDP. Between the first and the third year the lnGDP accelerates its response on lnIEP's shock. Reaching to its peak, then it follows a downward trend. So, a gradual decline is observed, starting from the period four until the end of the forecast period. Therefore, the initial positive effects weaken over time. Thus, in the case of lnIEP, the outcomes of an innovation are transitory positive to a great extent, whilst the positive reaction remains even in the long-run. Hence, increases in industrial electricity prices, would have a positive impact on the economic growth that abates gradually in the course of time.

A shock derived from crude oil prices agonizes the European GDP significantly. However, lnGDP has a positive short-term response to a one standard deviation shock from lnCOP. After a period of three years the negative effects of lnCOP to real GDP are evident. Moreover, they are persistent and expand over time. In fact, during the three last periods the lnGDP stabilizes the variations from lnCOP, though it does not recover. Therefore, crude oil prices have a long-term impact on the European economic growth, even if their negative effects are not obvious at first glance. Shocks from oil prices lead to a marginal increase in real output for a short time period resulting finally to growth sluggishness. This is expected from the macroeconomic theory; The EU trying to stabilize the economy is forced to conduct an expansionary monetary policy via increasing the money supply. However, EU achieves to restrain the oil crises' implications and finally a decline close to 2% is evident in the long-run horizon.

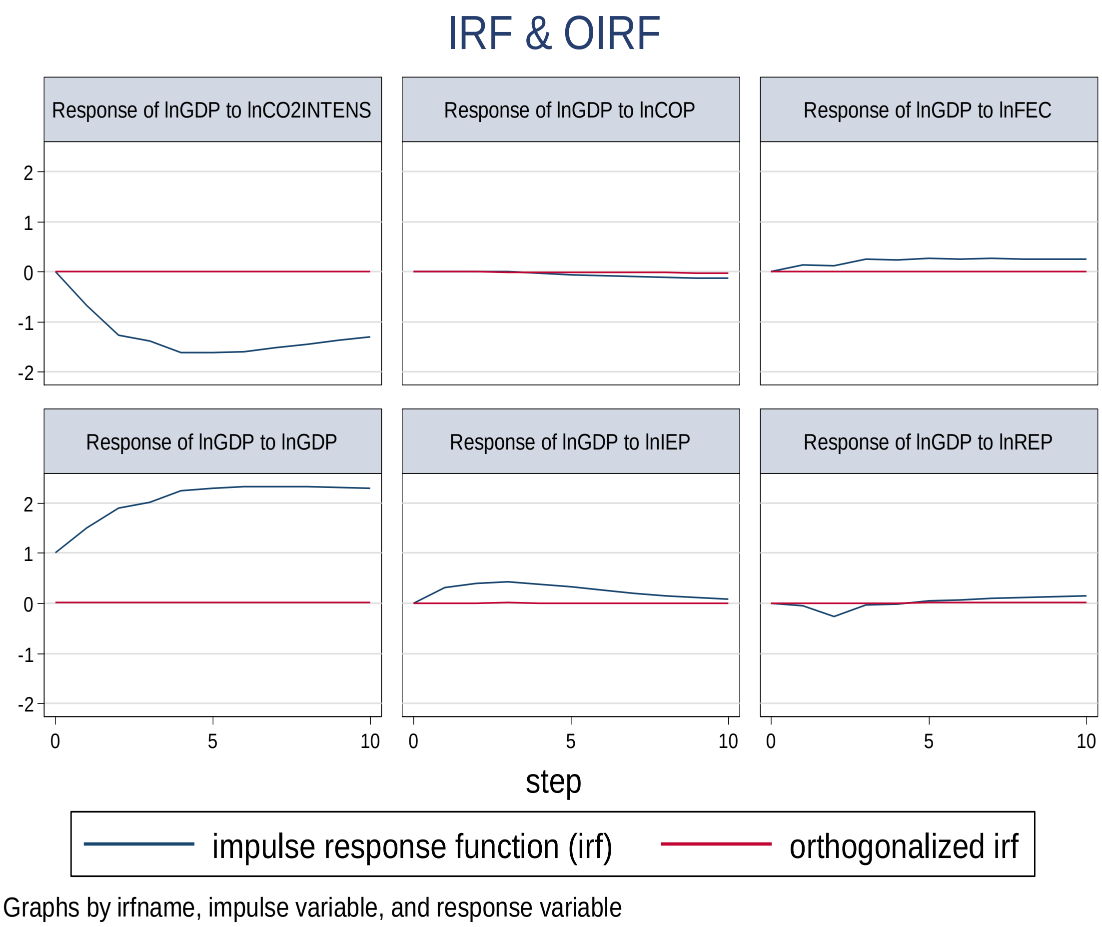

Figure 7 Responses of lnGDP to impulses from lnREP, lnIEP, lnCOP, lnCO2INTENS and lnFEC

The graph with respect to CO2INTEN indicates a negative interaction with lnGDP. In fact, a shock of CO2INTENS decreases the most lnGDP. A one standard-deviation shock to lnCO2INTENS provokes a steep decline on lnGDP, with an initial drop close to -0,7% during the period one. The continuous downward trend reaches finally to -1,62% at the fifth period. Then the response of lnGDP ameliorates and rises moderately. Thus, shocks to innovations of lnCO2INTENS are translated to negative shocks for real GDP, while their effects are not counterbalanced over time. Hence, measures that pose limits to conventional energy used (green certificates, ECT etc) which are associated closely to CO2 emissions lessen the output's production. While the persistent negative impact underlines the need of political action. Therefore, the adoption of countervailing measures is straightforward.

The response of lnGDP, as a result to one standard-deviation impulse of the lnFEC has a positive sign. Even in the first period a positive interaction is observed. Thus, lnGDP reacts rapidly to a shock from the lnFEC. During the forecast horizon a stable increase is evident. However, between the second and the third period the response of lnGDP declines slightly and then boosts during the fourth period which corresponds to its peak value. Then it fluctuates lightly in the following period and finally returns again to its previous level. After a five year period, the lnGDP neutralizes the effects of a shock to lnFEC and stabilizes its positive response. Therefore, the fluctuations in the total final energy consumption do not affect the real GDP, whereas the two variables follow a similar path. Finally, an interesting deduction from the graphical representation of IRFs is that the shocks of all the examined variables have long-term effects on the European economic activity.

Providing that the effects to a shock of all the endogenous variables on lnGDP are measured and the purpose of this study is to investigate reciprocally the dynamics among the real economic growth and the energy prices it is appropriate to shed light on the shocks of lnGDP to the other endogenous variables too. The IRFs now will reveal the effect over time of a one-time unit increase to one of the lnGDP's shocks, holding the other factors constant[124].

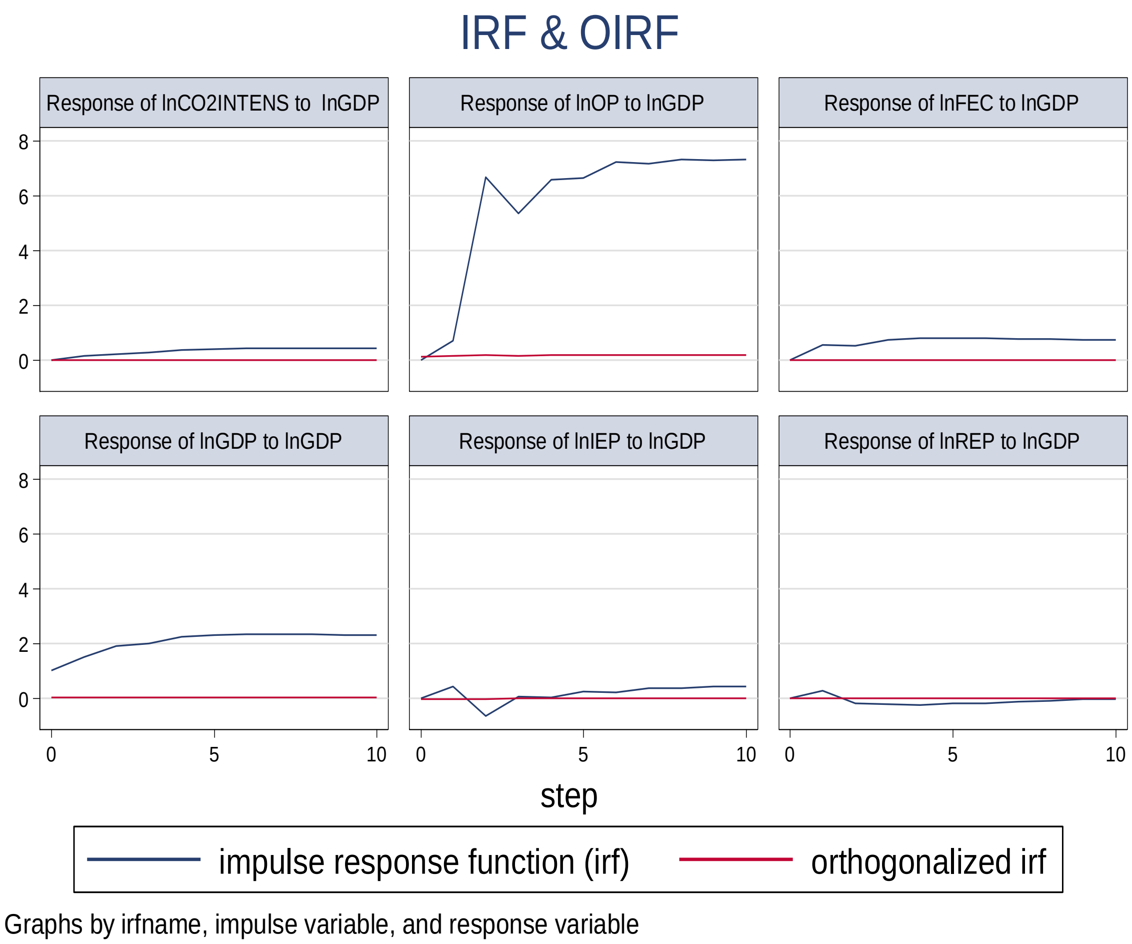

Figure 8 Responses of lnREP, lnIEP, lnCOP, lnCO2INTENS and lnFEC to impulses from lnGDP

The above graph presents the effects of a one standard-deviation shock of lnGDP to other endogenous variables included in the VECM system. The response of lnGDP to its own shocks has been already analyzed. In general, real GDP exhibits a positive response to its own innovations. Real GDP increases above its steady state value and maintains the positive effects in the long-run.

In contrast, lnREP reacts negatively to a one standard-deviation shock of lnGDP. Initially, the shock increases lnREP, but this positive response declines rapidly. The decrease in lnREP

124 Baum, C.F. (2013). VAR, SVAR and VECM Models. *EC 823: Applied Econometrics*. Boston College.

continues until the fourth period, where a moderate increase is observed. Finally, lnREP does not eradicate the negative effects of lnGDP's shock and does not return into the previous state of equilibrium. However, the decrease in lnREP is relatively low. Thus, a positive shock from the real GDP's side may pressures the residential electricity price slightly. Though, the decrease is permanent.

The industrial electricity prices exhibit alternating positive and negative effects from a shock of lnGDP. The lnIEP reacts rapidly to changes in lnGDP. At a first glance a positive impact on lnIEP appears, yet abates during the first and the second period. The lnIEP recovers between the third and the fourth period and finally it scales up until the end of the forecast period. However, the increase in lnIEP is too low. As a consequence a positive shock to real GDP may push up the industrial electricity price. However, the increase is negligible.

Crude oil price also interact positively to GDP's shocks. lnCOP follows an upward trend, reaching finally to 0,7% in the period six, after it fluctuates slightly and the stabilizes the effects of lnGDP's shock. As the European economy is a strong one, it has a relative power over the international commodity markets. If the economy accelerates, i.e. experiences the expansion phase of its cycle then the European demand for oil will increase, resulting to a possible increase in oil prices.

The response of lnCO2INTENS to a one standard-deviation shock of lnGDP is also positive, while lnCO2 reacts positively both in the short-run and in the long-run. The lnCO2INTES approaches its highest value during the fith period, where the effects are finally counterbalanced. The steady annually increase in lnCO2INTENS's response is explained through the prism of economic development. As it expected the GDP's growth is linked to higher level of production and thus higher levels of carbon emissions.

The graph illustrating the response of total final energy consumption to a one standard-deviation shock of real GDP depicts a positive relation between the two variables. lnGDP improves significantly the lnFEC that reacts positively during the forecast horizon. During the first year the lnFEC increases near to 0,6%, whereas it improves on a yearly basis. Its highest value is observed during the sixth period, i.e. six years after the initial outbreak. Afterwards, the lnFEC is stabilized maintaining the positive outcomes. Hence, prosperity improves total final energy consumption.

5.6 Variance Decomposition Analysis

The precedence of VEC systems vis-à-vis other alternatives is inextricably linked to the fact that VECMs permits a comprehensive examination of the interdependence among the variables. Variance decomposition enables to define how much of the variability in one endogenous variable is explained by shocks to other variables or by its own shocks. Through the variance decomposition of forecast errors the aforementioned causal and effect relationships among the variables would be better explained via examining the unexpected variations in one variable due to shocks to other variables.

Therefore, in this part of this study the focus is on the future uncertainty over the real GDP growth due to future energy price shocks or shocks of final energy consumption's and gas emissions' side. Understanding if the impulses of the other variables in the system are a stimulus for changes in real GDP will have significant economic implications for the European Union. The Table below shows the decomposed variance of lnGDP for a ten years period. The variance of lnGDP is equal to 1. However, the proportion of the variations is expressed to percentage points in order to assess the economic impact on the European economy.

Starting with lnGDP we observe that in the short-run the forecast-error variance in real GDP is explained by itself. Hence, lnGDP is strongly endogenous, especially from period one to period four. After the expiry of a five year period the influence of the other variables increases moderately. At the end of the forecast horizon the lnGDP seems to influence itself by 35%. Hence, lnGDP exhibits strong endogeneity. The other variables have weak influence in predicting future values of real GDP. Analytically, the lnREP increases its influence over time, provoking in the short-run –the second period- 1,9% of variations on lnGDP. Augmenting its impact, accounts 18,7% of lnGDP's variations at the end of the forecast period. Hence, lnREP exhibits a weak long-term endogeneity.

In contrast, the lnIEP's impact on lnGDP diminishes steadily on a yearly basis. After a decade finally the 6,7% of lnGDP's variations are due to shocks on lnIEP. Whilst lnCOP stipulates lnGDP in the long-run; specifically the lnCOP increases its influence over lnGP significantly at the end of the fifth period. Thereafter, the impact of crude oil prices accelerates gradually. In the end of the decade the lnCOP causes the 37% of variations on lnGDP. Finally, lnCOP becomes strongly endogenous providing that in the period ten it affects lnGDP as much as itself.

The same pattern is also observed in the case of lnCO2INTENS; it follows an upward trend. However, the lnCO2INTENS's impact remains at a relatively low rate, and only the 2,13% of variations on lnGDP is expainded by shocks from CO2INTENS in the long-run. Moreover, its highest value is observed at the sixth period. Thus, lnCO2INTENS is strongly exogenous to lnGDP. Finally, the findings over the lnFEC's influence on lnGDP support a strong exogeneity. Though, a gradual increase exists which causes a peak response during the sixth period.

Table 9
Forecasting Error Variance Decomposition:
Impulse variables: lnREP, lnIEP, lnCOP, lnCO2INTENS, lnFEC, Response variable: lnGDP

Period	**Impulse = lnGDP, and response = lnGDP**	**impulse = lnREP, and response = lnGDP**	**impulse = lnIEP, and response = lnGDP**	**impulse = lnCOP, and response = lnGDP**	**Impulse= lnCO2INTENS, and response = lnGDP**	**impulse = lnFEC, and response = lnGDP**
1	100	0	0	0	0	0
2	84.6659	1.9047	12.2881	0.4552	0.4691	0.2169
3	77.3896	1.9655	16.9309	1.3069	2.1909	0.2162
4	70.3822	3.2983	20.251	3.2191	2.4318	0.4177
5	64.0913	5.8684	18.1421	8.5901	2.8277	0.4803
6	57.0614	9.0423	15.3961	15.105	2.8724	0.5229
7	50.4178	12.0277	12.4841	21.7647	2.7853	0.5203
8	44.4454	14.698	10.0534	27.7178	2.5773	0.5079
9	39.3206	16.9042	8.134	32.8038	2.3541	0.4833
10	35.0687	18.6901	6.703	36.9446	2.1356	0.458

To conclude, real GDP exhibits a strong endogeneity vis-à-vis to the system's variables. That implies that real GDP is subject to a variety of macroeconomic conditions -external to our system- that influence significantly the GDP's formation, for instance the inflation rate, the interest rates, the unemployment etc. Though, signs of interdependence are obvious; at least exogenous are both the residential and the industrial electricity prices. An interesting inference is the existence of a trade-off relationship among the electricity prices in relation to the magnitude of their influence on lnGDP. Whilst both the prices have a positive impact on lnGDP even in the short-run the effects of lnIEP lessen over, whereas the effects of lnREP escalate. Thus, a positive shock of lnIEP is more persistent in the shor-term while the opposite happens in the case of lnREP which has a long-term impact. In addition, the crude oil prices stipulate the most the variations of lnGDP in the long-run. Thus, a shock on crude oil price which is a leading indicator according to macroeconomic theory has significant long-term implications in real GDP. Thus, oil prices are a precursor of changes in economic growth, while the stabilization policies- monetary and fiscal policy measures- suffer from time inconsistency and their effects are evident after year. To sum up, all the examined energy prices are important for the European output growth.

So, the real influence that a variable has upon another can be anchored to variance decomposition analysis. Taking into consideration that FEVD measures future uncertainty of one time series due to future shocks into other time series it is appropriate to examine the variations of shocks arising from lnGDP to energy prices, total final energy consumption and carbon dioxide emissions from energy intensity.

At this point, Table 12 presents the forecasr-error varianceof each variable in the VECM system as a response to a one standard-devaition shock of lnGDP. Thus, only the percentage of unexpected variations in lnREP, lnIEP, lnCOP, lnCO2INTENS and lnFEC that emerges from lnGDP's impulses.

As it is already mentioned previously the lnGDP is strongly endogenous in the short-run, while after a period of five years its response abates gradually. Until the end of the forecast horizon lnGDP diminishes endogeneity and shock arising from the lnREP, lnIEP and lnFEC increase their impact, providing that they contribute significantly to economic prosperity.

Examining the effects of a one standard deviation shock arising from lnGDP to lnREP it is observed the real output affect significantly the level of the residential electricity price. The influence of lnGDP's shocks range from 6,4% to 14,17% in the during the first two years. Thereafter, the GDP's impact decreases gradually reaching to approximately 3,35% during the fifth period, where it remains by the end of the ten-year period. Thus, a shock to the real GDP may explain the variations in energy electricity prices.

Furthermore, impulses from lnGDP stimulate changes in lnIEP. The forecast-error variance of 37,42% at the first period indicates that the lnaGDP is endogenous to lnIEP. This dynamic relationship is more robust in the short-run, while decreases at a steady rate over the years. Though the lnGDP explains the 4,2% of the variations in IEP. Hence, shocks to real GDP may provoke fluctuations to the industrial electricity prices.

The real GDP also is closely related to crude oil prices. As it was expected the fluctuations on the oil prices may jeopardize the European GDP. As it was expected socks from crude oil prices may cause variations on real GDP. However, the findings prove a mutual reaction, suggesting that lnGDP may cause also irritate crude oil prices. Even in the initial stage of a shock to lnGDP the lnCOP has a quick response; a 28% of variations of lnCOP are duc to a lnGDP's shocks. While the effects scales up on a yearly basis, resulting finally close to 40%.

The lnCO2INTENS also responds rapidly to shocks from lnGDP, implying that lnGDP is strongly endogenous with respect to lnGDP. The variations on lnCO2INTENS range from 35,62% to 27,4% during the first two years. Then lnGDP decreases slightly its influence on lnCO2INTENS during the next four years and it increases resulting to 22,8% at the period ten.

Likewise the findings on lnFEC, indicates a quick reaction to lnGDP's shocks. In the short-run it seems that shocks from lnGDP stimulates variations on lnFEC (close to 6% from period one to period four), while the effects of lnGDP on lnFEC do not expire, but they lessen year by year.

To conclude, from the FEVD analysis there is evidence on the interdependence among the real GDP, the energy prices, the gas emissions intensity and the total final consumption as well.

Table 10
Cholesky FEVD: Innovations of lnGDP to other system's variables

Period	impulse = lnGDP, and response = lnGDP	impulse = lnGDP, and response = lnREP	impulse = lnGDP, and response = lnIEP	impulse = lnGDP, and response = lnCOP	impulse = lnGDP, and response = lnCO2INTENS	impulse = lnGDP, and response = lnFEC
0	0	0	0	0	0	0
1	100	6.3752	37.4272	27.7372	35.6238	6.8747
2	84.6659	14.177	35.422	32.031	27.4404	5.2046
3	77.3896	5.3472	20.5397	37.1946	20.016	5.8929
4	70.3822	4.2604	14.3011	36.5217	19.3217	5.0969
5	64.0913	3.5758	10.6318	36.9322	20.0867	4.6714
6	57.0614	3.5113	8.2865	37.1605	20.9153	3.9014
7	50.4178	3.3905	6.706	37.6064	21.5808	3.3049
8	44.4454	3.4117	5.6145	37.9174	22.1388	2.7551
9	39.3206	3.4225	4.8325	38.2884	22.5002	2.3235
10	35.0687	3.4557	4.249	38.6271	22.7001	01.9797

6. Conclusions

The increasing energy demand, the severe recessions and the need to mitigate the climate change breathed life into the study of energy and growth nexus. Whereas the scientific concerns are oriented aplenty towards the energy consumption and economic growth, the interference of energy prices into shaping the conditions of macroeconomic prosperity is underestimated. To bridge the literature's gap for both advanced and emerging economies is essential, especially under the spectrum of internationalization of energy markets. Energy prices may be subject to serious fluctuations in global energy markets that may agonize the real output.

This thesis intends to assess the energy prices impact within the context of EU energy policies. In pursuit of the potential dynamics among the economic growth and the energy prices in the EU an extensive empirical analysis has materialized on the basis of the ECM methodology. Analytically, taking into consideration the magnitude of the total final consumption and that one of intensity, a model that incorporates the residential final electricity prices, the industrial final electricity prices, the crude oil prices, the real GDP, the energy use and the carbon dioxide emissions intensity has finally taken shape. The reference period is determined from 1990 to 2018 on the grounds that during that decade serious efforts towards the abatement of CO2 emissions take place. This section highlights the empirical findings presented in the previous sub-sections from the Engle-Granger 2-step procedure, the VECM, the Wald tests as well as the IRFs and the FEVD analysis. Hence, it offers the final inferences over the interrelations among the examined aggregates.

The starting point is the existence of cointegration among the macroeconomic time series. The fact that the time series are cointegrated gives a new impetus to explore the short-run and long-run dynamics. First of all, convergence to the long-run equilibrium is proved through the negative and statistically significant error-correction term of -0, 46 that is statistically significant at the 5% significance level. The error-correction term reveals that the speed of adjustment towards the long-run equilibrium reaches to 46% within the first year of deviation. The speed of adjustment is moderate. The economic theory suggests that divergence from the long-run equilibrium is temporary due to market forces that restore the state of equilibrium. Furthermore, in the case of an intervention, i.e. stabilization policies, the monetary and fiscal measures demand time as they suffer from time lag.

The long-run equilibrium relations are confirmed from the OLS estimates (Engle-Granger 1st step regression) indicating that an increase in residential electricity prices (lnREP) may provoke a slight decline by -0,5 percentage point in real GDP. On the front of industrial electricity prices an increase by 1% implies a marginal increase in real GDP, whereas an increase in crude oil prices does not seem to agonize the European economic growth. On the contrary a tradeoff is observed as far as the real GDP and the levels of intensity, namely a change in the latter restricts the GDP by approximately -2%. Finally, the OLS technique does not provide information over the total final energy consumption (lnFEC) as the coefficient is statistically insignificant. Notwithstanding, total final consumption is found to be positively related with the GDP by the FMOLS and CCR estimations which deduce that an increase by approximately 0, 5% in GDP is observed when total final energy consumption goes up by 1%. The aforementioned findings - except the lnFEC's case - are also verified by the estimates of FMOLS and CCR that are used as a sensitivity analysis aiming to results‟ robustness.

Things differ with regard to short-run dynamics obtained from the 2nd step regression. The short-run relations are not verified expecting the residential electricity price which seems to have a short-term effect on GDP, though at the 10% significance level. Hence, according to ECM, none of the energy prices affect the European real GDP in the short-run.

Proceeding to VECM the long-run relationships are also evident via imposing the Johansen normalization. The estimates offer the same conclusions over the effects of the explanatory variables on lnGDP. Hence, residential electricity prices have a negative impact on real output, whereas industrial electricity prices have a positive one. Furthermore, the crude oil prices again they do not pose a risk to European economic growth, while intensity restrains the real output. Finally, the total final energy consumption improves the real GDP and is statistically significant at the 1% significance level in conflict with the OLS estimate.

Regarding the causality arising from the system's variables to GDP, there is evidence of short-run causality from the industrial electricity prices significant at the 1% significance level. The short-run causality derived from residential electricity prices is significant at the 10% significance level. However, the coefficients on lnGDP equation mark the same negative and positive interaction with the real GDP as in the previous findings; thus, a positive one to industry electricity price and a negative one with respect to household electricity price.

Long-run and short-run causal effects are observed with respect to residential electricity prices. The error-correction term at -0,168 shows that the deviation from the long-run equilibrium is restored within the first year around 17%. The residential electricity price has the highest tolerance level in the short-run. In short-run, causal effects appear from lnGDP, lnIEP and lnCOP. In addition both the industrial electricity prices and the crude oil prices have a negative impact on lnREP. Therefore, energy prices in the EU influence each other. However, total final energy consumption also presents some causal effects but significant at the 10% significance level.

In addition, in the industrial electricity price only long-run causality is observed, under the adjustment coefficient of -0,28 which is statistically significant at the 1% significance level, betraying that deviations from the long-run equilibrium is restored by 28% within the first year which is a relative low rate.

The findings over carbon dioxide emission intensity do not assert that a convergence into long-run equilibrium is achieved. Hence, only short-run causal effects are evident from residential electricity prices significant at the 5% significance level and from industry electricity prices significant at the 10% significance level respectively. Likewise, the estimates for total energy consumption imply the presence of causal effects on the grounds of residential and industrial electricity prices respectively.

Proceeding to Wald tests finally, signs of strong causal effects are observed in the electricity prices and real GDP, providing that the ECT, the coefficient of lnGDP and the chi-square in Wald test are all statistically significant. The residential electricity price and the industrial electricity can Granger cause real GDP in the EU in accordance with the previous findings of the VECM. A unidirectional causality derives from industrial electricity prices to real GDP. So, the findings favour the growth hypothesis. However, in the case of residential prices there is evidence on the feedback hypothesis, providing that a bi-directional causality exists between the lnGDP and the lnREP.

The residential electricity prices also yield from the lnIEP and lnCOP. The Wald tests similarly to VECM denote the presence of bidirectional causality between lnFEC and lnREP, though significant at the 10% significance level. Nevertheless, both lnREP and lnIEP can Granger cause lnCO2INTENS. Furthermore, the unidirectional causality from lnIEP to lnFEC is also deduced from the Wald tests. Therefore, the estimates from Wald tests are identical to that of the VECM.

Moreover, aspiring to ascertain if the energy prices prompt changes to real output the IRFs and a FEVD analysis take shape. IRFs and FEVD serve as an alternative channel to assess the variability on GDP due to shocks from the other variables.

Both the IRFs and the FEVD have a forecast horizon of a ten years period, enough to capturing adequately the potential dynamics. The IRF in conjunction with the variance decomposition suggest that the European GDP exhibits strong endogeneity in the short-run, implying that the majority of variations are explained by its own innovations. Nevertheless, in the course of time the other variables augment their impact on the real GDP.

In fact, the energy prices appear to be at least endogenous to real GDP. More explicitly, the residential and the industrial electricity prices have both permanent effects on real GDP. The negative effects arising from shocks to residential prices may affect the GDP, but after a period of four years are neutralized, modifying the initial negative impact to a steady ascent. The FEVD suggests that the lnREP augments its influence over time, provoking in the short-run–the second period-1, 9% of variations on lnGDP. Increasing its impact results to 18, 7% of lnGDP variations at the end of the forecast period. Hence, lnREP exhibits a weak long-term endogeneity.

Also it is ascertained the magnitude of industrial electricity prices for the European economy. One standard deviation shock of lnIEP stimulates rapidly lnGDP that between the first and the third year accelerates its response on lnIEP's shock. In lnIEP's case, the outcomes of an innovation are transitory positive to a great extent. The FEVD analysis delineates that the lnIEP's impact on lnGDP diminishes gradually on a yearly basis. After a decade finally the 6, 7% of lnGDP's variations are due to shocks on lnIEP.

However, a shock derived from crude oil prices poses limits to the European GDP in the long-run. In the end of the decade the lnCOP causes the 37% of variations on lnGDP. Finally, lnCOP becomes strongly endogenous providing that in the end of the forecast period affects the lnGDP as much as itself. Hence, the positive short-term lnGDP's response expires beyond the period of three years and the negative effects of lnCOP to real GDP come to light.

The IRF graph with respect to intensity also entails a negative interaction with lnGDP. In fact, a one standard-deviation shock to lnCO2INTENS attributes to a prompt decline in lnGDP, with a drop close to -0, 7% during the initial period. The continuous downward trend reaches finally to -1, 62% in the fifth period. Then the response of lnGDP improves moderately. The same pattern is observed also in the FEVD analysis; the lnCO2INTENS's does not counterbalanced over time, though it remains at a relatively low rate, and only the 2, 13% of variations on lnGDP is expainded by shocks from CO2INTENS in the long-run.

The findings over the lnFEC's influence on lnGDP support a strong exogeneity. However, a gradual increase exists which causes a peak response during the sixth period, suggesting that the lnGDP's response to one standard-deviation impulse of the lnFEC is at least positive. After a five year period, the lnGDP neutralizes the effects of a shock to lnFEC and stabilizes its positive response.

Measuring the shocks derived from lnGDP to the other endogenous variables is also of a great importance as the thesis's quest is to investigate mutually the cause and effects links among the macroeconic aggregates.

lnREP reacts negatively to a one standard-deviation shock of lnGDP. Initially, the shock increases the lnREP, but this positive response declines rapidly. Finally, the lnREP does not eradicate the negative effects of lnGDP's shock, returning into the previous state of equilibrium. According to VDC analysis, the influence of lnGDP's shocks range from 6, 4%

to 14, 17% during the first two years. Thereafter, the GDP's impact decreases gradually reaching to approximately 3, 35% during the fifth period, where it remains by the end of the ten year period. Thus, a shock to the real GDP may explain the variations in energy electricity prices in the short-run.

Alternating positive and negative effects seem to exhibit the industrial electricity prices due to a shock on lnGDP. At first glance a positive impact on lnIEP appears, yet calms between the first and the second period. The lnIEP recovers during the third and the fourth period and finally it ramps up until the end of the tenth period. However, the increase is negligible. Similarly, the forecast-error variance of 37, 42% at the first period indicates that the lnaGDP is endogenous to lnIEP. The interaction appears tighter in the short-run, while it decreases at a steady rate over the years. Though, shocks emerged from real GDP may attribute to fluctuations in the industrial electricity prices.

On the front of the real GDP's impact on crude oil prices, the results support that the variables irritate each other mutually. Hence, shocks from GDP may cause variations on crude oil price. The lnCOP has a prompt response to a shock of lnGDP; approximately 28% of variations of lnCOP are due to lnGDP's innovations in the short-run. While its leverage scales up on a yearly basis, finally resulting near 40%. As the European economy is strong, it has a relative power over the international commodity markets. Likewise the variance decomposition indicates that lnCOP stabilizes the effects of lnGDP at the end of the sixth period.

Regarding the response of intensity on a one deviation shock from real GDP, the findings render a positive reaction both in the short-run and in the long-run. Therefore real GDP is endogenous with respect to intensity.

Finally exploring the response of total final energy consumption to a one standard-deviation shock of real GDP a positive relation concerns the two variables. In the initial stage a percentage close to 6% of the lnFEC's variations account for lnGDP shocks; though, the leverage of lnGDP on lnFEC does not extinct. Nevertheless, the lnFEC succeed to lessen the effects of real GDP's shocks after a six period from the initial outbreak.

To conclude, this thesis aspires to investigate the inking of potential interdependence among the real economic growth, the electricity prices, the intensity and the total final consumption in the EU framework. The evidence of cointegrating relations offers a breeding ground for the interpretation of long-run and short-run dynamics among the aforementioned aggregates. Assessing the involvement of one to another variable via OLS, FMOLS and CCR techniques we obtain similar results for the model's components. While the IRF and the FEVD estimations provide also meaningful results.

Hence, it is evident that electricity prices in the EU are mainly inelastic to price changes. However, a negative relation between the economic growth and the residential electricity price emerges from all the estimation methods, including the VECM and the IRF-FEVD analyses. The industrial electricity prices improve slightly the real GDP, providing an increase by 1%. However changes in their relative prices do not seem to harm the output production. Crude oil prices have notably long-run impact on GDP, whereas in the short-run the GDP renders a positive reaction to oil shocks. Intensity is strongly endogenous to real GDP and a reduction on its level tantalizes the GDP growth. A rise in total final consumption also improves the GDP.

An interesting inference from the above empirical endeavor is that signs of the *"feedback hypothesis"* are observed in the case of household electricity price and GDP. However, as the resident electricity prices can Granger cause GDP at 10% according to VECM's output, we cannot conclude that bi-directional causality concerns the lnREP and the lnGDP; though evidence of *"growth hypothesis"* is identified. Notwithstanding, the existence of causality derived from GDP to residential electricity prices is ascertained. Therefore, our findings favor the *"conservation hypothesis"*. Likewise the bi-directional hypothesis with respect to lnFEC and lnREP is significant at 10% significance level. In contrast, a unidirectional short-run causality seems to emerge from industrial electricity prices to GDP. Thus, there is evidence on the *growth hypothesis* as far as the GDP and the industry price. Finally, causality yields from crude oil prices and industrial electricity prices to residential electricity prices in the short-run.

7. Discussion & Policy Remarks

This scientific attempt pursues the interference of energy prices on economic development within the framework of the European Union. The conclusions sustain the existence of long-run relations implying some interesting remarks on the European policies.

First of all, the energy prices seem to entrain each other in the EU, as signs of causality among them are observed. Furthermore, the effects of appreciations do not tantalize the economic growth. As it was expected from the economic orthodoxy increases in prices restricts the consumption, and thus may pose limits to GDP. However, in the EU a relative small reduction is observed due to an increase in residential electricity price, at approximately -0,5%. Nevertheless, the estimates indicate that the effects of an unexpected change in the European household electricity price are not counterbalanced for more than three years.

In contrast to the industry's sector, electricity prices demonstrate a small increase in real GDP. Thus, industrial electricity prices offer an alternative channel to EU to accomplish certain environmental and energy targets via imposing levies and taxes. In the case that the European institutions chose the path of further economic burdens, the taxation has to be relatively low. Furthermore, as the results sustain the absence of negative effects we conclude that the EU policies like the Emissions Trading Scheme do not harm the European welfare.

However, the significant negative relation that is evident in the case of the intensity and the real GDP implies the need of political action. Therefore, the adoption of countervailing measures is straightforward as the authorities impose new limits in conventional energy use.

Moreover, growth slowness due to crude oil shocks is not evident at first glance that favours the energy resources diversification in the EU economy. However, the IRF and FEVD interpretation support the existence of a long-term negative impact. The initial positive effect will be explained under the prism of monetary interventions. The Central Bank seeking to abate the shock's impact will execute a more loose monetary policy. While the stabilization and discretionary policies suffer from time lag, so as their positive impact are evident when the initial outbreak is expired.

From the estimates over the energy prices, it is entailed that increases in crude oil prices that may have a direct impact on the industrial electricity price are offset via reductions in residential electricity prices. Similarly, ascents in industrial electricity price result in reductions in the residential electricity sector. Furthermore, the decline in residential electricity price implies the leverage of the energy regulations with regard to consumer's protection and conditions of perfect competition. Finally, an interesting deduction comes from the graphical representation of IRFs which indicate that the GDP exhibits a long-run influence due to shocks from the examined variables.

To conclude, signs of interrelations have been found using four different estimation methods. Nevertheless, further research is needed vis-à-vis the energy prices and the economic prosperity.

Alternative models embodied with renewable energy prices and natural gas prices are necessary to conduct aiming to come to a safe conclusion over the causal and effect links among the energy prices and the European economic growth. That kind of models fosters the investigation of the potential results of the implemented energy policies, while it gives breathe to new measures and assumptions.

Furthermore, incorporating other significant macroeconomic aggregates like the unemployment, the inflation or the money supply can be used in order to assess the energy and growth transmission channels. Moreover, seasonal indicators, such as the cooling and heating days-included in the Eurostat's database- can be used. Data over the energy taxes and subsidies would be also meaningful tools for examining the impact of European energy and environmental policy measures and to what extent the member-states comply with the European rules.

The aforementioned models would be developed through VAR and VECM systems or by using the 2-Stage Least Squares or 3-Stage Least Squares allowing for instrumental and dummy variables. Another alternative is the ARDL models that permit the estimation among time series with different order of integration. ARDL models applied with an ECM and bounds tests offer an alternative for causality and permit the interpretation of short-run and long-run dynamics.

Delving deeply into the subject of energy prices and the breakthrough in the field of behavior economics, the future research would be orientated towards the investigation of herd behavior in the energy markets. Under the spectrum of herd behavior it will be assessed if imitation of investments decisions among the market participants would provoke excess price volatility and market instability in the EU markets. This would offer significant policy remarks over the establishment and the well-functioning of the European Energy Market, examining if the target model offers an open window for speculative tactics and finally tantalize the security of supply.

An example comes from the study of Palao and Padro (2016) that shed light on the case of herding in the EU ETS[125] or following the Trück and Yu's path trace out the investors herding on renewable sector[126].

Scientific attempts over the herding would be investigating with the aim of GARCH models that permit the examination of volatility and uncertainty as well.

A useful alternative is that of Generalized Capital Asset Pricing Model (GCAPM) which permits the examination of nonlinear relations among specific asset returns and the average market return[127] while the development of artificial neural networks would be used to predict the herding behavior, as in the Shen's (2018) study for different energy sectors of the Chinese Stock Exchange.

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APPENDIX

1.Unit Root Tests

Unit roots tests for lnGDP

```
. varsoc lnGDP

   Selection-order criteria
   Sample:  1984 - 2017                         Number of obs      =        34
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	7.57303				.039775	-.386649	-.371339	-.341756
1	96.3657	177.59*	1	0.000	.000227	-5.55093	-5.52031*	-5.46114*
2	97.506	2.2805	1	0.131	.000226*	-5.55918*	-5.51325	-5.4245
3	98.2912	1.5704	1	0.210	.000229	-5.54654	-5.4853	-5.36697
4	98.386	.18969	1	0.663	.000241	-5.4933	-5.41675	-5.26883

```
   Endogenous:  lnGDP
    Exogenous:  _cons
```

Dickey-Fuller

```
. dfuller lnGDP, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        36
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-1.529	-4.279	-3.556	-3.214

```
MacKinnon approximate p-value for Z(t) = 0.8188


. dfuller lnGDP,lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        36
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-1.534	-3.675	-2.969	-2.617

```
MacKinnon approximate p-value for Z(t) = 0.5168
```

```
. varsoc d.lnGDP

   Selection-order criteria
   Sample:  1985 - 2017                          Number of obs      =        33

  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC       HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  90.4757                       .000258  -5.42277  -5.40751  -5.37742  |
  |  1 |  92.5516  4.1517*   1  0.042  .000242* -5.48798* -5.45746* -5.39728* |
  |  2 |  92.9075  .71184    1  0.399  .000252  -5.44894  -5.40317   -5.3129   |
  |  3 |  93.2025  .58994    1  0.442  .000263  -5.40621  -5.34518  -5.22482  |
  |  4 |  93.2037  .00248    1  0.960   .00028  -5.34568  -5.26939  -5.11894  |
  +---------------------------------------------------------------------------+
   Endogenous:  D.lnGDP
    Exogenous:  _cons

. dfuller d.lnGDP, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.260            -4.288            -3.560            -3.216
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0036

. dfuller d.lnGDP, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.834            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0026

. pperron lnGDP, notrend

Phillips-Perron test for unit root                 Number of obs   =        37
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -0.625           -18.016           -12.884           -10.440
 Z(t)             -1.302            -3.668            -2.966            -2.616
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.6283
```

```
. pperron lnGDP, trend

Phillips-Perron test for unit root                 Number of obs   =        37
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)          -2.993          -24.036           -18.812           -16.176
 Z(t)            -1.030           -4.270            -3.552            -3.211
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9399

. pperron d.lnGDP

Phillips-Perron test for unit root                 Number of obs   =        36
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)         -22.199          -17.948           -12.852           -10.420
 Z(t)            -4.060           -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0011

. pperron d.lnGDP,trend

Phillips-Perron test for unit root                 Number of obs   =        36
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)         -22.270          -23.908           -18.736           -16.128
 Z(t)            -4.235           -4.279            -3.556            -3.214
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0040

. dfgls lnGDP

DF-GLS for lnGDP                                         Number of obs =    28
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------
    9            -1.211           -3.770            -2.727            -2.369
    8            -1.253           -3.770            -2.758            -2.422
    7            -1.339           -3.770            -2.815            -2.493
    6            -1.425           -3.770            -2.893            -2.579
    5            -1.234           -3.770            -2.984            -2.673
    4            -1.422           -3.770            -3.081            -2.769
    3            -1.333           -3.770            -3.179            -2.863
    2            -1.047           -3.770            -3.270            -2.949
    1            -1.300           -3.770            -3.348            -3.020

Opt Lag (Ng-Perron seq t) =  1 with RMSE  .0147572
Min SC   = -8.194031 at lag  1 with RMSE  .0147572
Min MAIC = -8.220019 at lag  1 with RMSE  .0147572
```

```
. dfgls d.lnGDP

DF-GLS for D.lnGDP                                   Number of obs =    27
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------
    9            -1.081           -3.770            -2.739            -2.369
    8            -1.601           -3.770            -2.761            -2.416
    7            -2.024           -3.770            -2.813            -2.485
    6            -2.092           -3.770            -2.889            -2.571
    5            -2.141           -3.770            -2.981            -2.667
    4            -2.573           -3.770            -3.082            -2.767
    3            -2.540           -3.770            -3.183            -2.865
    2            -2.842           -3.770            -3.279            -2.954
    1            -3.795           -3.770            -3.360            -3.030

Opt Lag (Ng-Perron seq t) = 0 [use maxlag(0)]
Min SC   = -8.146724 at lag  1 with RMSE  .0150643
Min MAIC = -6.791585 at lag  9 with RMSE  .0141808

. kpss lnGDP

KPSS test for lnGDP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnGDP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0            .71
    1           .375
    2           .265
    3           .212

. kpss lnGDP, notrend

KPSS test for lnGDP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnGDP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           3.76
    1           1.95
    2           1.34
    3           1.03
```

```
. kpss d.lnGDP

KPSS test for D.lnGDP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnGDP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0            .106
    1            .082
    2           .0798
    3             .08

. kpss d.lnGDP, notrend

KPSS test for D.lnGDP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnGDP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0            .335
    1            .249
    2             .23
    3            .219
```

Unit root tests for lnREP

```
. varsoc lnREP

   Selection-order criteria
   Sample:  1984 - 2016                        Number of obs     =        33
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	32.0185				.008935	-1.87991	-1.86465	-1.83456
1	77.3098	90.583	1	0.000	.00061	-4.56423	-4.53371	-4.47353
2	79.8353	5.051	1	0.025	.000556	-4.65668	-4.61091	-4.52064
3	82.4048	5.139*	1	0.023	.000506*	-4.75181*	-4.69077*	-4.57041*
4	83.3988	1.988	1	0.159	.000507	-4.75144	-4.67515	-4.5247

```
   Endogenous:  lnREP
    Exogenous:  _cons
```

```
. dfuller lnREP, trend lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        33

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.563            -4.306            -3.568            -3.221
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.8066

. dfuller lnREP, notrend lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        33

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.640            -3.696            -2.978            -2.620
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4623


. varsoc d.lnREP

   Selection-order criteria
   Sample:  1985 - 2016                         Number of obs      =        32
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	74.423				.000595	-4.58894	-4.57376	-4.54313
1	76.9368	5.0276*	1	0.025	.000541	-4.68355	-4.65319	-4.59194
2	78.8462	3.8187	1	0.051	.000512*	-4.74039*	-4.69484*	-4.60297*
3	79.3861	1.0798	1	0.299	.000527	-4.71163	-4.6509	-4.52841
4	79.3861	.0001	1	0.992	.000562	-4.64913	-4.57322	-4.42011

```
   Endogenous:  D.lnREP
    Exogenous:  _cons

. dfuller d.lnREP, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        34

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.803            -4.297            -3.564            -3.218
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0164

. dfuller d.lnREP

Dickey-Fuller test for unit root                   Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.233            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0006
```

```
. pperron lnREP, trend

Phillips-Perron test for unit root                Number of obs   =        36
                                                  Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)          -0.753          -23.908           -18.736           -16.128
 Z(t)            -0.360           -4.279            -3.556            -3.214
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.9880

. pperron lnREP, notrend

Phillips-Perron test for unit root                Number of obs   =        36
                                                  Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)          -0.701          -17.948           -12.852           -10.420
 Z(t)            -0.299           -3.675            -2.969            -2.617
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.9257


. pperron d.lnREP, trend

Phillips-Perron test for unit root                Number of obs   =        35
                                                  Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)         -24.939          -23.780           -18.660           -16.080
 Z(t)            -5.245           -4.288            -3.560            -3.216
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0001

. pperron d.lnREP, notrend

Phillips-Perron test for unit root                Number of obs   =        35
                                                  Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)         -24.848          -17.880           -12.820           -10.400
 Z(t)            -4.329           -3.682            -2.972            -2.618
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0004
```

```
. dfgls lnREP

DF-GLS for lnREP                                         Number of obs =    27
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------

    9           -1.496           -3.770            -2.739            -2.369
    8           -1.666           -3.770            -2.761            -2.416
    7           -1.720           -3.770            -2.813            -2.485
    6           -1.905           -3.770            -2.889            -2.571
    5           -2.434           -3.770            -2.981            -2.667
    4           -2.130           -3.770            -3.082            -2.767
    3           -1.711           -3.770            -3.183            -2.865
    2           -1.179           -3.770            -3.279            -2.954
    1           -0.483           -3.770            -3.360            -3.030

Opt Lag (Ng-Perron seq t) =  2 with RMSE   .020973
Min SC   = -7.362833 at lag  2 with RMSE   .020973
Min MAIC = -7.476573 at lag  1 with RMSE  .0227066

. dfgls d.lnREP

DF-GLS for D.lnREP                                       Number of obs =    26
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------

    9           -1.255           -3.770            -2.756            -2.371
    8           -1.590           -3.770            -2.766            -2.411
    7           -1.389           -3.770            -2.812            -2.476
    6           -1.394           -3.770            -2.885            -2.562
    5           -1.345           -3.770            -2.978            -2.660
    4           -1.196           -3.770            -3.082            -2.764
    3           -1.272           -3.770            -3.188            -2.866
    2           -1.490           -3.770            -3.288            -2.960
    1           -2.005           -3.770            -3.373            -3.039

Opt Lag (Ng-Perron seq t) = 0 [use maxlag(0)]
Min SC   = -7.389164 at lag  1 with RMSE  .0219301
Min MAIC = -7.231867 at lag  3 with RMSE  .0209934

. kpss lnREP

KPSS test for lnREP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnREP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0          .832
    1          .433
    2          .299
    3          .234
```

```
. kpss lnREP, notrend

KPSS test for lnREP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnREP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           .977
    1           .512
    2           .356
    3            .28


. kpss d.lnREP

KPSS test for D.lnREP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnREP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0           .218
    1           .175
    2           .152
    3           .136

. kpss d.lnREP, notrend

KPSS test for D.lnREP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnREP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0            .72
    1            .53
    2           .424
    3           .357
```

Unit root tests for lnIEP

```
. varsoc lnIEP

   Selection-order criteria
   Sample:  1984 - 2016                        Number of obs      =        33
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	8.42577				.037332	-.450047	-.434788	-.404698
1	54.0111	91.171*	1	0.000	.002504*	-3.15219*	-3.12167*	-3.06149*
2	54.0238	.02545	1	0.873	.002659	-3.09235	-3.04658	-2.95631
3	54.0709	.09411	1	0.759	.002819	-3.0346	-2.97356	-2.8532
4	55.0971	2.0525	1	0.152	.002818	-3.03619	-2.9599	-2.80945

```
   Endogenous:  lnIEP
    Exogenous:  _cons

. dfuller lnIEP, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        35
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-1.181	-4.288	-3.560	-3.216

```
MacKinnon approximate p-value for Z(t) = 0.9143

. dfuller lnIEP, notrend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        35
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	0.093	-3.682	-2.972	-2.618

```
MacKinnon approximate p-value for Z(t) = 0.9656

. varsoc d.lnIEP

   Selection-order criteria
   Sample:  1985 - 2016                        Number of obs      =        32
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	52.1143				.002399*	-3.19465*	-3.17946*	-3.14884*
1	52.1345	.04025	1	0.841	.002551	-3.1334	-3.10304	-3.0418
2	52.2038	.13876	1	0.710	.002705	-3.07524	-3.02969	-2.93783
3	53.1509	1.894	1	0.169	.002716	-3.07193	-3.0112	-2.88871
4	53.8036	1.3056	1	0.253	.002779	-3.05023	-2.97431	-2.82121

```
   Endogenous:  D.lnIEP
    Exogenous:  _cons
```

```
. dfuller d.lnIEP, trend

Dickey-Fuller test for unit root                   Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.668            -4.288            -3.560            -3.216
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller d.lnIEP, notrend

Dickey-Fuller test for unit root                   Number of obs   =        35

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.495            -3.682            -2.972            -2.618
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. pperron lnIEP, trend

Phillips-Perron test for unit root                 Number of obs   =        36
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -3.017           -23.908           -18.736           -16.128
 Z(t)             -1.182            -4.279            -3.556            -3.214
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9142

. pperron lnIEP, notrend

Phillips-Perron test for unit root                 Number of obs   =        36
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -0.111           -17.948           -12.852           -10.420
 Z(t)             -0.068            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.9526

. pperron d.lnIEP, trend

Phillips-Perron test for unit root                 Number of obs   =        35
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)          -36.165           -23.780           -18.660           -16.080
 Z(t)             -5.677            -4.288            -3.560            -3.216
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. pperron d.lnIEP, notrend

Phillips-Perron test for unit root                 Number of obs   =        35
                                                   Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)         -36.205           -17.880           -12.820           -10.400
 Z(t)            -5.539            -3.682            -2.972            -2.618
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000

. dfgls lnIEP

DF-GLS for lnIEP                                        Number of obs =    27
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
    9           -1.058           -3.770            -2.739            -2.369
    8           -1.743           -3.770            -2.761            -2.416
    7           -1.353           -3.770            -2.813            -2.485
    6           -2.118           -3.770            -2.889            -2.571
    5           -2.262           -3.770            -2.981            -2.667
    4           -1.997           -3.770            -3.082            -2.767
    3           -1.503           -3.770            -3.183            -2.865
    2           -1.046           -3.770            -3.279            -2.954
    1           -0.927           -3.770            -3.360            -3.030

Opt Lag (Ng-Perron seq t) = 0 [use maxlag(0)]
Min SC   = -5.767549 at lag  1 with RMSE   .049497
Min MAIC = -5.864819 at lag  1 with RMSE   .049497

. dfgls d.lnIEP

DF-GLS for D.lnIEP                                      Number of obs =    26
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value            Value
──────────────────────────────────────────────────────────────────────────────
    9           -1.579           -3.770            -2.756            -2.371
    8           -2.131           -3.770            -2.766            -2.411
    7           -1.466           -3.770            -2.812            -2.476
    6           -2.046           -3.770            -2.885            -2.562
    5           -1.460           -3.770            -2.978            -2.660
    4           -1.368           -3.770            -3.082            -2.764
    3           -1.507           -3.770            -3.188            -2.866
    2           -1.963           -3.770            -3.288            -2.960
    1           -3.097           -3.770            -3.373            -3.039

Opt Lag (Ng-Perron seq t) =  8 with RMSE  .0385621
Min SC   = -5.722103 at lag  1 with RMSE  .0504707
Min MAIC = -5.152353 at lag  3 with RMSE  .0480244
```

```
. kpss lnIEP

KPSS test for lnIEP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnIEP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0          .771
    1          .404
    2           .28
    3          .219

. kpss lnIEP, notrend

KPSS test for lnIEP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnIEP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0          2.46
    1          1.28
    2           .89
    3          .693

. kpss d.lnIEP

KPSS test for D.lnIEP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnIEP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0          .111
    1          .111
    2          .111
    3          .102

. kpss d.lnIEP, notrend

KPSS test for D.lnIEP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnIEP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           .28
    1          .269
    2          .257
    3          .228
```

Unit Roots Tests lnCOP

```
. varsoc lnCOP
```

Selection-order criteria
Sample: 1984 - 2017 Number of obs = 34

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-25.1382				.272444	1.53754	1.55285	1.58243
1	-1.65825	46.96*	1	0.000	.072617*	.215191*	.245811*	.304977*
2	-1.57511	.16628	1	0.683	.076666	.269124	.315053	.403803
3	-1.52778	.09465	1	0.758	.081137	.325164	.386403	.504736
4	-.915718	1.2241	1	0.269	.083097	.347983	.424532	.572448

Endogenous: lnCOP
Exogenous: _cons

```
. dfuller lnCOP, trend lags(1)
```

Augmented Dickey-Fuller test for unit root Number of obs = 36

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.288	-4.279	-3.556	-3.214

MacKinnon approximate p-value for Z(t) = 0.4405

```
. dfuller lnCOP, notrend lags(1)
```

Augmented Dickey-Fuller test for unit root Number of obs = 36

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.828	-3.675	-2.969	-2.617

MacKinnon approximate p-value for Z(t) = 0.3666

```
. varsoc d.lnCOP
```

Selection-order criteria
Sample: 1985 - 2017 Number of obs = 33

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-3.37099				.07631*	.264908*	.280167*	.310257*
1	-3.37099	3.7e-06	1	0.998	.081089	.325514	.356031	.416212
2	-3.1471	.44778	1	0.503	.085024	.372551	.418327	.508597
3	-2.92105	.4521	1	0.501	.089169	.419457	.480491	.600852
4	-2.85812	.12584	1	0.723	.094489	.47625	.552542	.702994

Endogenous: D.lnCOP
Exogenous: _cons

```
. dfuller d.lnCOP, trend

Dickey-Fuller test for unit root                   Number of obs   =        36

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.721            -4.279            -3.556            -3.214
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller d.lnCOP, notrend

Dickey-Fuller test for unit root                   Number of obs   =        36

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.700            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000


. pperron lnCOP, trend

Phillips-Perron test for unit root                 Number of obs   =        37
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -6.542           -24.036           -18.812           -16.176
 Z(t)             -2.227            -4.270            -3.552            -3.211
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.4745

. pperron lnCOP, notrend

Phillips-Perron test for unit root                 Number of obs   =        37
                                                   Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)           -5.919           -18.016           -12.884           -10.440
 Z(t)             -1.929            -3.668            -2.966            -2.616
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.3184
```

```
. pperron d.lnCOP, trend

Phillips-Perron test for unit root                Number of obs   =        36
                                                  Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)         -34.424           -23.908           -18.736           -16.128
 Z(t)            -5.713            -4.279            -3.556            -3.214
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. pperron d.lnCOP, notrend

Phillips-Perron test for unit root                Number of obs   =        36
                                                  Newey-West lags =         3

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)         -34.293           -17.948           -12.852           -10.420
 Z(t)            -5.692            -3.675            -2.969            -2.617
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000


. dfgls lnCOP

DF-GLS for lnCOP                                        Number of obs =    28
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------
    9            -1.931           -3.770            -2.727            -2.369
    8            -2.299           -3.770            -2.758            -2.422
    7            -2.183           -3.770            -2.815            -2.493
    6            -1.849           -3.770            -2.893            -2.579
    5            -1.406           -3.770            -2.984            -2.673
    4            -1.126           -3.770            -3.081            -2.769
    3            -1.313           -3.770            -3.179            -2.863
    2            -1.128           -3.770            -3.270            -2.949
    1            -1.457           -3.770            -3.348            -3.020

Opt Lag (Ng-Perron seq t) = 0 [use maxlag(0)]
Min SC   = -2.598205 at lag  1 with RMSE  .2421713
Min MAIC = -2.638955 at lag  2 with RMSE  .2347801
```

```
. dfgls d.lnCOP

DF-GLS for D.lnCOP                                     Number of obs =    27
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------

    9            -1.315           -3.770            -2.739            -2.369
    8            -0.993           -3.770            -2.761            -2.416
    7            -0.690           -3.770            -2.813            -2.485
    6            -0.671           -3.770            -2.889            -2.571
    5            -0.865           -3.770            -2.981            -2.667
    4            -1.479           -3.770            -3.082            -2.767
    3            -2.335           -3.770            -3.183            -2.865
    2            -2.374           -3.770            -3.279            -2.954
    1            -4.362           -3.770            -3.360            -3.030

Opt Lag (Ng-Perron seq t) = 0 [use maxlag(0)]
Min SC   =  -2.54298 at lag  1 with RMSE  .2481906
Min MAIC = -1.886181 at lag  6 with RMSE  .2353627

. kpss lnCOP

KPSS test for lnCOP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnCOP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0           .625
    1           .343
    2           .248
    3             .2


. kpss lnCOP, notrend

KPSS test for lnCOP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnCOP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           .951
    1           .513
    2           .364
    3           .289
```

```
. kpss d.lnCOP

KPSS test for D.lnCOP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnCOP is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0           .122
    1           .122
    2           .134
    3           .134

. kpss d.lnCOP, notrend

KPSS test for D.lnCOP

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnCOP is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           .223
    1            .22
    2           .235
    3           .229
```

Unit Root Tests lnCO2INTENS

```
. varsoc lnCO2INTENS

   Selection-order criteria
   Sample:  1984 - 2014                        Number of obs      =        31
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	39.1503				.004996	-2.46131	-2.44623	-2.41505
1	98.5258	118.75	1	0.000	.000116	-6.22747	-6.19731	-6.13495
2	100.608	4.1653*	1	0.041	.000108*	-6.29732*	-6.25208*	-6.15854*
3	101.016	.81424	1	0.367	.000112	-6.25907	-6.19875	-6.07404
4	101.028	.02536	1	0.873	.00012	-6.19537	-6.11997	-5.96408

```
   Endogenous:  lnCO2INTENS
    Exogenous:  _cons

. dfuller lnCO2INTENS, trend lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs    =        32
```

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.197	-4.316	-3.572	-3.223

```
MacKinnon approximate p-value for Z(t) = 0.0849
```

```
. dfuller lnCO2INTENS, notrend lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        32

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -1.541            -3.702            -2.980            -2.622
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.5129

. varsoc d.lnCO2INTENS

   Selection-order criteria
   Sample:  1985 - 2014                        Number of obs      =        30
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  95.0195                       .000111  -6.26796  -6.25302  -6.22126  |
  |  1 |  97.1094  4.1798*   1  0.041  .000103* -6.34062* -6.31074* -6.24721* |
  |  2 |  97.9478  1.6769    1  0.195  .000104  -6.32985  -6.28503  -6.18973  |
  |  3 |  97.9524  .00911    1  0.924  .000112  -6.26349  -6.20372  -6.07666  |
  |  4 |  98.1462  .38768    1  0.534  .000118  -6.20975  -6.13504  -5.97621  |
  +---------------------------------------------------------------------------+
   Endogenous:  D.lnCO2INTENS
    Exogenous:  _cons

. dfuller d.lnCO2INTENS, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        32

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.414            -4.316            -3.572            -3.223
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0496

. dfuller d.lnCO2INTENS, lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        32

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -3.341            -3.702            -2.980            -2.622
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0131
```

```
. pperron lnCO2INTENS, trend

Phillips-Perron test for unit root                 Number of obs   =        34
                                                   Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)           -8.467           -23.652           -18.584           -16.032
 Z(t)             -3.517            -4.297            -3.564            -3.218
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0376

. pperron lnCO2INTENS, notrend

Phillips-Perron test for unit root                 Number of obs   =        34
                                                   Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)           -1.401           -17.812           -12.788           -10.380
 Z(t)             -2.468            -3.689            -2.975            -2.619
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.1234

. pperron d.lnCO2INTENS, trend

Phillips-Perron test for unit root                 Number of obs   =        33
                                                   Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)          -47.245           -23.524           -18.508           -15.984
 Z(t)             -7.635            -4.306            -3.568            -3.221
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000

. pperron d.lnCO2INTENS, notrend

Phillips-Perron test for unit root                 Number of obs   =        33
                                                   Newey-West lags =         3

                               ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)          -45.706           -17.744           -12.756           -10.360
 Z(t)             -7.290            -3.696            -2.978            -2.620
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000
```

```
. dfgls lnCO2INTENS

DF-GLS for lnCO2INTENS                                   Number of obs =    25
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------

    9            -1.102           -3.770            -2.779            -2.377
    8            -0.956           -3.770            -2.775            -2.407
    7            -1.421           -3.770            -2.812            -2.468
    6            -1.415           -3.770            -2.882            -2.552
    5            -1.421           -3.770            -2.975            -2.652
    4            -1.151           -3.770            -3.081            -2.759
    3            -1.107           -3.770            -3.191            -2.866
    2            -1.160           -3.770            -3.296            -2.965
    1            -1.166           -3.770            -3.386            -3.049

Opt Lag (Ng-Perron seq t) =  1 with RMSE  .0082979
Min SC   = -9.326004 at lag  1 with RMSE  .0082979
Min MAIC =  -9.36163 at lag  1 with RMSE  .0082979

. dfgls d.lnCO2INTENS

DF-GLS for D.lnCO2INTENS                                 Number of obs =    24
Maxlag = 9 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------

    9            -0.791           -3.770            -2.811            -2.388
    8            -1.111           -3.770            -2.788            -2.406
    7            -1.525           -3.770            -2.814            -2.460
    6            -1.171           -3.770            -2.879            -2.542
    5            -1.078           -3.770            -2.971            -2.643
    4            -0.985           -3.770            -3.080            -2.754
    3            -1.405           -3.770            -3.195            -2.866
    2            -1.900           -3.770            -3.305            -2.970
    1            -2.500           -3.770            -3.400            -3.058

Opt Lag (Ng-Perron seq t) = 0 [use maxlag(0)]
Min SC   = -9.258524 at lag  1 with RMSE  .0085512
Min MAIC = -8.745823 at lag  4 with RMSE  .0080804

KPSS test for lnCO2INTENS

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnCO2INTENS is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0           .527
    1           .307
    2           .225
    3           .185
```

```
. kpss lnCO2INTENS, notrend

KPSS test for lnCO2INTENS

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnCO2INTENS is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           3.28
    1           1.75
    2           1.22
    3           .961

KPSS test for D.lnCO2INTENS

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnCO2INTENS is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0           .122
    1           .181
    2           .161
    3           .167


KPSS test for D.lnCO2INTENS

Maxlag = 3 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnCO2INTENS is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           .329
    1            .44
    2           .372
    3           .359
```

Unit Root Test lnFEC

```
. varsoc lnFEC

   Selection-order criteria
   Sample:  1994 - 2016                            Number of obs      =        23
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	44.7798				.001301	-3.80693	-3.79452	-3.75757
1	54.7899	20.02	1	0.000	.000594	-4.59043	-4.5656	-4.49169*
2	55.8455	2.1112	1	0.146	.000592	-4.59526	-4.55801	-4.44715
3	56.5899	1.4888	1	0.222	.000607	-4.57304	-4.52337	-4.37556
4	59.354	5.5282*	1	0.019	.000522*	-4.72644*	-4.66435*	-4.47959

```
   Endogenous:  lnFEC
    Exogenous:  _cons

. dfuller lnFEC, trend lags(4)

Augmented Dickey-Fuller test for unit root          Number of obs   =        22
```

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.458	-4.380	-3.600	-3.240

```
MacKinnon approximate p-value for Z(t) = 0.8432

. dfuller lnFEC, notrend lags(4)

Augmented Dickey-Fuller test for unit root          Number of obs   =        22
```

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.314	-3.750	-3.000	-2.630

```
MacKinnon approximate p-value for Z(t) = 0.1676

. varsoc d.lnFEC

   Selection-order criteria
   Sample:  1995 - 2016                            Number of obs      =        22
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	50.0063				.00068	-4.45512	-4.44344	-4.40553
1	51.6713	3.3299	1	0.068	.000641*	-4.51557*	-4.49221*	-4.41639*
2	51.8506	.35857	1	0.549	.000691	-4.44096	-4.40591	-4.29218
3	52.9157	2.1303	1	0.144	.000689	-4.44688	-4.40015	-4.24851
4	53.73	1.6285	1	0.202	.000703	-4.43	-4.37158	-4.18203

```
   Endogenous:  D.lnFEC
    Exogenous:  _cons
```

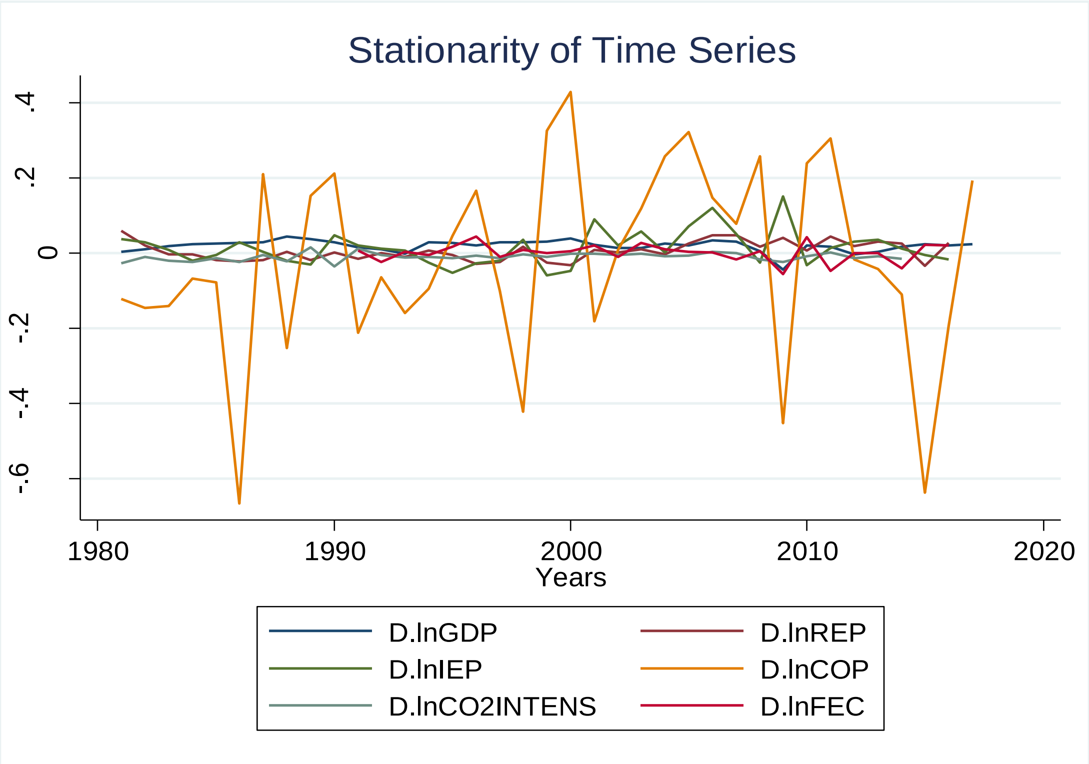
```
. dfuller d.lnFEC, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        24

                              ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(t)             -3.546            -4.380            -3.600            -3.240
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0347

. dfuller d.lnFEC, notrend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =        24

                              ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(t)             -3.149            -3.750            -3.000            -2.630
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0231

. pperron lnFEC, trend

Phillips-Perron test for unit root                 Number of obs   =        26
                                                   Newey-West lags =         2

                              ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)           -4.580           -22.628           -17.976           -15.648
 Z(t)             -1.462            -4.371            -3.596            -3.238
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.8419

. pperron lnFEC, notrend

Phillips-Perron test for unit root                 Number of obs   =        26
                                                   Newey-West lags =         2

                              ────────── Interpolated Dickey-Fuller ─────────
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
──────────────────────────────────────────────────────────────────────────────
 Z(rho)           -5.062           -17.268           -12.532           -10.220
 Z(t)             -1.699            -3.743            -2.997            -2.629
──────────────────────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.4314
```

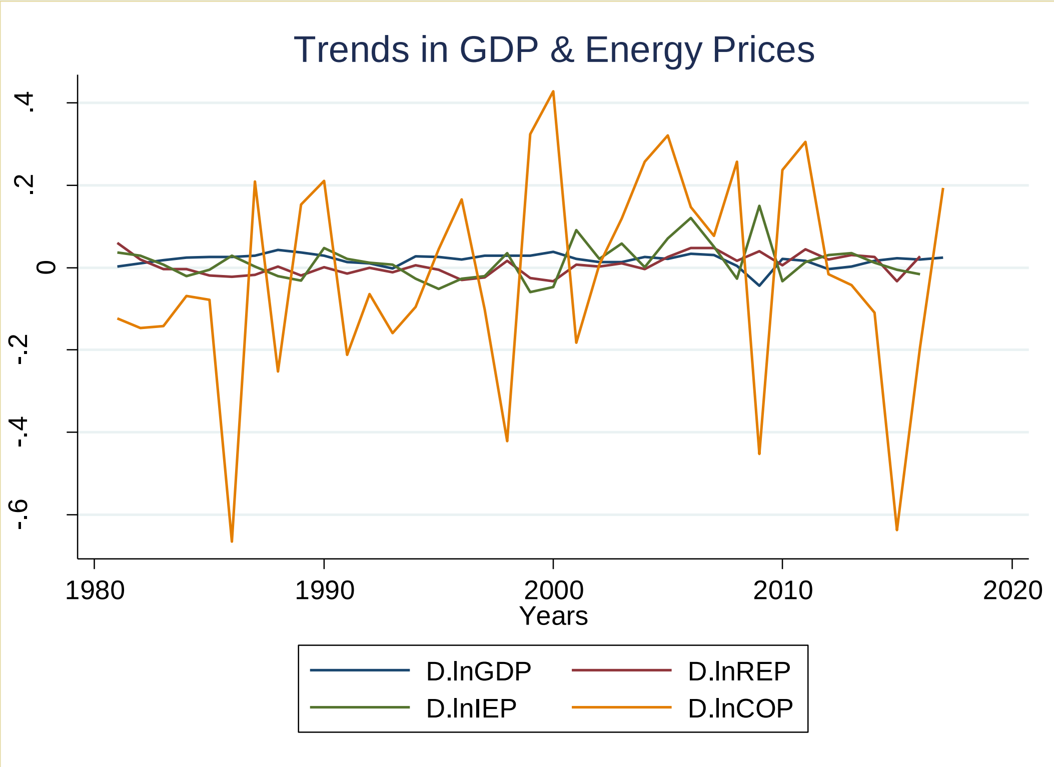
```
. pperron d.lnFEC, trend

Phillips-Perron test for unit root                 Number of obs   =        25
                                                   Newey-West lags =         2

                              ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)          -36.278           -22.500           -17.900           -15.600
 Z(t)             -7.127            -4.380            -3.600            -3.240
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000


. pperron d.lnFEC, notrend

Phillips-Perron test for unit root                 Number of obs   =        25
                                                   Newey-West lags =         2

                              ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(rho)          -36.800           -17.200           -12.500           -10.200
 Z(t)             -6.845            -3.750            -3.000            -2.630
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

. dfgls lnFEC

DF-GLS for lnFEC                                         Number of obs =    18
Maxlag = 8 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------
    8            -1.665           -3.770            -3.101            -2.534
    7            -1.876           -3.770            -2.946            -2.462
    6            -1.889           -3.770            -2.903            -2.476
    5            -1.586           -3.770            -2.947            -2.555
    4            -1.665           -3.770            -3.052            -2.678
    3            -1.832           -3.770            -3.194            -2.824
    2            -0.922           -3.770            -3.347            -2.972
    1            -0.658           -3.770            -3.485            -3.102

Opt Lag (Ng-Perron seq t) =  3 with RMSE  .0179336
Min SC   = -7.399856 at lag  3 with RMSE  .0179336
Min MAIC = -7.438195 at lag  1 with RMSE  .0222297
```

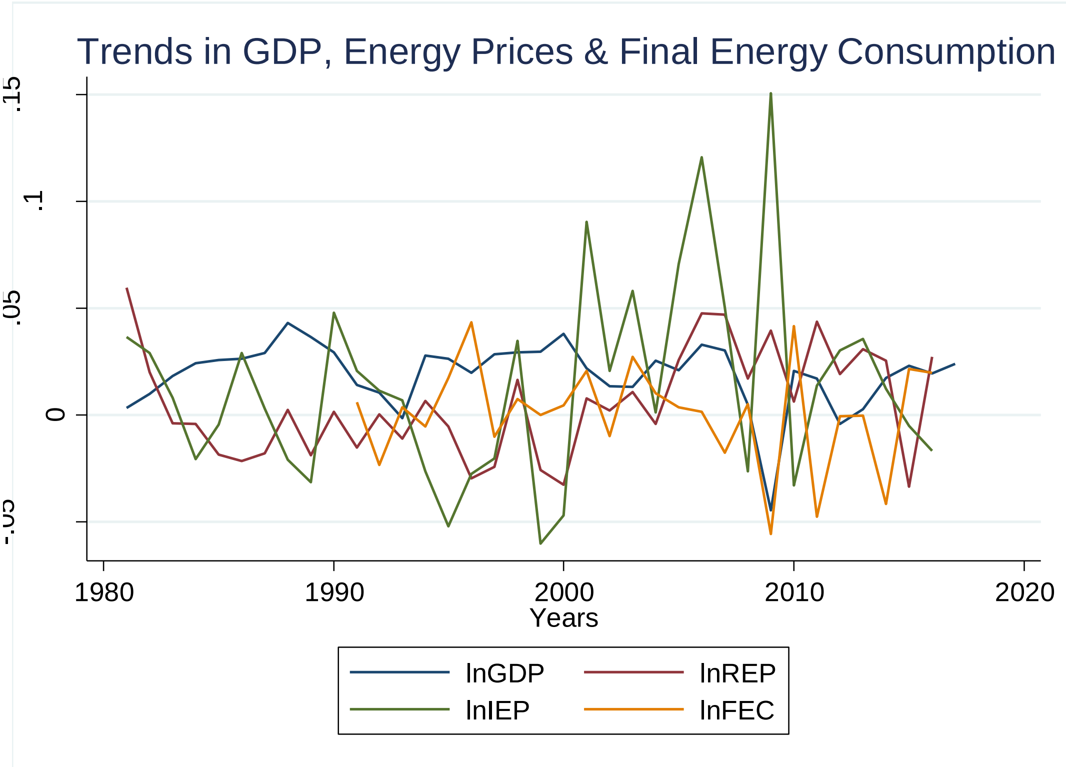
```
. dfgls d.lnFEC

DF-GLS for D.lnFEC                                      Number of obs =    17
Maxlag = 8 chosen by Schwert criterion

               DF-GLS tau      1% Critical       5% Critical      10% Critical
  [lags]     Test Statistic        Value             Value             Value
------------------------------------------------------------------------------
    8           -1.333          -3.770            -3.240            -2.611
    7           -1.342          -3.770            -3.014            -2.488
    6           -1.244          -3.770            -2.927            -2.471
    5           -1.147          -3.770            -2.946            -2.534
    4           -1.386          -3.770            -3.043            -2.654
    3           -1.323          -3.770            -3.188            -2.805
    2           -1.371          -3.770            -3.349            -2.963
    1           -2.875          -3.770            -3.498            -3.103

Opt Lag (Ng-Perron seq t) =  2 with RMSE   .020026
Min SC   = -7.321474 at lag  2 with RMSE   .020026
Min MAIC = -5.647917 at lag  2 with RMSE   .020026

. kpss lnFEC

KPSS test for lnFEC

Maxlag = 2 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnFEC is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0          .548
    1           .31
    2          .221

. kpss lnFEC, notrend

KPSS test for lnFEC

Maxlag = 2 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: lnFEC is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0           .716
    1           .402
    2           .285

. kpss d.lnFEC

KPSS test for D.lnFEC

Maxlag = 2 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnFEC is trend stationary

10%: 0.119  5% : 0.146  2.5%: 0.176  1% : 0.216

Lag order    Test statistic
    0          .0525
    1          .0885
    2          .0883
```

```
. kpss d.lnFEC, notrend

KPSS test for D.lnFEC

Maxlag = 2 chosen by Schwert criterion
Autocovariances weighted by Bartlett kernel

Critical values for H0: D.lnFEC is level stationary

10%: 0.347  5% : 0.463  2.5%: 0.574  1% : 0.739

Lag order    Test statistic
    0            .136
    1            .216
    2            .201
```

2.Graphs




Trends in GDP & Energy Prices
.4
.2
0
-.2
-.4
-.6
1980
1990
2000
2010
2020
Years
D.lnGDP
D.lnREP
D.lnIEP
D.lnCOP


Trends in GDP, Energy Prices & Final Energy Consumption
.15
.1
.05
0
-.05
1980
1990
2000
2010
2020
Years
lnGDP
lnREP
lnIEP
lnFEC

3.Johansen test for Cointegration

Selection-order criteria
Sample: 1994 - 2014 Number of obs = 21

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	208.839				1.6e-16	-19.318	-19.2532	-19.0196
1	357.91	298.14	36	0.000	4.1e-21	-30.0867	-29.6333	-27.9977
2	442.031	168.24*	36	0.000	1.2e-22	-34.6696	-33.8276	-30.79
3	.	.	36	.	-1.7e-83*	.	.	.
4	3878.56	.	36	.	.	-357.387*	-356.027*	-351.12*

Endogenous: lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC
Exogenous: _cons

Johansen test according to Likelihood Ratio (LR)

Case 1: unrestricted trend

```
. vecrank lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, trend(trend) max levela
```

Johansen tests for cointegration
Trend: trend Number of obs = 23
Sample: 1992 - 2014 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	1% critical value
0	48	364.67863		230.7262	104.94	114.36
1	59	413.82252	0.98607	132.4384	77.74	85.78
2	68	443.03501	0.92115	74.0135	54.64	61.21
3	75	456.71693	0.69570	46.6496	34.55	40.49
4	80	468.15746	0.63021	23.7685	18.17	23.46
5	83	475.64934	0.47872	8.7848	3.74	6.40
6	84	480.04174	0.31747			

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value	1% critical value
0	48	364.67863		98.2878	42.48	48.17
1	59	413.82252	0.98607	58.4250	36.41	41.58
2	68	443.03501	0.92115	27.3638	30.33	35.68
3	75	456.71693	0.69570	22.8811	23.78	28.83
4	80	468.15746	0.63021	14.9838	16.87	21.47
5	83	475.64934	0.47872	8.7848	3.74	6.40
6	84	480.04174	0.31747			

Case2: restricted trend

```
. vecrank lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, trend(rtrend) max levela
```

Johansen tests for cointegration

Trend: rtrend Number of obs = 23

Sample: 1992 - 2014 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	1% critical value
0	42	362.66335		234.7568	114.90	124.75
1	54	412.53152	0.98692	135.0204	87.31	96.58
2	64	442.18661	0.92413	75.7103	62.99	70.05
3	72	455.92821	0.69727	48.2270*1	42.44	48.45
4	78	467.43213	0.63225	25.2192*5	25.32	30.45
5	82	474.9502	0.47991	10.1831	12.25	16.26
6	84	480.04174	0.35773			

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value	1% critical value
0	42	362.66335		99.7363	43.97	49.51
1	54	412.53152	0.98692	59.3102	37.52	42.36
2	64	442.18661	0.92413	27.4832	31.46	36.65
3	72	455.92821	0.69727	23.0078	25.54	30.34
4	78	467.43213	0.63225	15.0361	18.96	23.65
5	82	474.9502	0.47991	10.1831	12.52	16.26
6	84	480.04174	0.35773			

Case 3: unrestricted constant

```
. vecrank lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, trend(constant) max level99
```

Johansen tests for cointegration

Trend: constant Number of obs = 23

Sample: 1992 - 2014 Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	1% critical value
0	42	362.66335	.	205.8754	103.18
1	53	409.94635	0.98362	111.3094	76.07
2	62	438.84572	0.91897	53.5106*	54.46
3	69	451.64388	0.67139	27.9143	35.65
4	74	460.31044	0.52934	10.5812	20.04
5	77	465.41143	0.35826	0.3792	6.65
6	78	465.60104	0.01635		

maximum rank	parms	LL	eigenvalue	max statistic	1% critical value
0	42	362.66335	.	94.5660	45.10
1	53	409.94635	0.98362	57.7987	38.77
2	62	438.84572	0.91897	25.5963	32.24
3	69	451.64388	0.67139	17.3331	25.52
4	74	460.31044	0.52934	10.2020	18.63
5	77	465.41143	0.35826	0.3792	6.65
6	78	465.60104	0.01635		

Case 4: restricted constant

```
. vecrank lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, trend(rconstant) max levela

                       Johansen tests for cointegration
Trend: rconstant                                        Number of obs =      23
Sample:  1992 - 2014                                             Lags =       2
-------------------------------------------------------------------------------
maximum                                      trace    5% critical  1% critical
  rank    parms       LL       eigenvalue  statistic     value        value
    0      36    351.20253                 228.7970     102.14       111.01
    1      48    398.64435     0.98384     133.9134      76.07        84.45
    2      58    427.94366     0.92174      75.3148      53.12        60.16
    3      66    443.31991     0.73738      44.5623      34.91        41.07
    4      72    453.42467     0.58467      24.3527*1    19.96        24.60
    5      76     462.0865     0.52914       7.0291*5     9.42        12.97
    6      78    465.60104     0.26333
-------------------------------------------------------------------------------
maximum                                       max     5% critical  1% critical
  rank    parms       LL       eigenvalue  statistic     value        value
    0      36    351.20253                  94.8836      40.30        46.82
    1      48    398.64435     0.98384      58.5986      34.40        39.79
    2      58    427.94366     0.92174      30.7525      28.14        33.24
    3      66    443.31991     0.73738      20.2095      22.00        26.81
    4      72    453.42467     0.58467      17.3237      15.67        20.20
    5      76     462.0865     0.52914       7.0291       9.24        12.97
    6      78    465.60104     0.26333
-------------------------------------------------------------------------------
```

Case 5: no trend no constant

```
. vecrank lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, trend(none) max levela

                       Johansen tests for cointegration
Trend: none                                             Number of obs =      23
Sample:  1992 - 2014                                             Lags =       2
-------------------------------------------------------------------------------
maximum                                      trace    5% critical  1% critical
  rank    parms       LL       eigenvalue  statistic     value        value
    0      36    351.20253                 183.1368      82.49        90.45
    1      47    387.81491     0.95857     109.9120      59.46        66.52
    2      56    416.35695     0.91642      52.8279      39.89        45.58
    3      63     429.4548     0.67984      26.6322*1    24.31        29.75
    4      68    438.87735     0.55928       7.7871*5    12.53        16.31
    5      71    442.51817     0.27137       0.5055       3.84         6.51
    6      72    442.77092     0.02174
-------------------------------------------------------------------------------
maximum                                       max     5% critical  1% critical
  rank    parms       LL       eigenvalue  statistic     value        value
    0      36    351.20253                  73.2248      36.36        41.00
    1      47    387.81491     0.95857      57.0841      30.04        35.17
    2      56    416.35695     0.91642      26.1957      23.80        28.82
    3      63     429.4548     0.67984      18.8451      17.89        22.99
    4      68    438.87735     0.55928       7.2816      11.44        15.69
    5      71    442.51817     0.27137       0.5055       3.84         6.51
    6      72    442.77092     0.02174
-------------------------------------------------------------------------------
```

4.Engle-Granger 2-step procedure

```
. egranger lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, lags(1) reg
Replacing variable _egresid...

Augmented Engle-Granger test for cointegration        N (1st step)  =        25
Number of lags    =  1                                N (test)      =        23
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.609	-6.409	-5.438	-4.981

Critical values from MacKinnon (1990, 2010)

Engle-Granger 1st-step regression

lnGDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnREP	-.6724846	.2853075	-2.36	0.029	-1.26964	-.075329
lnIEP	.2498798	.1170697	2.13	0.046	.00485	.4949095
lnCOP	.0557998	.0256049	2.18	0.042	.0022081	.1093914
lnCO2INTENS	-1.920597	.1864961	-10.30	0.000	-2.310938	-1.530256
lnFEC	.4765385	.3552157	1.34	0.196	-.2669366	1.220014
_cons	30.72377	3.595177	8.55	0.000	23.19898	38.24857

Engle-Granger test regression

D._egresid	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_egresid						
L1.	-1.26695	.2258751	-5.61	0.000	-1.736683	-.7972165
LD.	.5620376	.1743815	3.22	0.004	.1993914	.9246838

```
. egranger lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, ecm lags(1) reg
Replacing variable _egresid...

Engle-Granger 2-step ECM estimation                N (1st step)  =       25
Number of lags    =  1                             N (2nd step)  =       24
```

Engle-Granger 1st-step regression

lnGDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnREP	-.6724846	.2853075	-2.36	0.029	-1.26964	-.075329
lnIEP	.2498798	.1170697	2.13	0.046	.00485	.4949095
lnCOP	.0557998	.0256049	2.18	0.042	.0022081	.1093914
lnCO2INTENS	-1.920597	.1864961	-10.30	0.000	-2.310938	-1.530256
lnFEC	.4765385	.3552157	1.34	0.196	-.2669366	1.220014
_cons	30.72377	3.595177	8.55	0.000	23.19898	38.24857

Engle-Granger 2-step ECM

D.lnGDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_egresid						
L1.	-.4597502	.1700268	-2.70	0.016	-.820191	-.0993095
lnGDP						
LD.	.922855	.2627068	3.51	0.003	.3659413	1.479769
lnREP						
LD.	-.2596662	.1952185	-1.33	0.202	-.673511	.1541787
lnIEP						
LD.	.1749058	.0985161	1.78	0.095	-.0339391	.3837507
lnCOP						
LD.	-.0214163	.0152105	-1.41	0.178	-.0536611	.0108286
lnCO2INTENS						
LD.	-.5482922	.4954302	-1.11	0.285	-1.598557	.5019728
lnFEC						
LD.	-.1631966	.1475591	-1.11	0.285	-.4760079	.1496148
_cons	-.0021785	.0079847	-0.27	0.788	-.0191053	.0147483

Post-estimation Tests

1st step regression

Durbin Watson & Breusch-Godfrey

```
. estat dwatson

Durbin-Watson d-statistic(  2,    23) =   1.94826


. estat durbinalt, small

Durbin's alternative test for autocorrelation
```

lags(p)	F	df	Prob > F
1	0.007	(1, 20)	0.9352

H0: no serial correlation

```
. estat bgodfrey, small

Breusch-Godfrey LM test for autocorrelation
```

lags(p)	F	df	Prob > F
1	0.008	(1, 20)	0.9305

H0: no serial correlation

ARCH Effects

```
. estat archlm, lags(1)
LM test for autoregressive conditional heteroskedasticity (ARCH)
```

lags(p)	chi2	df	Prob > chi2
1	1.994	1	0.1580

H0: no ARCH effects   vs. H1: ARCH(p) disturbance

2nd step regression

Durbin-Watson & Breusch-Godfrey

```
. estat dwatson

Durbin-Watson d-statistic(  8,    24) =  2.332916
```

```
. estat durbinalt, small
```

Durbin's alternative test for autocorrelation

lags(p)	F	df	Prob > F
1	1.335	(1, 15)	0.2660

H0: no serial correlation

```
. estat bgodfrey, small
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	F	df	Prob > F
1	1.961	(1, 15)	0.1817

H0: no serial correlation

ARCH Effects (testing that errors are autoregressive conditional heteroskedastic)

```
. estat archlm, lags(1)
```

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	1.092	1	0.2960

H0: no ARCH effects *vs.* H1: ARCH(*p*) disturbance

5. FMOLS

```
. cointreg lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, est(fmols) vlag(1) bmeth(andrews) nodivn
```

Cointegration regression (FMOLS):

VAR lag(user)	=	1	Number of obs	=	24
Kernel	=	bartlett	R2	=	.9630417
Bandwidth(andrews)	=	0.5677	Adjusted R2	=	.9527755
			S.e.	=	.0294609
			Long run S.e.	=	.0183994

lnGDP	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnREP	-.580765	.218226	-2.66	0.008	-1.00848	-.15305
lnIEP	.1945369	.0914563	2.13	0.033	.0152858	.373788
lnCOP	.0622266	.0198604	3.13	0.002	.023301	.1011522
lnCO2INTENS	-1.927966	.1491546	-12.93	0.000	-2.220303	-1.635628
lnFEC	.5059371	.2653626	1.91	0.057	-.014164	1.026038
_cons	30.27942	2.698963	11.22	0.000	24.98955	35.56929

6. CCR

```
. cointreg lnGDP lnREP lnIEP lnCOP lnCO2INTENS lnFEC, est(ccr) vlag(1) bmeth(andrews) stage (3)

Cointegration regression (CCR):

VAR lag(user)          =    1                   Number of obs     =         24
Kernel                 =    bartlett            R2                =   .9600603
Bandwidth(andrews)     =    0.5677              Adjusted R2       =    .948966
                                                S.e.              =   .0328309
                                                Long run S.e.     =   .0196675
```

lnGDP	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnREP	-.6231971	.2891945	-2.15	0.031	-1.190008	-.0563862
lnIEP	.2962164	.1336623	2.22	0.027	.0342432	.5581896
lnCOP	.0487596	.0270551	1.80	0.072	-.0042674	.1017866
lnCO2INTENS	-1.886813	.1315658	-14.34	0.000	-2.144678	-1.628949
lnFEC	.6205941	.3868187	1.60	0.109	-.1375566	1.378745
_cons	29.23073	3.856058	7.58	0.000	21.67299	36.78846

7. VECM

VECM: includes unrestricted constant and 2 lags

```
. vec lnGDP lnREP  lnIEP lnCOP lnCO2INTENS lnFEC, trend(constant)

Vector error-correction model

Sample:  1992 - 2014                                 No. of obs      =        23
                                                     AIC             = -31.03881
Log likelihood =  409.9463                           HQIC            = -30.38075
Det(Sigma_ml)  =  1.33e-23                           SBIC            = -28.42224
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnGDP	8	.014774	0.7468	44.23107	0.0000
D_lnREP	8	.010354	0.8910	122.5828	0.0000
D_lnIEP	8	.039743	0.6743	31.05871	0.0001
D_lnCOP	8	.246538	0.2540	5.107689	0.7460
D_lnCO2INTENS	8	.006003	0.7803	53.27201	0.0000
D_lnFEC	8	.02179	0.4717	13.39504	0.0990

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnGDP						
_ce1						
L1.	.0594782	.0344012	1.73	0.084	-.0079468	.1269033
lnGDP						
LD.	.4390951	.3256298	1.35	0.178	-.1991277	1.077318
lnREP						
LD.	-.4016555	.2082024	-1.93	0.054	-.8097246	.0064136
lnIEP						
LD.	.4200368	.1355871	3.10	0.002	.1542911	.6857826
lnCOP						
LD.	.0406756	.0326564	1.25	0.213	-.0233299	.104681
lnCO2INTENS						
LD.	-.7790739	.5674381	-1.37	0.170	-1.891232	.3330843
lnFEC						
LD.	-.0206892	.1659944	-0.12	0.901	-.3460324	.3046539
_cons	.0030236	.0094797	0.32	0.750	-.0155563	.0216034
D_lnREP						
_ce1						
L1.	-.1685536	.0241082	-6.99	0.000	-.2158048	-.1213024
lnGDP						
LD.	.4330332	.2282001	1.90	0.058	-.0142308	.8802972
lnREP						
LD.	.190926	.1459074	1.31	0.191	-.0950473	.4768992
lnIEP						
LD.	-.3123415	.0950189	-3.29	0.001	-.4985751	-.1261079
lnCOP						
LD.	-.0830584	.0228855	-3.63	0.000	-.1279132	-.0382037
lnCO2INTENS						
LD.	-.1228218	.3976584	-0.31	0.757	-.9022179	.6565743
lnFEC						
LD.	.2060317	.1163283	1.77	0.077	-.0219675	.4340309
_cons	-.0065508	.0066433	-0.99	0.324	-.0195714	.0064699

D_lnIEP						
_ce1						
L1.	-.2836592	.092541	-3.07	0.002	-.4650362	-.1022822
lnGDP						
LD.	.7149443	.8759617	0.82	0.414	-1.001909	2.431798
lnREP						
LD.	-.7477484	.5600755	-1.34	0.182	-1.845476	.3499794
lnIEP						
LD.	-.2969193	.3647365	-0.81	0.416	-1.01179	.417951
lnCOP						
LD.	-.0504461	.0878475	-0.57	0.566	-.2226242	.1217319
lnCO2INTENS						
LD.	-.3451035	1.526439	-0.23	0.821	-3.336869	2.646662
lnFEC						
LD.	.0439273	.4465339	0.10	0.922	-.8312632	.9191177
_cons	-.0089008	.0255009	-0.35	0.727	-.0588815	.04108

D_lnCOP						
_ce1						
L1.	.8211134	.5740607	1.43	0.153	-.3040249	1.946252
lnGDP						
LD.	-.1159906	5.433865	-0.02	0.983	-10.76617	10.53419
lnREP						
LD.	3.142066	3.474324	0.90	0.366	-3.667484	9.951615
lnIEP						
LD.	2.99666	2.262575	1.32	0.185	-1.437904	7.431225
lnCOP						
LD.	.6442913	.5449458	1.18	0.237	-.4237829	1.712365
lnCO2INTENS						
LD.	-2.787071	9.468978	-0.29	0.769	-21.34593	15.77179
lnFEC						
LD.	1.499811	2.76999	0.54	0.588	-3.929269	6.928892
_cons	-.0033652	.1581898	-0.02	0.983	-.3134114	.3066811

D_lnCO2INTENS						
_ce1						
L1.	-.0047569	.0139768	-0.34	0.734	-.032151	.0226372
lnGDP						
LD.	.1642259	.1323	1.24	0.214	-.0950773	.4235291
lnREP						
LD.	-.2153482	.0845904	-2.55	0.011	-.3811424	-.049554
lnIEP						
LD.	.1072689	.0550876	1.95	0.052	-.0007008	.2152386
lnCOP						
LD.	.0055031	.013268	0.41	0.678	-.0205016	.0315078
lnCO2INTENS						
LD.	-.0878689	.2305441	-0.38	0.703	-.5397271	.3639893
lnFEC						
LD.	-.0041149	.0674418	-0.06	0.951	-.1362984	.1280686
_cons	-.0124024	.0038515	-3.22	0.001	-.0199512	-.0048536

D_lnFEC						
_ce1						
L1.	.0650793	.0507376	1.28	0.200	-.0343645	.1645231
lnGDP						
LD.	.4936421	.4802647	1.03	0.304	-.4476594	1.434944
lnREP						
LD.	-.5546528	.3070733	-1.81	0.071	-1.156505	.0471999
lnIEP						
LD.	.4144269	.1999745	2.07	0.038	.022484	.8063698
lnCOP						
LD.	.0450611	.0481643	0.94	0.349	-.0493392	.1394613
lnCO2INTENS						
LD.	-1.307944	.8369027	-1.56	0.118	-2.948243	.3323553
lnFEC						
LD.	-.688694	.2448218	-2.81	0.005	-1.168536	-.2088522
_cons	-.016973	.0139814	-1.21	0.225	-.044376	.01043

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	5	1865.856	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnGDP	1	.	.	.	.	.
lnREP	6.017424	.2806819	21.44	0.000	5.467298	6.567551
lnIEP	-1.763515	.1256149	-14.04	0.000	-2.009716	-1.517315
lnCOP	-.590021	.0266312	-22.16	0.000	-.6422171	-.5378248
lnCO2INTENS	1.787819	.1544007	11.58	0.000	1.485199	2.090438
lnFEC	2.704432	.3245548	8.33	0.000	2.068316	3.340548
_cons	-72.06947	.	.	.	.	.

Post-estimation tests

. veclmar

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	31.0545	36	0.70274
2	35.0550	36	0.51337

H0: no autocorrelation at lag order

```
. vecnorm
```

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_lnGDP	16.527	2	0.00026
D_lnREP	0.665	2	0.71725
D_lnIEP	1.507	2	0.47083
D_lnCOP	1.420	2	0.49160
D_lnCO2INTENS	0.168	2	0.91937
D_lnFEC	14.729	2	0.00063
ALL	35.015	12	0.00047

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_lnGDP	-1.5279	8.948	1	0.00278
D_lnREP	-.40362	0.624	1	0.42939
D_lnIEP	.41729	0.668	1	0.41392
D_lnCOP	.60282	1.393	1	0.23790
D_lnCO2INTENS	.06599	0.017	1	0.89719
D_lnFEC	1.0769	4.445	1	0.03500
ALL		16.095	6	0.01325

Kurtosis test

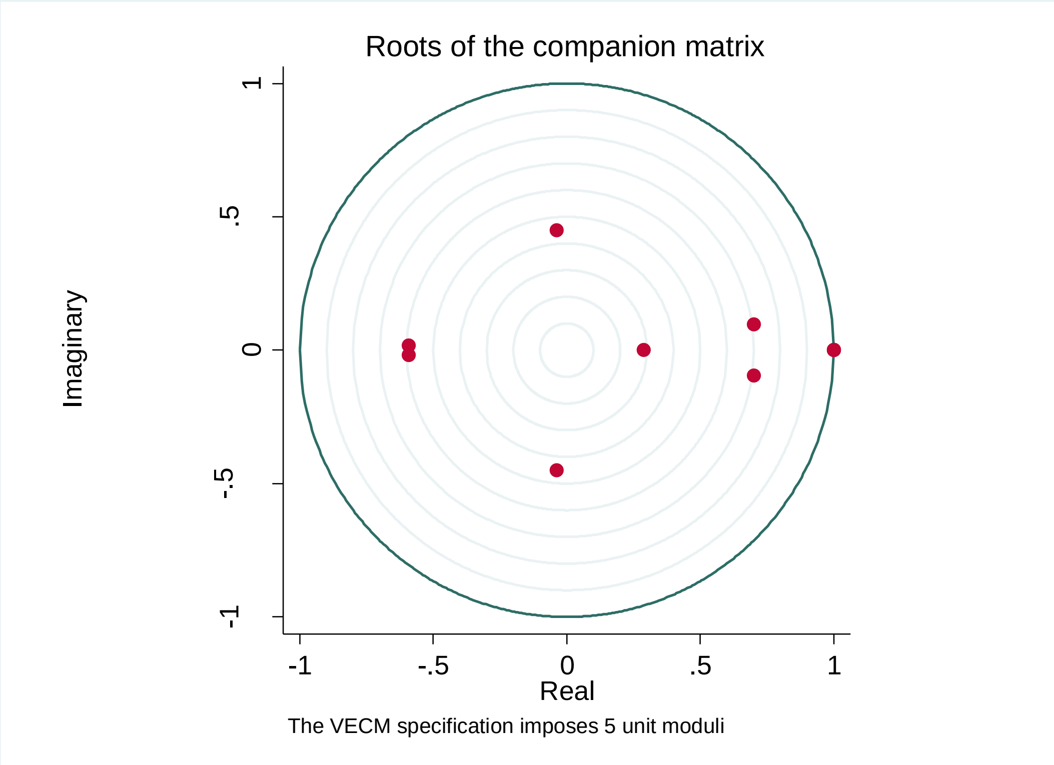
Equation	Kurtosis	chi2	df	Prob > chi2
D_lnGDP	5.8121	7.578	1	0.00591
D_lnREP	2.7952	0.040	1	0.84110
D_lnIEP	2.0643	0.839	1	0.35968
D_lnCOP	2.8316	0.027	1	0.86904
D_lnCO2INTENS	3.3975	0.151	1	0.69716
D_lnFEC	6.2758	10.284	1	0.00134
ALL		18.920	6	0.00430

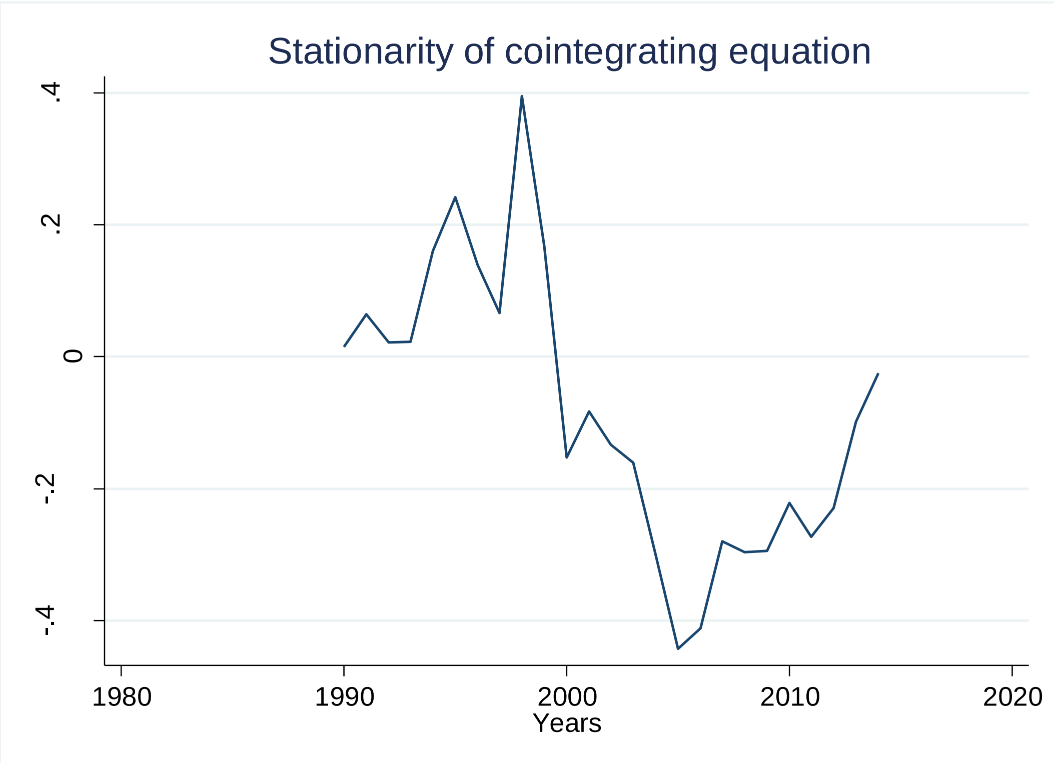
```
. vecstable, graph
```

Eigenvalue stability condition

Eigenvalue	Modulus
1	1
1	1
1	1
1	1
1	1
.7012789 + .09614219i	.707839
.7012789 - .09614219i	.707839
-.5930442 + .01792042i	.593315
-.5930442 - .01792042i	.593315
-.03821697 + .4506623i	.45228
-.03821697 - .4506623i	.45228
.2892756	.289276

The VECM specification imposes 5 unit moduli.


Roots of the companion matrix
Imaginary
Real
-1
-.5
0
.5
1
The VECM specification imposes 5 unit moduli


Stationarity of cointegrating equation
.4
.2
0
-.2
-.4
1980
1990
2000
2010
2020
Years

8.Wald Tests

lnGDP

```
test ([D_lnGDP ]: LD.lnREP )

 ( 1)  [D_lnGDP]LD.lnREP = 0

           chi2(  1) =    3.72
         Prob > chi2 =    0.0537

. test ([D_lnGDP ]: LD.lnIEP )

 ( 1)  [D_lnGDP]LD.lnIEP = 0

           chi2(  1) =    9.60
         Prob > chi2 =    0.0019

. test ([D_lnGDP ]: LD.lnCOP )

 ( 1)  [D_lnGDP]LD.lnCOP = 0

           chi2(  1) =    1.55
         Prob > chi2 =    0.2129

. test ([D_lnGDP ]: LD.lnCO2INTENS )

 ( 1)  [D_lnGDP]LD.lnCO2INTENS = 0

           chi2(  1) =    1.89
         Prob > chi2 =    0.1698

. test ([D_lnGDP ]: LD.lnFEC )

 ( 1)  [D_lnGDP]LD.lnFEC = 0

           chi2(  1) =    0.02
         Prob > chi2 =    0.9008

. test ( [D_lnGDP]: LD.lnREP LD.lnIEP LD.lnCOP LD.lnCO2INTENS LD.lnFEC )

 ( 1)  [D_lnGDP]LD.lnREP = 0
 ( 2)  [D_lnGDP]LD.lnIEP = 0
 ( 3)  [D_lnGDP]LD.lnCOP = 0
 ( 4)  [D_lnGDP]LD.lnCO2INTENS = 0
 ( 5)  [D_lnGDP]LD.lnFEC = 0

           chi2(  5) =   11.50
         Prob > chi2 =    0.0423
```

lnREP

```
. test ([D_lnREP ]: LD.lnGDP )

 ( 1)  [D_lnREP]LD.lnGDP = 0

           chi2(  1) =    3.60
         Prob > chi2 =    0.0577

. test ([D_lnREP ]: LD.lnIEP )

 ( 1)  [D_lnREP]LD.lnIEP = 0

           chi2(  1) =   10.81
         Prob > chi2 =    0.0010

. test ([D_lnREP ]: LD.lnCOP )

 ( 1)  [D_lnREP]LD.lnCOP = 0

           chi2(  1) =   13.17
         Prob > chi2 =    0.0003


. test ([D_lnREP ]: LD.lnCO2INTENS )

 ( 1)  [D_lnREP]LD.lnCO2INTENS = 0

           chi2(  1) =    0.10
         Prob > chi2 =    0.7574

. test ([D_lnREP ]: LD.lnFEC )

 ( 1)  [D_lnREP]LD.lnFEC = 0

           chi2(  1) =    3.14
         Prob > chi2 =    0.0765

. test ( [D_lnREP]: LD.lnGDP LD.lnIEP LD.lnCOP LD.lnCO2INTENS LD.lnFEC)

 ( 1)  [D_lnREP]LD.lnGDP = 0
 ( 2)  [D_lnREP]LD.lnIEP = 0
 ( 3)  [D_lnREP]LD.lnCOP = 0
 ( 4)  [D_lnREP]LD.lnCO2INTENS = 0
 ( 5)  [D_lnREP]LD.lnFEC = 0

           chi2(  5) =   17.94
         Prob > chi2 =    0.0030
```

lnIEP

```
. test ([D_lnIEP ]: LD.lnGDP )

 ( 1)  [D_lnIEP]LD.lnGDP = 0

           chi2(  1) =    0.67
         Prob > chi2 =    0.4144

. test ([D_lnIEP ]: LD.lnREP )

 ( 1)  [D_lnIEP]LD.lnREP = 0

           chi2(  1) =    1.78
         Prob > chi2 =    0.1818

. test ([D_lnIEP ]: LD.lnCOP )

 ( 1)  [D_lnIEP]LD.lnCOP = 0

           chi2(  1) =    0.33
         Prob > chi2 =    0.5658

. test ([D_lnIEP ]: LD.lnCO2INTENS )

 ( 1)  [D_lnIEP]LD.lnCO2INTENS = 0

           chi2(  1) =    0.05
         Prob > chi2 =    0.8211

. test ([D_lnIEP ]: LD.lnFEC )

 ( 1)  [D_lnIEP]LD.lnFEC = 0

           chi2(  1) =    0.01
         Prob > chi2 =    0.9216

. test ( [D_lnIEP]: LD.lnGDP LD.lnREP LD.lnCOP LD.lnCO2INTENS LD.lnFEC)

 ( 1)  [D_lnIEP]LD.lnGDP = 0
 ( 2)  [D_lnIEP]LD.lnREP = 0
 ( 3)  [D_lnIEP]LD.lnCOP = 0
 ( 4)  [D_lnIEP]LD.lnCO2INTENS = 0
 ( 5)  [D_lnIEP]LD.lnFEC = 0

           chi2(  5) =    2.72
         Prob > chi2 =    0.7424
```

lnCOP

```
. test ([D_lnCOP ]: LD.lnGDP )

 ( 1)  [D_lnCOP]LD.lnGDP = 0

           chi2(  1) =    0.00
         Prob > chi2 =    0.9830

. test ([D_lnCOP ]: LD.lnREP )

 ( 1)  [D_lnCOP]LD.lnREP = 0

           chi2(  1) =    0.82
         Prob > chi2 =    0.3658

. test ([D_lnCOP ]: LD.lnIEP )

 ( 1)  [D_lnCOP]LD.lnIEP = 0

           chi2(  1) =    1.75
         Prob > chi2 =    0.1854

. test ([D_lnCOP ]: LD.lnCO2INTENS )

 ( 1)  [D_lnCOP]LD.lnCO2INTENS = 0

           chi2(  1) =    0.09
         Prob > chi2 =    0.7685

. test ([D_lnCOP ]: LD.lnFEC )

 ( 1)  [D_lnCOP]LD.lnFEC = 0

           chi2(  1) =    0.29
         Prob > chi2 =    0.5882

. test ( [D_lnCOP]: LD.lnGDP LD.lnREP LD.lnIEP LD.lnCO2INTENS LD.lnFEC)

 ( 1)  [D_lnCOP]LD.lnGDP = 0
 ( 2)  [D_lnCOP]LD.lnREP = 0
 ( 3)  [D_lnCOP]LD.lnIEP = 0
 ( 4)  [D_lnCOP]LD.lnCO2INTENS = 0
 ( 5)  [D_lnCOP]LD.lnFEC = 0

           chi2(  5) =    4.32
         Prob > chi2 =    0.5042
```

lnCO2INTENS

```
. test ([D_lnCO2INTENS ]: LD.lnGDP )

 ( 1)  [D_lnCO2INTENS]LD.lnGDP = 0

           chi2(  1) =    1.54
         Prob > chi2 =    0.2145

. test ([D_lnCO2INTENS ]: LD.lnREP )

 ( 1)  [D_lnCO2INTENS]LD.lnREP = 0

           chi2(  1) =    6.48
         Prob > chi2 =    0.0109
```

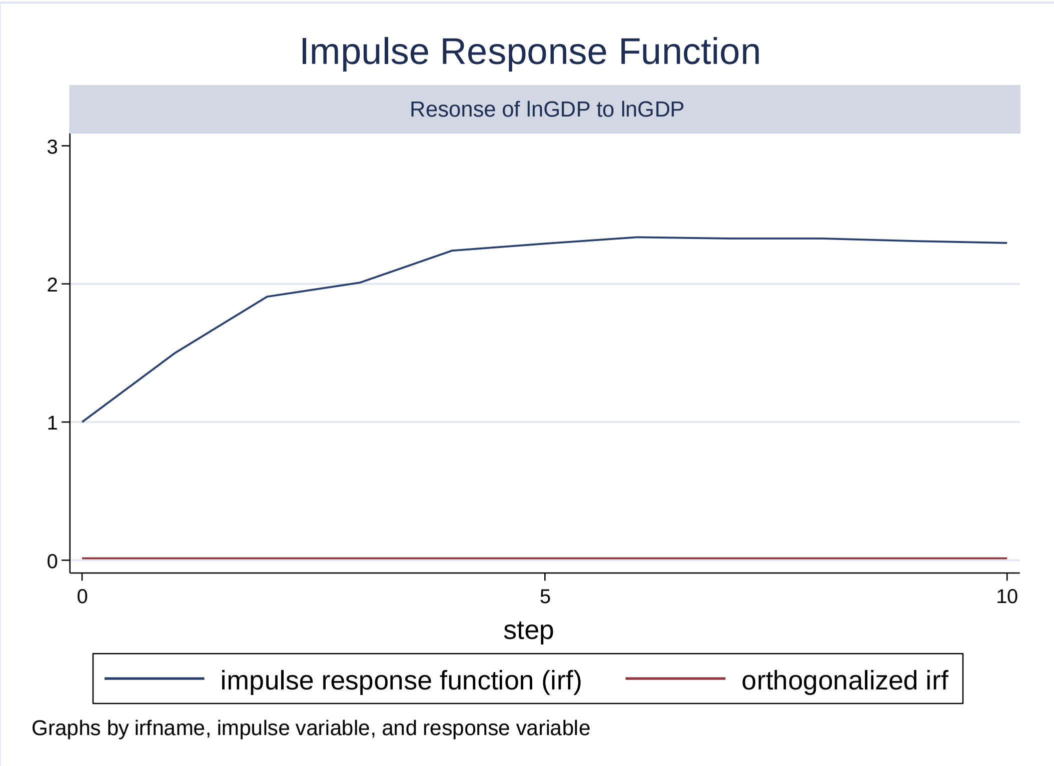
```
. test ([D_lnCO2INTENS ]: LD.lnIEP )

 ( 1)  [D_lnCO2INTENS]LD.lnIEP = 0

           chi2(  1) =    3.79
         Prob > chi2 =    0.0515

. test ([D_lnCO2INTENS ]: LD.lnCOP )

 ( 1)  [D_lnCO2INTENS]LD.lnCOP = 0

           chi2(  1) =    0.17
         Prob > chi2 =    0.6783


. test ([D_lnCO2INTENS ]: LD.lnFEC )

 ( 1)  [D_lnCO2INTENS]LD.lnFEC = 0

           chi2(  1) =    0.00
         Prob > chi2 =    0.9513

. test ( [D_lnCO2INTENS ]: LD.lnGDP LD.lnREP LD.lnIEP LD.lnCOP LD.lnFEC)

 ( 1)  [D_lnCO2INTENS]LD.lnGDP = 0
 ( 2)  [D_lnCO2INTENS]LD.lnREP = 0
 ( 3)  [D_lnCO2INTENS]LD.lnIEP = 0
 ( 4)  [D_lnCO2INTENS]LD.lnCOP = 0
 ( 5)  [D_lnCO2INTENS]LD.lnFEC = 0

           chi2(  5) =    9.66
         Prob > chi2 =    0.0853
```

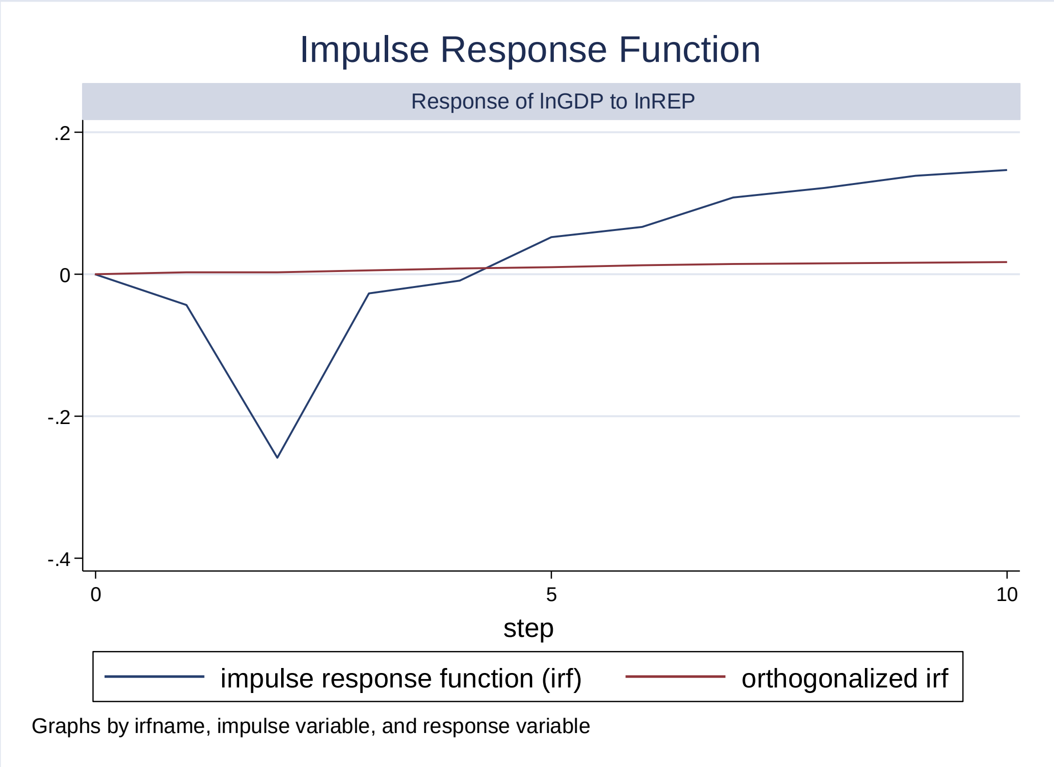
lnFEC

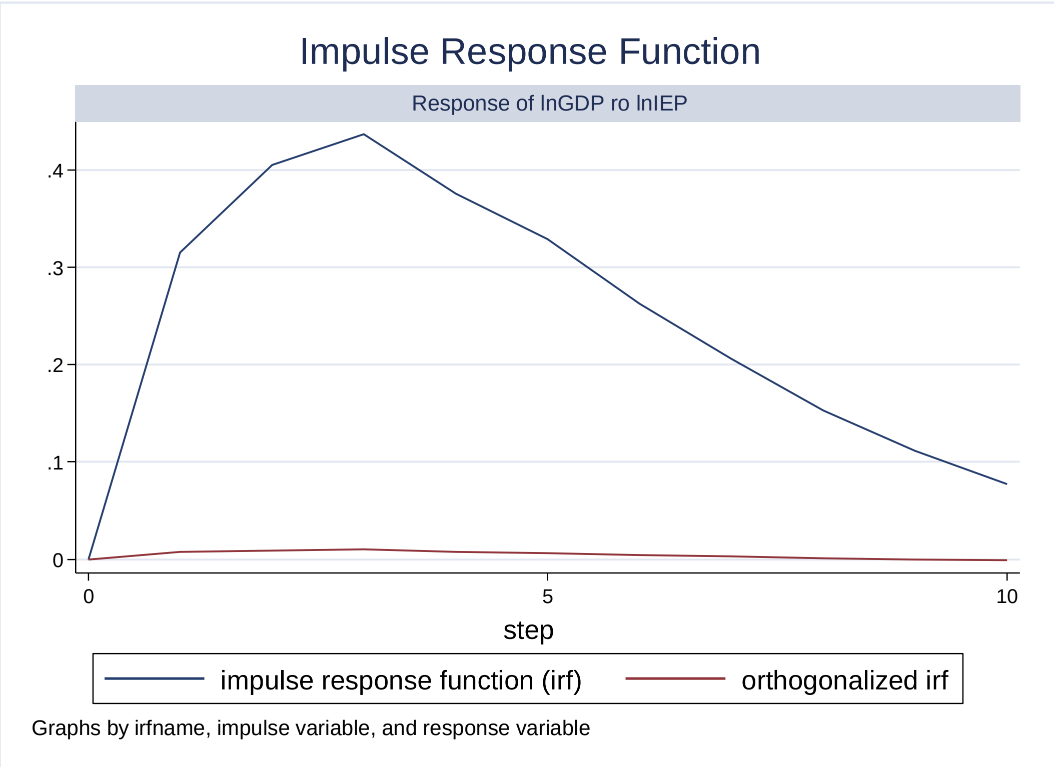
```
. test ([D_lnFEC ]: LD.lnGDP )

 ( 1)  [D_lnFEC]LD.lnGDP = 0

           chi2(  1) =    1.06
         Prob > chi2 =    0.3040

. test ([D_lnFEC ]: LD.lnREP )

 ( 1)  [D_lnFEC]LD.lnREP = 0

           chi2(  1) =    3.26
         Prob > chi2 =    0.0709
```

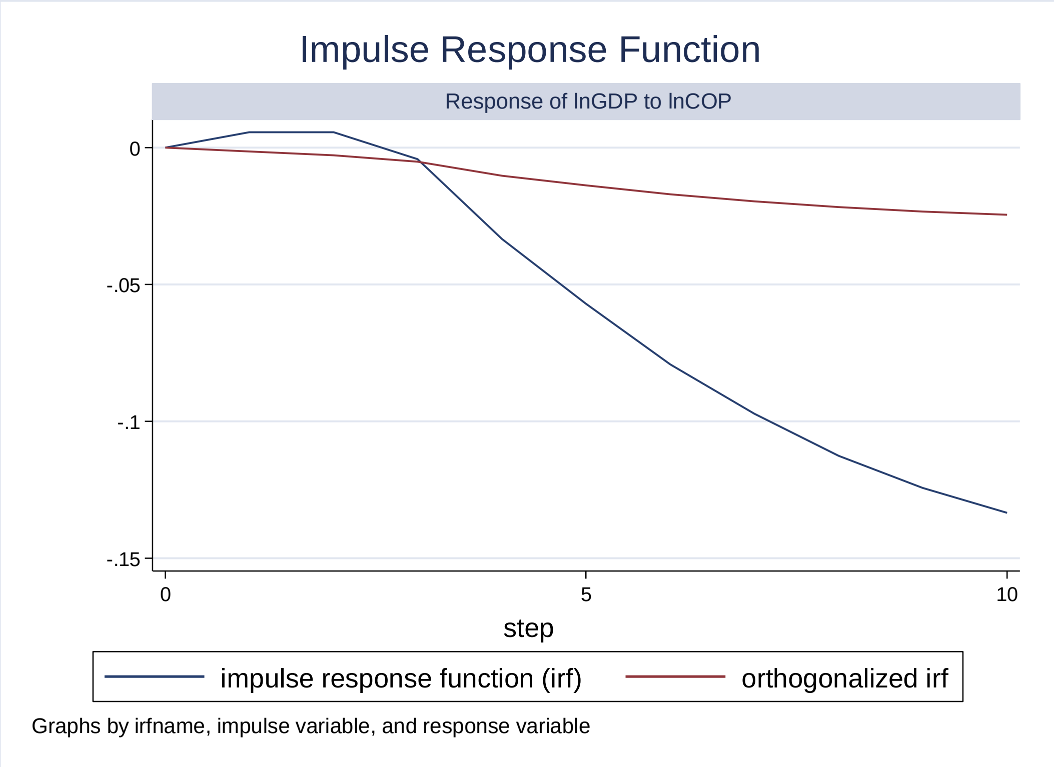
```
. test ([D_lnFEC ]: LD.lnIEP )

 ( 1)  [D_lnFEC]LD.lnIEP = 0

           chi2(  1) =    4.29
         Prob > chi2 =    0.0382

. test ([D_lnFEC ]: LD.lnCOP )

 ( 1)  [D_lnFEC]LD.lnCOP = 0

           chi2(  1) =    0.88
         Prob > chi2 =    0.3495

. test ([D_lnFEC ]: LD.lnCO2INTENS )

 ( 1)  [D_lnFEC]LD.lnCO2INTENS = 0

           chi2(  1) =    2.44
         Prob > chi2 =    0.1181

. test ( [D_lnFEC ]: LD.lnGDP LD.lnREP LD.lnIEP LD.lnCOP LD.lnCO2INTENS )

 ( 1)  [D_lnFEC]LD.lnGDP = 0
 ( 2)  [D_lnFEC]LD.lnREP = 0
 ( 3)  [D_lnFEC]LD.lnIEP = 0
 ( 4)  [D_lnFEC]LD.lnCOP = 0
 ( 5)  [D_lnFEC]LD.lnCO2INTENS = 0

           chi2(  5) =    6.59
         Prob > chi2 =    0.2529
```

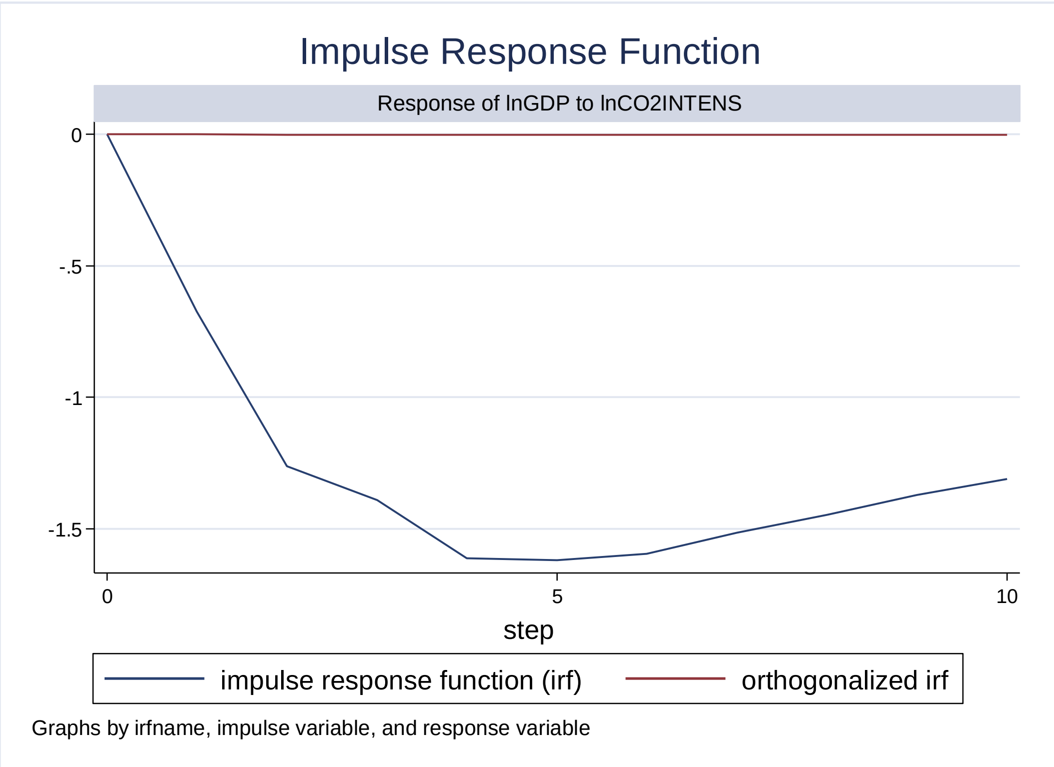
9.IRF Graphs Responses of lnGDP

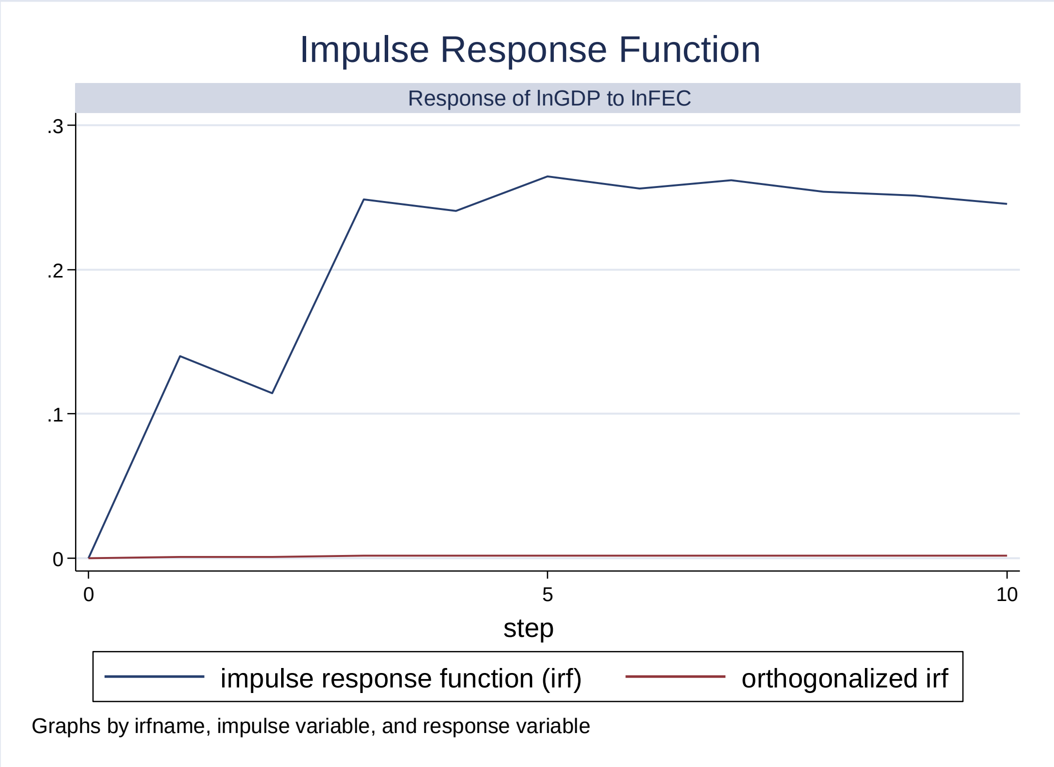



Impulse Response Function
Response of lnGDP to lnREP
.2
0
-.2
-.4
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable


Impulse Response Function
Response of lnGDP ro lnIEP
.4
.3
.2
.1
0
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable


Impulse Response Function
Response of lnGDP to lnCOP
0
-.05
-.1
-.15
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable


Impulse Response Function
Response of lnGDP to lnCO2INTENS
0
-.5
-1
-1.5
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable



10. IRF Tables Responses of lnGDP

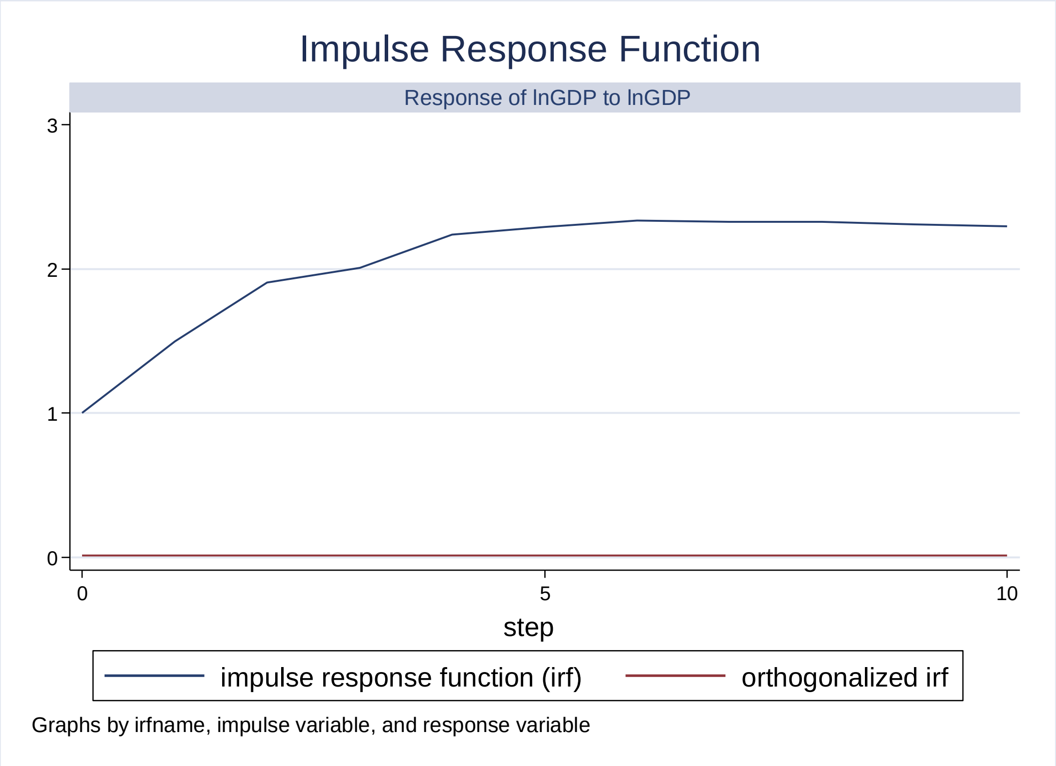
```
. graph save Graph "C:\Users\User\Desktop\Graph.gph", replace
(file C:\Users\User\Desktop\Graph.gph saved)
irf table irf, irf(vec2) response(lnGDP)
```

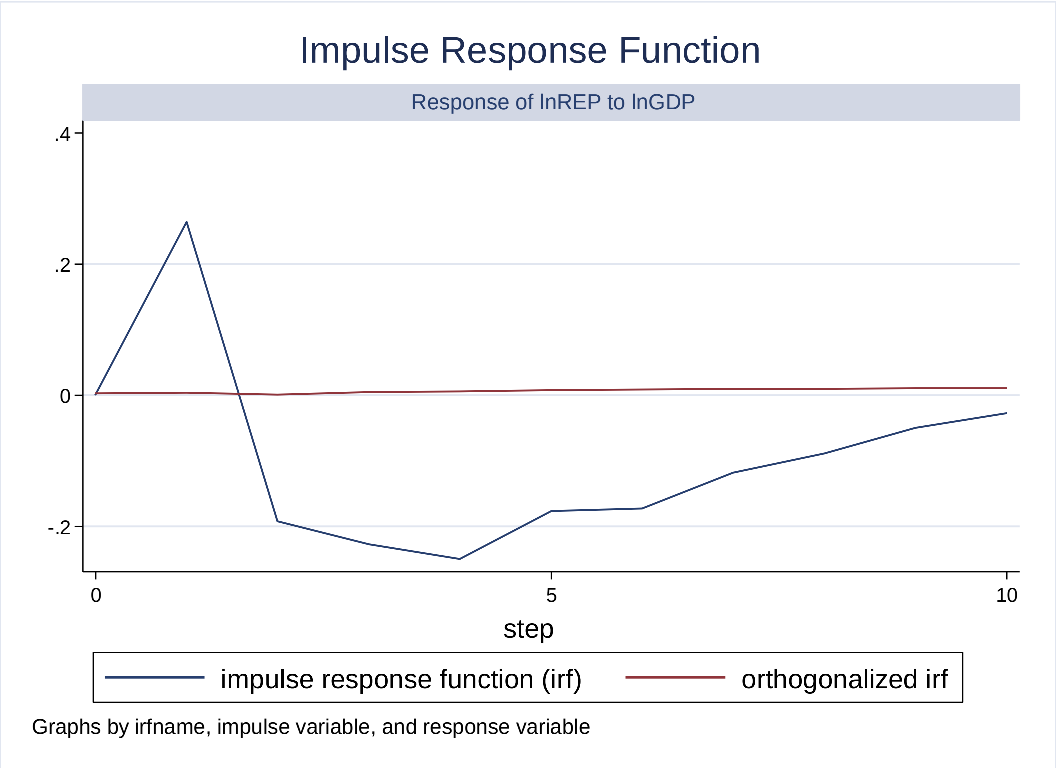
Results from vec2

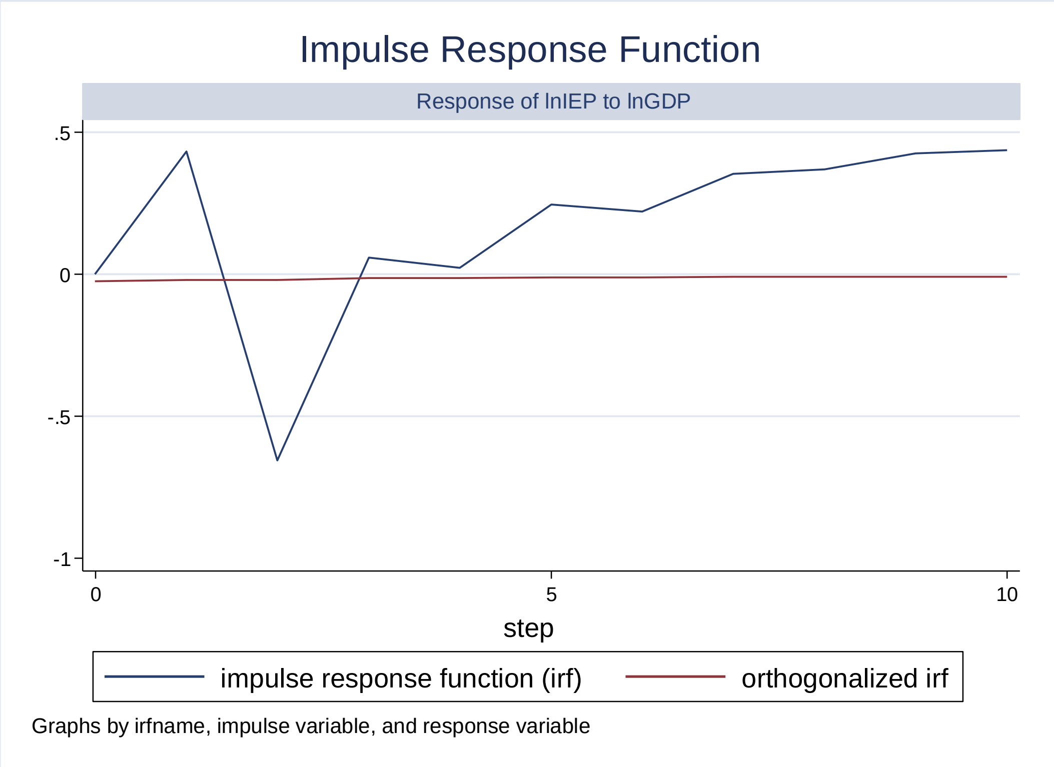
step	(1) irf	(2) irf	(3) irf	(4) irf	(5) irf	(6) irf
0	1	0	0	0	0	0
1	1.49857	-.04375	.315146	.005582	-.672738	.140166
2	1.90594	-.258811	.404953	.005637	-1.26138	.114245
3	2.0066	-.027201	.436719	-.004341	-1.39026	.248563
4	2.23938	-.009245	.375167	-.033547	-1.61017	.240797
5	2.29292	.051736	.32875	-.057072	-1.61849	.264652
6	2.33526	.066234	.262487	-.079101	-1.59429	.256103
7	2.32764	.107539	.206278	-.097105	-1.51325	.262065
8	2.32665	.12124	.152923	-.112627	-1.44642	.253923
9	2.30826	.138581	.111658	-.124357	-1.37106	.251343
10	2.29369	.146701	.077294	-.13351	-1.30976	.245547

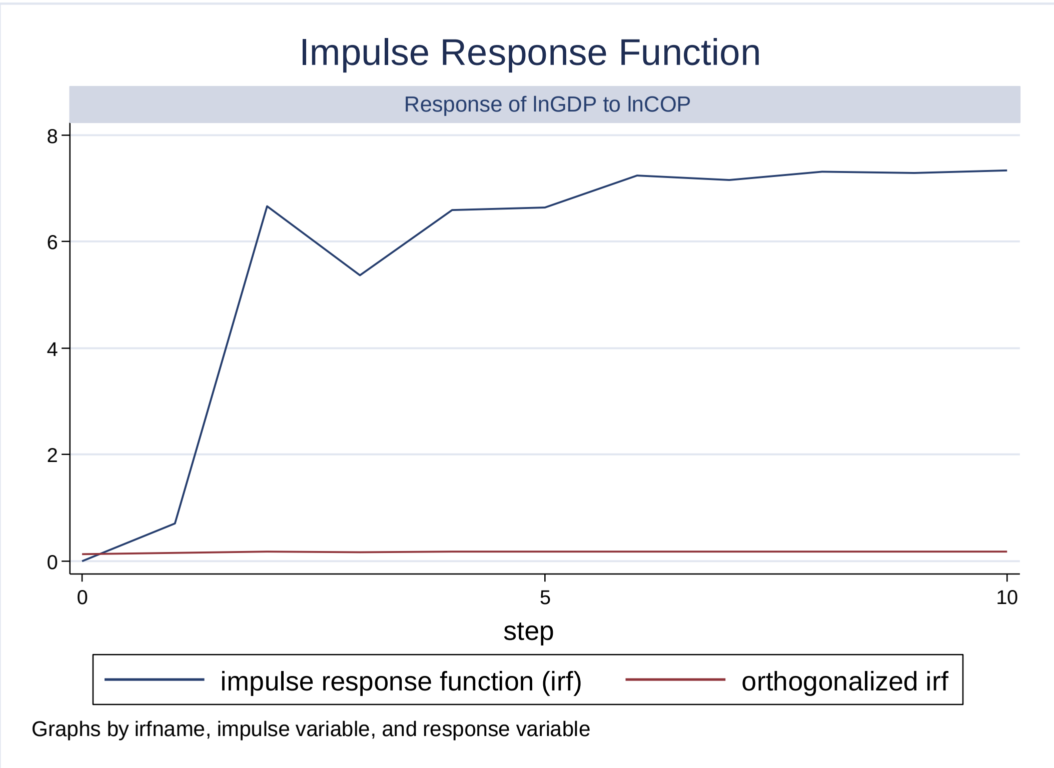
```
(1) irfname = vec2, impulse = lnGDP, and response = lnGDP
(2) irfname = vec2, impulse = lnREP, and response = lnGDP
(3) irfname = vec2, impulse = lnIEP, and response = lnGDP
(4) irfname = vec2, impulse = lnCOP, and response = lnGDP
(5) irfname = vec2, impulse = lnCO2INTENS, and response = lnGDP
(6) irfname = vec2, impulse = lnFEC, and response = lnGDP

.
```

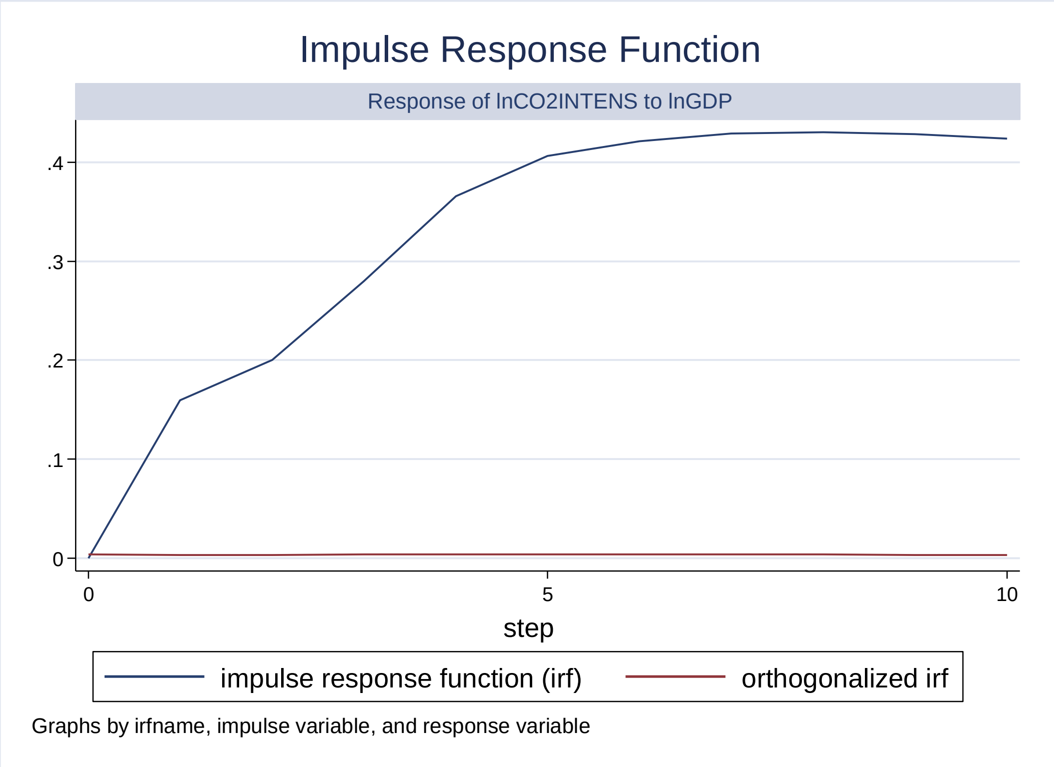
11. IRF Graphs Impulse of lnGDP

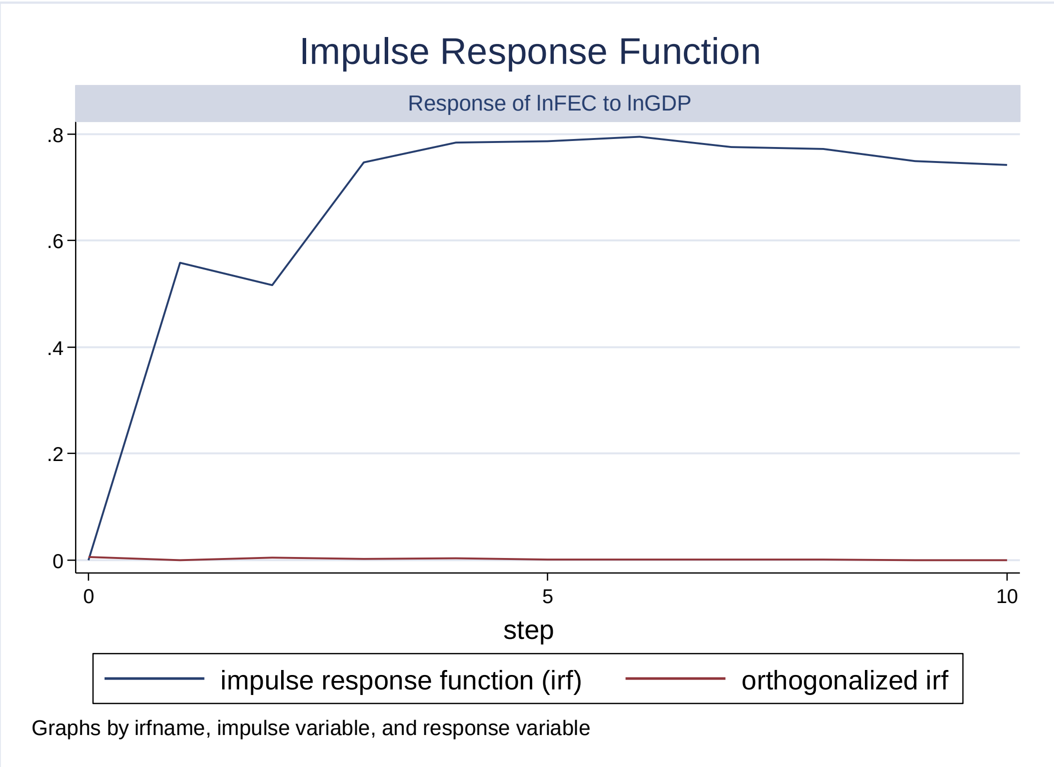





Impulse Response Function
Response of lnIEP to lnGDP
.5
0
-.5
-1
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable


Impulse Response Function
Response of lnGDP to lnCOP
8
6
4
2
0
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable


Impulse Response Function
Response of lnCO2INTENS to lnGDP
.4
.3
.2
.1
0
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable


Impulse Response Function
Response of lnFEC to lnGDP
.8
.6
.4
.2
0
0
5
10
step
impulse response function (irf)
orthogonalized irf
Graphs by irfname, impulse variable, and response variable

13. IRF Table Impuses of lnGDP

```
. graph save Graph "C:\Users\User\Desktop\Graph.gph", replace
(file C:\Users\User\Desktop\Graph.gph saved)
irf table irf, irf(vec2) impulse(lnGDP)
```

Results from vec2

step	(1) irf	(2) irf	(3) irf	(4) irf	(5) irf	(6) irf
0	1	0	0	0	0	0
1	1.49857	.26448	.431285	.705123	.159469	.558721
2	1.90594	-.192133	-.656399	6.66453	.200579	.516705
3	2.0066	-.226548	.058835	5.36439	.27977	.746503
4	2.23938	-.249378	.022714	6.58677	.365882	.784342
5	2.29292	-.17647	.244165	6.64557	.406119	.786508
6	2.33526	-.172832	.221284	7.24144	.421017	.795399
7	2.32764	-.117976	.35237	7.1543	.428871	.775855
8	2.32665	-.088841	.369891	7.31751	.43049	.771832
9	2.30826	-.049701	.424209	7.29293	.428232	.749582
10	2.29369	-.027437	.437365	7.33337	.423949	.742264

```
(1) irfname = vec2, impulse = lnGDP, and response = lnGDP
(2) irfname = vec2, impulse = lnGDP, and response = lnREP
(3) irfname = vec2, impulse = lnGDP, and response = lnIEP
(4) irfname = vec2, impulse = lnGDP, and response = lnCOP
(5) irfname = vec2, impulse = lnGDP, and response = lnCO2INTENS
(6) irfname = vec2, impulse = lnGDP, and response = lnFEC

.
```

14. FEVD TABLE responses of lnGDP

```
. irf table fevd, irf(vec1) response(lnGDP)
```

Results from vec1

step	(1) fevd	(2) fevd	(3) fevd	(4) fevd	(5) fevd	(6) fevd
0	0	0	0	0	0	0
1	1	0	0	0	0	0
2	.846659	.019047	.122881	.004552	.004691	.002169
3	.773896	.019655	.169309	.013069	.021909	.002162
4	.703822	.032983	.20251	.032191	.024318	.004177
5	.640913	.058684	.181421	.085901	.028277	.004803
6	.570614	.090423	.153961	.15105	.028724	.005229
7	.504178	.120277	.124841	.217647	.027853	.005203
8	.444454	.14698	.100534	.277178	.025773	.005079
9	.393206	.169042	.08134	.328038	.023541	.004833
10	.350687	.186901	.06703	.369446	.021356	.00458

```
(1) irfname = vec1, impulse = lnGDP, and response = lnGDP
(2) irfname = vec1, impulse = lnREP, and response = lnGDP
(3) irfname = vec1, impulse = lnIEP, and response = lnGDP
(4) irfname = vec1, impulse = lnCOP, and response = lnGDP
(5) irfname = vec1, impulse = lnCO2INTENS, and response = lnGDP
(6) irfname = vec1, impulse = lnFEC, and response = lnGDP
```

15.FEVD TABLE impulse variable lnGDP response variables the independent variables

```
. irf table fevd, irf(vec1) impulse(lnGDP)
```

Results from vec1

step	(1) fevd	(2) fevd	(3) fevd	(4) fevd	(5) fevd	(6) fevd
0	0	0	0	0	0	0
1	1	.063752	.374272	.277372	.356238	.068747
2	.846659	.14177	.35422	.32031	.274404	.052046
3	.773896	.053472	.205397	.371946	.20016	.058929
4	.703822	.042604	.143011	.365217	.193217	.050969
5	.640913	.035758	.106318	.369322	.200867	.046714
6	.570614	.035113	.082865	.371605	.209153	.039014
7	.504178	.033905	.06706	.376064	.215808	.033049
8	.444454	.034117	.056145	.379174	.221388	.027551
9	.393206	.034225	.048325	.382884	.225002	.023235
10	.350687	.034557	.04249	.386271	.227001	.019797

```
(1) irfname = vec1, impulse = lnGDP, and response = lnGDP
(2) irfname = vec1, impulse = lnGDP, and response = lnREP
(3) irfname = vec1, impulse = lnGDP, and response = lnIEP
(4) irfname = vec1, impulse = lnGDP, and response = lnCOP
(5) irfname = vec1, impulse = lnGDP, and response = lnCO2INTENS
(6) irfname = vec1, impulse = lnGDP, and response = lnFEC
```

16. Forecasting