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The economic and environmental efficiency assessment in EU cross-country: Evidence from DEA and quantile regression approach

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ABSTRACT

This article aims to estimate the efficiency of 26 different European Countries over 2001 and 2012 comparing their performance. Data Envelopment Analysis technique is used in a first step to evaluate the performance of each European country. The output-oriented model was used with two specifications (Variable and Constant Returns to Scale) including as inputs labour and capital productivity, the weight of fossil energy and the share of renewable energy in GDP (gross domestic product), being the output GDP per GHG (greenhouse gases) emissions. In a second step, the quantile regression technique was used, to explain different efficiency scores through variables as Environmental Taxes Revenues, Resources Productivity and Domestic Material Consumption. Results indicate that share of renewables and non-renewable energy sources are important to explain differences in emissions. They suggest a significant change in the trend of economic and environmental efficiency in European countries and put forward the high disparities existing among them. Policy recommendations point for the need of higher steps if the goal is to equal countries efficiency scores. Moreover, environmental tax revenue effects are negatively stronger in less efficient countries, whereas also exerting negative influence over those more eco-efficient. Transport taxes affect negatively more eco-efficient countries and positively less eco-efficient countries. Energy taxes only seem to positively influence the lower eco-efficient countries. There is also evidence for a negative premium of efficiency considering domestic materials consumption. Finally, resources productivity shows a positive and significant influence independently of the country technical eco-efficiency level.

1. Introduction

Eco-efficiency main goals are to increase the value of a good or service, optimize resources use and to reduce environmental impacts. It was defined by OECD (1998) as "the efficiency with which ecological resources are used to meet human needs" and by Picazo-Tadeo et al. (2011) as "the ability of firms, industries or economies to produce goods and services while incurring less impact on the environment and consuming fewer natural resources".

Robaina-Alves et al. (2015) study the eco-efficiency problem of 27 European countries in two distinct periods (2000–2004 and 2005–2011) to account for the Kyoto Protocol in 2005. The authors specified a new stochastic frontier model where the ratio between GDP (gross domestic product) and GHG (greenhouse gases) emissions is maximized given the values of fossil fuel consumption, renewable energy consumption, capital and labour as inputs. Their empirical results show the most efficient countries (Portugal, Slovakia, Hungary and Ireland) and the least efficient ones (Bulgaria, Italy, Romania and Denmark) and they noticed that there has been a great effort by some countries in the second period of the analysis to converge to the efficiency frontier. This period coincides with the period after the ratification of the Kyoto protocol. Those with average growth rates between 4% and 8% are among the least efficient, from a technical and environmental perspective, and those that are more eco-efficient, are countries for which GDP grew at more moderate rates (on average between −1% and 2%).

In this article, we have two objectives: 1) to analyze the eco-efficiency of the European countries, in a comparative way, through a ranking, and the evolution of this efficiency over time; 2) to see what variables affect this eco-efficiency. We try to evaluate the eco-efficiency of 26 European countries as Robaina-Alves et al. (2015) do, but instead of using absolute values, for ranking establishment we use ratios. The use of ratios in the inputs is justified by the use of the variable output also as a ratio, to which relative variations in the inputs imply relative variations in the output, hence to guarantee this consistency in the input-output relation in the optimization problem. We also contribute to previous empirical

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findings because instead of only establishing a ranking in terms of levels of eco-efficiency differences, we try to explain through several variables the ranking differences (namely, fiscal, production and domestic material consumption variables). A final difference respects to the way estimations are to be performed.[1]

For environmental policymaking purposes, it is necessary to have indicators in this context. That is, indicators of economic and environmental efficiency, to compare the evolution of eco-efficiency among countries, set goals and to simultaneously implement effective environmental taxation policies (whose aim is to justify the level of differences in goal commitment harmonization of environmental taxation policy in the European Union (EU)). These aims justify why it is very important to consider simultaneously in the analysis the energy and non-energy resources productivity, as well as the environmental taxation revenues in every country.

With this in mind, the present article uses the non-parametric Data Envelopment Analysis (DEA), which has been extensively used in the empirical literature at the macro level operation management performance evaluation. An additional contribution to previous empirical findings is that we look at the efficiency drivers in a two-stage process, focusing directly on the causes of technical efficiency. Therefore, during the first phase we identify eco-efficiency scores and rank European countries, according to the output variable and some inputs following Kuosmanen and Kortelainen (2005), Picazo-Tadeo et al. (2011), Robaina-Alves et al. (2015) and Rashidi et al. (2015). In a second phase, we proceed with the estimation of a quantile regression to assess the impact of other determinants, such as, environmental taxes revenue (as indicated in Filipovic and Golusin, 2015), including energy taxes, transport taxes and taxes on pollution/resources. We add also resources productivity and domestic materials consumption into these determinants to understand if these explanatory variables are able to explain economic and environmental efficiency levels.

The article is composed of six sections. After this introduction, Section 2 covers the literature review and presents the tested hypothesis, while the methodology used in this article is presented in Section 3. Results and discussion are presented in Sections 4 and 5, respectively. Finally, conclusions are presented in section 6.

2. Literature review and hypotheses

Eco-efficiency of countries and/or economic sectors have already been assessed through DEA techniques. For example, Haynes et al. (1993) measure technical efficiency in pollution prevention activities, using chemical as input and chemical waste as output, among other traditional inputs and outputs. Picazo-Tadeo and Prior (2009) use DEA and directional distance functions to conclude that intensive technology economic activities can diminish environmental damages without compromising output maximization.

Literature suggests the existence of a relationship between economic growth and environmental degradation (or inversely with the level of eco-efficiency). This relationship could be positive before economies cross a certain level of income (Kuznets, 1955). Reaching a 'sustainable development' is possible, thus turning economic growth compatible with environmental quality, after that certain level of income (Hu et al., 2011). The ecological modernization theory suggests that through time the economic impact on the environment should decrease, with higher probabilities of occurrence in economically developed countries, thus increasing eco-efficiency. But recently, Jorgenson (2016) concluded that economic development might decrease the environmental degradation even with higher levels of economic growth. The author argues that the economy development or GDP growth might continue harming the environment.

In this framework, DEA has been used for cross-country or cross-regions and over time comparisons of eco-efficiency like in Taskin and Zaim (2000). The authors measure eco-efficiency for 52 countries to conclude that high-income countries are more efficient than low and middle-income countries but they have not noticed major changes through time in none of the groups. Other studies using DEA for eco-efficiency evaluation can be pointed as follows. Yang et al. (2015) measure the efficiency of China regions using DEA. In addition, Chen et al. (2015) use DEA to evaluate the environmental efficiency of Chinese provinces. Yin et al. (2014) use eco-efficiency as an indicator to measure urban sustainable development cities using DEA, showing that the inefficient cities are located in the Southwest and Northwest of China. Zhang et al. (2015) measure ecological total factor efficiency incorporating environmental technology effects and including heterogeneity into Chinese regions. Results point for a significant evidence that provinces are not performing at high ecological energy efficiency level. Allowing for dynamic effects and using panel data (DEA window analysis – Charnes and Cooper, 1985), Halkos and Tzeremes (2009) calculate the eco-efficiency for 17 OECD countries constructing an efficiency ratio[2] also used by Zaim et al. (2001) and Zaim (2004).

Wang et al. (2012) estimate the environmental efficiency, economic efficiency, economic environmental efficiency and two-stage efficiency of different provinces in China by considering carbon dioxide (CO2) emissions. Empirical results show that the environmental and economic efficiency of China are generally low and there are comparatively large differences in different areas. The authors notice that when desirable outputs are adjusted to the optimal level, some provinces have still the possibility to further reduce CO2 emissions. They conclude that about half of the provinces are found to be in the status of high incoordination between environment and economy. Chen et al. (2015) investigate the horizontal and vertical difference of environmental efficiency in six Chinese regions and among years using the DEA technique. Results show a high statistical and significantly evidence to support the environmental policies adjustment into different regions.

Eco-efficiency has been studied not only at the country or regional level, but also at the sectoral level. Picazo-Tadeo et al. (2011, 2012) analyze eco-efficiency in the agricultural sector. Previously, Mandal and Madheswaran (2010) studied eco-efficiency in the cement industry of India. Moreover, Kuosmanen and Kortelainen (2005) analyzed the eco-efficiency of road transport in Finland through four different types of environmental pressures. More recently, Egilmez et al. (2013) use economic input-output life cycle assessment (Joshi, 1999) and DEA to measure eco-efficiency in US manufacturing sectors. Rashidi et al. (2015) use as energy inputs coal and petroleum consumption, non-energy inputs, labour force and precipitation average, and as outputs, a desirable output and undesirable CO2 emissions. They construct two informative indices (energy saving potential and undesirable output abatement potential) to study the relationship between energy inputs consumption and undesirable outputs production. Empirical results allowed them to conclude that countries producing high undesirable outputs may not operate in an eco-efficient way turning them able to have extreme potential to save energy resources. They also

[1] As in Robaina-Alves et al. (2015), technical efficiency was estimated and the maximized output is the GDP/GHG ratio. It should be noticed that the estimation of technical efficiency is a measure of eco-efficiency, just by replacing CO2 by a composite good of environmental pressures (GHG as do Schmidheiny and Zorraquin, 1996).

[2] Good efficiency through good output, due to a poor measure of efficiency using a bad output.

conclude that countries consuming low energy inputs may operate eco-efficiently and have lower potential to reduce undesirable outputs.

Robaina-Alves et al. (2015) and other referred studies, focuses over efficiency measures and not over estimated parameters of the production frontier, thus not revealing which input is actually behind the good or bad eco-efficiency performance of a country. In this work, we move one-step further by examining if resources productivity, domestic materials consumption and taxes on pollution over resources are a key determinant of different eco-efficiency levels.

Other studies analyze the influence of these key determinants over efficiency but not considering eco-efficiency scores. With respect to the possible variables explaining the different rankings, Filipovic and Golusin (2015) analyze the existing way of measuring financial effects of environmental taxation in EU27. In the EU, environmental policy and environmental taxation are regulated by EU laws and not by individual member countries legislations (Maastricht Treaty, 1992). Environmental taxes make existing tax distortions worse (Uddin and Holtedahl, 2013). There is also evidence that it is hardly possible to identify the suitable tax rates to internalize externalities (Golusin et al., 2013). As such, monitoring and auditing are regarded as essential activities for process control and follow up, thus contributing to performance improvements and useful in preventing or reducing environmental harms (Mironeasa and Codina, 2013). Having this in mind, we formulate our first testable hypotheses that environmental tax revenues may cause distorting effects in efficiency countries rankings.

Hatfield-Dodds et al. (2017) argue that resource efficiency and GHG abatement slow the growth of global resource extraction. Moreover, it is argued that resource efficiency reduces GHG emissions and boosts near-term economic growth. This economic gain pathway would result in emissions reduction by 2050 well below current levels, slower growth in resource extractions, and faster economic growth. Economic activities use material resources, labour and capital to produce goods and services. The consequence is the effect caused on the natural environment, inevitably generating pollution, such as GHG (Robaina-Alves et al., 2015; Yang and Zhang, 2016). As such, if resources are used inefficiently during the production process, economic outputs will be lower and emission levels higher. Domestic material consumption (DMC) provides a way to an economy access the absolute level of the use of resources. This indicator affords the basis for policies to decouple the growth of the economy from the use of natural resources. The goal is to achieve a reduction of environment degradation, which results from primary production, material processing, manufacturing, and waste disposal. As such, to achieve higher eco-efficiency scores countries are expected to have lower DMC levels. Considering these arguments our second testable hypothesis is that DMC negatively explains eco-efficiency scores.

When combining DMC with GDP, we could have further insights to whether decoupling between the use of natural resources and economic growth is taking place. Resource productivity measures the relation between economic activity and the consumption of natural resources.[3] It sheds light on whether they go hand-in-hand or the extent to which they are decoupled. As such, it is expected that resources productivity have a positive effect over eco-efficiency, giving the mote for our third testable hypothesis. Moreover, the EC eco-innovation scoreboard[4] evidences that countries with a higher score in the component of eco-innovation inputs also perform better with regard to resource efficiency.

3. Data and methodology

3.1. Data and variables

Data for the period 2001–2012 has been collected for 26 European countries: Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden and United Kingdom. Only 26 countries were chosen because it was for these that it was possible to obtain a balanced panel.The inputs labour productivity, capital productivity, the weight of fossil energy and the share of renewable energy in GDP were used, considering as output the ratio GDP per GHG emissions. Using these variables, technical efficiency was computed and a countries ranking was established. The GDP/GHG ratio is used as output and the other four ratios as inputs by using a log-linear Cobb-Douglas production function (Debertin, 2012).

The GDP by country was collected from Eurostat at market and constant prices of the year 2000, in millions of euro. GHG was collected in thousands of tonnes from the European Environment Agency. Labour productivity per hour worked is calculated as real output (deflated GDP measured in chain-linked volumes, reference year 2005) per unit of labour input (measured by the total number of hours worked).[5] Capital productivity is calculated as real output (deflated GDP measured in chain-linked volumes, reference year 2005) per unit of capital input (measured by the gross fixed capital formation at constant prices of the year 2000, in Millions of euro). Both productivity measures were taken from Eurostat.[6] Fossil fuel consumption is the sum of final energy consumption of solid fuels, gas and petroleum products measures in thousands of tonnes of oil equivalent (TOE) and taken from Eurostat. The weight of fossil fuel is computed over total energy produced. Renewable energy consumption is the final energy consumption of renewable and wastes in thousands of TOE also taken from Eurostat and renewable energy share was computed considering GDP.

In a second step we use resources productivity, domestic material consumption and environmental taxes revenues. Resource productivity is defined as the ratio between GDP and DMC. Data on resource productivity is derived from material flow accounts data collected under the Regulation (EU) 691/2011 on European environmental economic accounts. DMC[7] measures the total amount of materials directly used by an economy, and is defined as the annual quantity of raw materials extracted from the domestic territory, plus all physical imports minus all physical exports. It is expressed in tonnes per capita. This indicator is regularly published by Eurostat for individual countries and the EU as a whole. European statistics distinguish four different categories of environmental taxes relating to energy, transport, pollution, resources, and we use all of them. When comparing the level of environmental

[3] Natural resources include biomass, metal ores, non-metallic minerals and fossil energy materials.

[4] https://ec.europa.eu/environment/ecoap/scoreboard/resource-efficiency-outcomes_en

[5] As stated in Eurostat. (http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=tsdec310&plugin=1) measuring labour productivity per hour worked provides a better picture of productivity developments in the economy than labour productivity per person employed, as it eliminates differences in the full time/part time composition of the workforce across countries and years.

[6] This data source converts data in Euros from former national currencies using the irrevocably fixed rate for all years and in Purchasing Power Standards (PPS) at current prices. The authors used the national price index (for each country), also given by Eurostat, to transform current prices data into constant prices data. Therefore, we do not consider that the use of these data raises any issue, by being the usual procedure using monetary variables.

[7] Domestic Material Consumption. http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Domestic_material_consumption_(DMC).

taxation across European countries, differences should be analyzed with caution. For instance, low revenues from environmental taxes could signal relatively low environmental tax rates, or could result from high tax rates that have had the effect of changing behavioral patterns of consumption of the related products or activities. On the other hand, higher levels of environmental tax revenue could be due to low tax rates that incentivize non-residents to purchase taxed products across a border (as is the case for petrol or diesel).

Energy taxes presents the total energy tax revenues calculated for a calendar year measured in million euros. Total energy tax revenues include taxes on energy use paid by 'households', in 'industry and construction', 'agriculture, forestry and fishing', 'transportation and storage' and in the 'services' sector. Energy taxes include taxes on energy products used for both transport and stationary purposes. The most important energy products for transport purposes are petrol and diesel. Energy products for stationary use include fuel oils, natural gas, coal and electricity. The CO_2 taxes are included under energy taxes rather than under pollution taxes. Transport taxes mainly include taxes related to the ownership and use of motor vehicles. Taxes on other transport equipment (e.g. planes), and related transport services (e.g. duties on charter or schedule flights) are also included here, when they conform to the general definition of environmental taxes. The transport taxes may be 'one-off' taxes related to imports or sales of the equipment or recurrent taxes such as an annual road tax. The last group of pollution/resource taxes includes taxes on measured or estimated emissions to air and water, management of solid waste and noise.

3.2. Methodology

There are two main models to compute the DEA index. On one hand we have the Charnes-Cooper-Rhodes (CCR) which is a constant returns-to-scale model (Charnes et al., 1978) and on the other hand we have the Banker-Charnes-Cooper (BCC) which is a variable returns-to-scale model (Cooper et al., 2007). The main advantage of considering variable returns is that these allow capturing in part the heterogeneity among countries. Both developed models generate a piecewise-linear envelopment surface and are simultaneously input-or-output oriented, only depending if the goal is to maximize input contraction or output expansion, with output production or input consumption, respectively, kept constant. They yield identical envelopment or convex surfaces but are different in the way inefficient decision making units (DMUs) are projected onto the efficient frontier (Cooper et al., 2007).

A DMU is responsible for converting multiple inputs into multiple outputs and whose efficiency is to be evaluated (Cooper et al., 2007). DEA does not require a specific functional form not the a priori assignation of weights of each output and input (Cooper et al., 2007), instead it allows variables weights for each input and output to vary being derived from the data instead of being fixed or predetermined, which promotes objectivity and reduce bias (Cooper et al., 2007). The weights are determined as the best when the resulting output-to-input ratio is maximized for each European country.

The frontier model is given by $\ln y_n = f(x_n, \beta) + v_n - u_n$, with n = 1, 2, . . ., N, where N is the number of countries; f(.) is the production frontier; y_n is the scalar output (GDP/GHG) for country n; x_n is a row vector with logarithms of inputs (labour productivity, capital productivity, weight of fossil energy and share of renewable energy in GDP) for the country n; β is a column vector of parameters to estimate; v is a random variable representing noise; $u \geq 0$ is a one-sided random variable representing technical inefficiency.

3.2.1. Technical efficiency

Efficiency refers to the relationship between inputs and outputs. It can be improved by consuming fewer inputs while maintaining the same output level. Given that the output maximized is the ratio GDP/GHG, by estimating technical efficiency we are also measuring eco-efficiency.

Besides the input-oriented model, usually referred to as Constant Return Scale (CRS)–DEA, introduced by Charnes et al. (1978),[8] we also use the Variable Returns-to-Scale (VRS) model, meaning its variable version (Cooper et al., 2007). In the CRS-DEA model constant returns to scale are assumed to exist imposing that the set of production possibilities is formed with no scale effect. Usually, technical efficiency represents the success of a DMU, which produces at its maximum output when a specific group of inputs is used, being inputs exogenous and outputs endogenous. The CRS model of efficiency is probably one of the most used and known within DEA models.

Later on, Banker et al. (1984) raised the optimization problem considering VRS where the efficiency of a DMU depends over the size and the effect of increasing resources becomes different across the DMUs.

This model became known as the BCC (Banker, Charnes and Cooper) model and this relationship as the pure technical efficiency. Therefore, the BCC model is represented by a dual linear programming model.

Lee (2009) explains briefly the differences between CCR and BCC, which mainly persist with respect to the assumptions of production possibility sets. While CCR or technical efficiency assumes constant returns to scale (one unit of increase in investment generates output in one unit), BCC or pure technical efficiency assumes variable returns to scale (where the output scale changes).

DEA efficiency score is given by a specific value, between 0 and 1, where 1 indicates that a DMU shows the best performance localized in the production frontier and reveals no potential reduction. Any v lower than 1 indicates that the DMU uses inputs inefficiently. The model objective function maximizes the outputs ratio weighted by inputs as well as by the DMU analysed, under the condition that there are similar relations for all the DMUs in presenting efficiency scores equal to, or lower than 1. Both CRS and VRS model versions are estimated through DEA.

DEA allows the comparison of DMUs belonging to a same set. By calculating an efficiency score, this method allows to assess an entity's DMU capability in converting inputs into outputs. It is considered inefficient when a score below 100% is achieved. This comparison also allows to determine both input and output targets corresponding to an efficient operation. Charnes et al. (1978) considers that each DMU should adopt the most favorable set of weights when compared to others, implying that the efficiency of a target unit j_0 can be calculated as a maximizing function $e_{j_0} = \max \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$ where v_i and u_r represent the weights associated to the inputs (x) and outputs (y), respectively.

3.2.2. Quantile approach

In this section we present regression analysis methodology followed for the determinants of efficiency. Simar and Wilson (2007) and Zelenyuk and Zheka (2006) show that using the traditional tobit estimator into regression analysis of efficiency determinants is inappropriate and fails to address the dependency problem of DEA efficiency scores. To surpass this limitation, we propose to use here quantile regressions.

[8] Charnes, Cooper and Rhodes (CCR), that assumes constant returns to scale (CRS) (Charnes et al., 1978).

Using standard linear regression techniques provides solely a partial view of the relationship when we could be interested in describing the relationship at different points in the conditional distribution of y, whereas quantile regression allows that capability. Quantile regression has been applied for example for the willingness to pay for air and noise pollution reductions by O'Garra and Mourato (2007). Its main advantages are its robust properties even in the absence of normality and due to its power to estimate effects at different points of the conditional outcome distribution.

The basic idea in quantile regression and following O'Garra and Mourato (2007) is to estimate the p-th quantile of conditional efficiency over the different explanatory variables assuming that quantile may be expressed as a linear function of those same variables.

Standard linear regression techniques summarize the average relationship between a set of regressor and the outcome variable based on the conditional mean function E(y|x). This provides only a partial view of the relationship, as we might be interested in describing the relationship at different points in the conditional distribution of y. Quantile regression provides that capability (Baum, 2013). Analogous to the conditional mean function of linear regression, we may consider the relationship between the regressor and outcome using the conditional median function $Q_q(y|x)$, where the median is the 50th percentile, or quantile q, of the empirical distribution. The quantile $q \in (0, 1)$ is that y which splits the data into proportions q below and 1-q above: $F(y_q) = q$ and $y_q = F^{-1}(q)$: for the median, q = 0.5. In the present work, we have considered the following conditional quantiles: 0.10 (percentile 10%), 0.25 (lower quartile), 0.50 (median), 0.75 (upper quartile) and 0.90 (percentile 90%). For each situation, it was kept the explanatory variables that proved to be statistically significant.

Quantile regression minimizes a sum that gives asymmetric penalties $(1-q)\ |e_i|$ for over prediction and $q|e_i|$ for under prediction. Although its computation requires linear programming methods, the quantile regression estimator is asymptotically normally distributed. Median regression is more robust to outliers than least squares regression, and is semiparametric as it avoids assumptions about the parametric distribution of the error process.

By applying quantile regression techniques, it is possible to examine the determinants of eco-efficiency throughout the conditional distribution. The choice for these quantiles results from the distribution of economic environmental efficiency scores provided by the optimization solution problem.

The non-differentiable function will be minimized through the simplex method, which is guaranteed to yield a solution in a finite number of interactions. To ensure heteroskedastic-robust estimates, robust standard errors for OLS estimates are to be reported. Being the sufficient number of bootstrap repetitions inversely related to sample size, in quantile regression we do not report the Koenker and Basset standard errors but we provide bootstrapped standard errors using for that 1000 bootstrapping repetitions.

As previously stated we use as independent variables environmental taxation, productivity and DMC. Other variables could be used but we follow the literature reasoning. For example, Filipovic and Golusin (2015) argue that environmental taxation policy and its effects are of considerable importance for the EU for several reasons. First, environmental policy and its harmonization are questionable, and thus, measuring the effects of the EU member states is a very good way to determine the needs and direction of planned harmonization. Second, financial effects of environmental taxation can be considered significant in terms of total national revenues, presenting a source for investment in environmentally sound projects and contributing to the improvement of quality of life. These authors using the existing way of environmental tax revenues measuring (share in GDP and total revenues) showed significant differences in ranking of EU27 countries. In the first year of their study (2005), Environmental Taxation Revenues (ETR) average share in GDP in the EU27 region was 2.5%, with some discrepancies among countries. The highest share of ETR in GDP is made by Denmark (4.9%) and the Netherlands (4%), while Cyprus has a high share of ETR in GDP (3.5% respectively). The authors found that in many countries ETR share in GDP is above the average, while the most economically developed countries (Germany, UK and France) have ETR share in GDP at the average or even below the average of EU27(2.5%), example of France, which is the lowest-ranked (according to Table 1 in page 390 of Filipovic and Golusin, 2015).

Likewise, it was possible to observe that there has been a reduction in per capita DMC in the majority of countries over the period 2001–2012. The largest decline was recorded in Ireland (50%) and Spain (49%)—mainly caused by a collapse in construction activities—followed by Italy (38%) and Cyprus (32%). Per capita DMC increased in 13 countries, and the largest per-capita increases over this period—primarily due to large-scale infrastructure investments—was recorded in Romania (178%), Estonia (104%), Lithuania (54%), Bulgaria (46%) and Turkey (44%). On the other hand, the increase in resource productivity between 2001 and 2012 was highest in Ireland, Spain, Slovenia, Hungary, Czech Republic, Italy, Cyprus and the United Kingdom. Only two countries—Romania and Estonia—experienced a decline in resource productivity in the same period (see EEA's report SOE, 2015). Also taking these facts into account we considered environmental taxes, resources productivity and DMC into our second aim to understand if these variables are able to explain economic and environmental efficiency levels (scores reached during the first estimation phase).

4. Results

4.1. Eco-efficiency

This section starts by presenting the eco-efficiency (EE) scores obtained through the output-input maximization first procedure explained above. The closer the value of EE is from unit, the more efficient the country is, which means that at the value of 1 the country is making the best use of economic and energy resources to produce the maximum possible output (GDP) and at the same time is minimizing the environmental impact through GHG emissions. Table A1 in the Appendix presents some descriptive statistics for the estimates obtained through the DEA estimator with VRS and CRS. The DEA estimator provides the higher mean value of EE 0.8258 for VRS and 0.7278 for CRS. The range of standard deviation values goes from 7.62% (CRS) until 18.35% (VRS). Maximum CRS value reported is 89.02% in 2004 and minimum of 40.99% in 2012, whereas the maximum VRS scale EE value obtained was in 2008–2009 of 100% and the minimum of 29.57% in 2008. The standard deviation values of EE in this period are also greatest for the DEA-VRS estimator, while the minimum value of EE occur in 2008 (in Estonia) and the maximum value occur in 2008 and 2009 (in Sweden and Latvia respectively).

Fig. 1 provides the EE score results for the 26 European countries considered using the VRS version of DEA. The empirical evidence shows that in 2012 Ireland, Latvia, Sweden, Hungary and United Kingdom are the five most efficient countries, while Estonia, Czech Republic, Poland, Bulgaria and Germany constitute the five least efficient countries. In 2012, both Ireland and Latvia were 98.9% efficient and 1.1% inefficient. Table A1 at the Appendix ranks the countries by years according to the DEA-VRS estimates obtained in Fig. 1. There we may observe that Hungary, Portugal and Ireland were in the 17th, 19th and 23th position, respectively, in 2001 and that these same countries have changed the ranking to the 4th, 8th and 1st positions, respectively, in 2012. Conversely, Bulgaria,

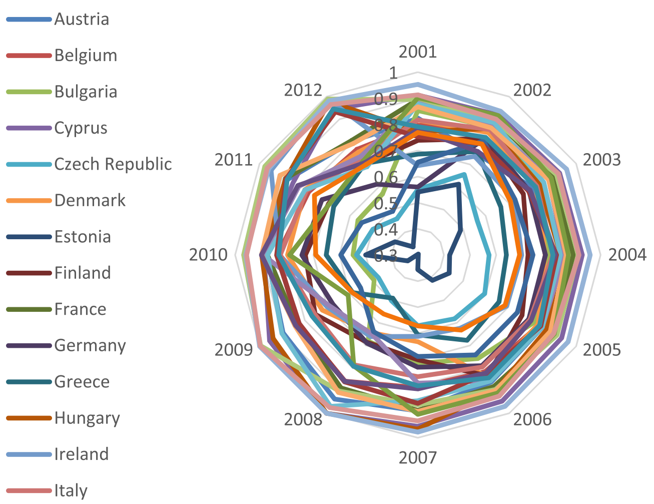

Fig. 1. Eco-Efficiency in European Countries – Output Oriented –Variable Return Scale.

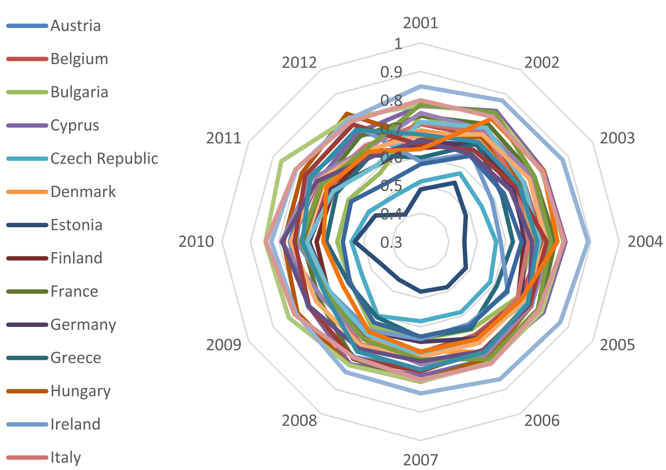

Fig. 2. Eco-Efficiency in European Countries – Output Oriented – Constant Returns-to-Scale.

Luxembourg and Romania were in the 10th, 8th and 4th position, respectively, in 2001 and ranked the 23th, 21th and 16th position in 2012, respectively.

From the results, we observe that there has been some effort done by countries to converge to the efficiency frontier (especially in Hungary, Slovenia and Latvia). In the first four positions as the most efficient ones, we are able to place Ireland, Latvia, Sweden and Hungary and in the last four positions (the least efficient), we have in accordance to the VRS results Bulgaria, Poland, Czech Republic and Estonia. Evidence presented in both Fig. 1 and in Table A2 at the appendix, allow us to state that Ireland, Hungary and Portugal are becoming relatively more efficient, while Bulgaria, Luxembourg and Romania became the least economic and environmental efficient countries in the entire period analysed.

Next, in Fig. 2 we present EE values obtained through DEA considering CRS. At a first analysis we may state that having VRS or CRS considered changes results in terms of ranking positions (see Figs. 1 and 2 and Tables A2 and A3 at the Appendix, for comparison).

It can be seen from Fig. 2 that in 2012 Hungary, Latvia, Sweden, UK and Ireland are the five most efficient countries, while Estonia, Czech Republic, Poland, Bulgaria and Germany constitute the five least efficient countries. When compared to VRS results in Fig. 1 only Hungary changes its first position in VRS with the fifth position to Ireland in VRS when in CRS those two same places are the opposite. In terms of the least five positions they coincide in both VRS and CRS. In 2012, Hungary and Latvia were 82% and 80.3% efficient, respectively, thus being less efficient when CRS are considered rather VRS, where values were 97.8% 98.9% respectively.

Moreover, according to Table A3 at the Appendix Ireland, Portugal and Hungary are ranked in 23rd, 19th and 16thplace, respectively, in 2001 and changed their rankings to 5th, 6th and 1st place, respectively, in 2012. This suggests a positive significant change in the trend of economic and environmental efficiency in some European countries. Conversely, Bulgaria, Romania and Luxembourg ranked in 7th, 3rd and 9th place, respectively, in 2001, observed the drop of their positions to the 23rd, 12nd and 21st places, respectively. In accordance to Table A3, Hungary is the most efficient country in 2012 where it accounts with a level of 82% of efficiency and the least efficient country is Estonia being only 41% efficient. This put forward the high disparities existing among the European group in terms of EE and conditions the need for higher steps if the goal is to turn equal the countries efficiency level.

Since the period analysed also encompasses the economic crisis, mentioned in the case of Spain to explain its decrease in consumption, but likely to have other effects, we have also separated the analysis into periods. Results are presented in Figs. 3 and 4, and reported in Table A4 at the appendix. Values obtained by period are based over geometric means. Taxes on vehicle properties and gas also rose due to the need of some countries to increase revenues from taxation. By presenting results considering different time spans separately, it would provide a clue.

By analysing both Figs. 3 and 4 we observe that values obtained for technical efficiency are always lower than those reached through pure technical efficiency. Moreover, and for most of the countries, efficiency values are lower considering the period 2009–2012 which includes the financial crisis period. This is not the case of for example Portugal, UK, Latvia and Ireland. Efficiency values are higher considering the period 2005–2008 where we had the start of the implementation of the Kyoto protocol, although it is not true for all countries like in Belgium, Bulgaria, Czech Republic, Greece, Latvia and Spain. This shows that the Kyoto implementation has been more effective in some countries than in others as well as we still observe differences when considering different time spans and if we are dealing with CRS or VRS.

With respect to values obtained by periods we should notice that when comparing 2009–2012 values with those of the previous 2005–2008 period, we observe that eco-efficiency scores reduced. This decrease may be explained in part by lower domestic material consumption and an increase in resources productivity as evidenced by data descriptive analysis of EU reports. The economic crisis affected all material intensive industries and thus decreased production and GDP, consequently affecting negatively eco-efficiency scores.

4.2. Quantile regression estimates

The results are shown in Tables 1 (DEA-VRS) and 2 (DEA – CRS). Regression estimates in both results (VRS and CRS) show a positive and significant influence of energy taxes (except in high eco-efficiency scores), transport taxes (except in high eco-efficiency scores) and resources productivity and a negative and significant influence of taxes on pollution/resources and domestic material consumption over eco-efficiency. Median (50%) quantile regression results, which correspond to the Minimum Absolute Deviation estimator, are in general significantly lower than OLS estimates.

The coefficient estimates of the 75% quantile shows in both VRS and CRS a positive influence of energy taxes and resources productivity and a negative influence of transport taxes, taxes on pollution/resources and domestic material consumption on the efficiency scores, while the coefficient estimates of the 90%

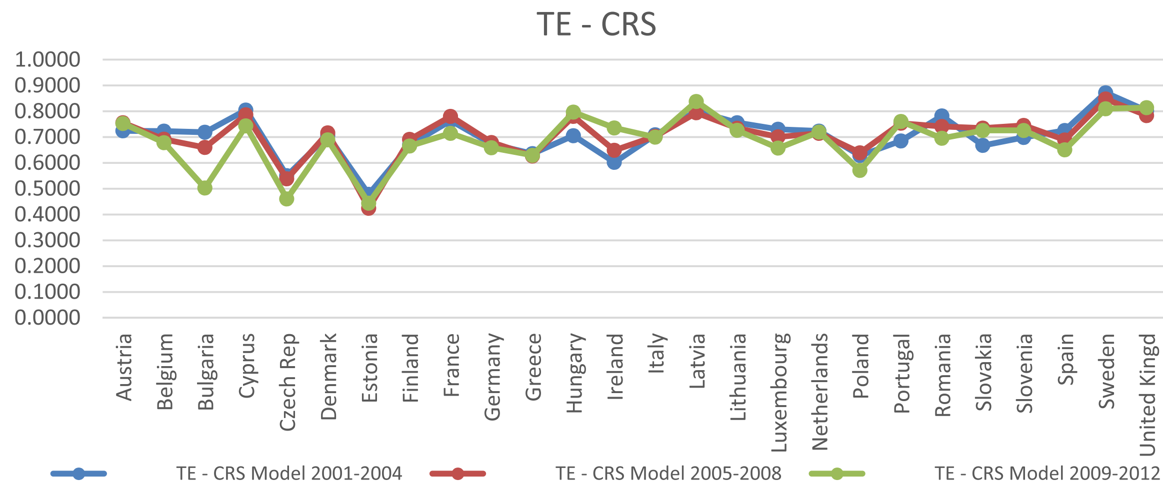

Fig. 3. Eco-Efficiency in European Countries by periods – Constant Returns-to-Scale.
Note: TE – technical efficiency; CRS – Constant returns to scale CCR model (Charnes, Cooper and Rhodes (CCR) (Charnes et al., 1978)). Data complemented in Table A4 in the appendix.

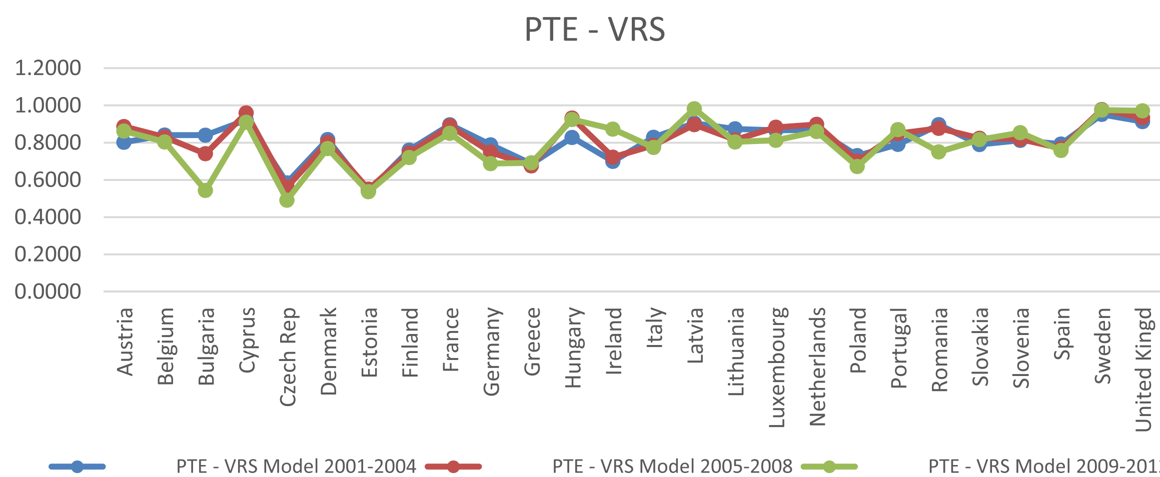

Fig. 4. Eco-Efficiency in European Countries by periods – Variable Returns-to-Scale.
Note: PTE – Pure technical efficiency; VRS – Variable returns to scale BCC model (Banker, Charnes and Cooper model (BCC) Banker et al. (1984)). Data complemented by Table A4 in the appendix.

Table 1
Results of OLS and Quantile Regression estimates (VRS).

Independent variables	OLS	Quantile Regression				
		Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)
Energy Taxes	0.0396 (0.042)**	0.0470 (0.082)*	0.0476 (0.034)**	0.0346 (0.172)	0.0137 (0.675)	−0.0161 (0.386)
Transport taxes	0.0480 (0.014)**	0.1146 (0.000)***	0.0525 (0.090)*	0.0153 (0.530)	−0.0174 (0.505)	−0.0268 (0.035)**
Taxes on Pollution/Resources	−0.1993 (0.012)**	−0.3592 (0.010)***	−0.1033 (0.488)	−0.0856 (0.325)	−0.2437 (0.0007***)	−0.2185 (0.000)***
Resource productivity	0.0.0609 (0.000)***	0.0683 (0.016)**	0.0756 (0.000)***	0.0538 (0.006)***	0.0684 (0.000)***	0.0373 (0.000)***
Domestic Material Consumption	−7.07e-08 (0.002)***	−6.18e-09 (0.883)	−4.03e-08 (0.145)	−1.05e-07 (0.003)***	−1.33e-07 (0.000)***	−1.34e-07 (0.000)***
Constant	0.6565 (0.000)***	0.4105 (0.000)***	0.5205 (0.000)***	0.7119 (0.000)***	0.8551 (0.000)***	1.0021 (0.000)***
Observations	312	312	312	312	312	312
R^2/Pseudo R^2	0.3600	0.3996	0.3177	0.2066	0.2491	0.3062

Dependent variable: Technical Efficiency Scores (based on the DEA model – Variable returns-to-scale). *p*-values in parenthesis; *, **, *** means significant at 10%, 5% and 1% respectively.

quantile (highest values of scores efficiency) shows in either a positive and significant influence of resources productivity and a negative and significant influence of transport taxes, taxes on pollution/resources and domestic material consumption over efficiency scores.

At the outset, it should be noticed that the same environmental taxes revenues effects (positive or negative) are present in all conditional quantiles analyzed. However, this influence is much stronger in the positive sense over the more inefficient European countries and exerts negative influence over more efficient European countries. Additionally, note also that the domestic materials consumption effect is significant at all upper quantiles for DEA – VRS and DEA-CRS, in the latter also highly significant for the least efficient countries (Q(0.10)). That is, there is a negative premium of efficiency, keeping other things equal, for domestic materials consumptions.

Table 2
Results of OLS and Quantile Regression estimates (CRS).

Independent variables	OLS	Quantile Regression				
		Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)
Energy Taxes	0.0231	0.0258	0.0178	0.0121	0.0050	−0.0043
	(0.048)**	(0.024)**	(0.163)	(0.507)	(0.845)	(0.827)
Transport taxes	0.0338	.0832	0.0659	0.0160	−0.0163	−0.0226
	(0.002)***	(0.000)***	(0.003)***	(0.259)	(0.441)	(0.050)**
Taxes on Pollution/Resources	−0.1468	−0.2068	−0.1364	−0.1267	−0.1333	−0.1968
	(0.003)***	(0.008)***	(0.153)	(0.147)	(0.022)**	(0.000)***
Resource productivity	0.0237	0.0311	0.0416	0.0194	0.0255	0.0237
	(0.001)***	(0.000)***	(0.008)***	(0.295)	(0.048)**	(0.030)**
Domestic Material Consumption	−1.63e-08	−4.44e-08	−1.51e-08	−4.26e-08	−5.88e-08	−8.00e-08
	(0.255)	(0.000)***	(0.445)	(0.084)*	(0.056)*	(0.021)**
Constant	0.6336	0.4758	0.5264	0.6844	.7669	0.8424
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	312	312	312	312	312	312
R^2/Pseudo R^2	0.3029	0.4567	0.2843	0.2236	0.2225	0.2671

Dependent variable: Technical Efficiency Scores (based on the DEA model- Constant returns-to-scale). *p*-values in parenthesis; *, **, *** means significant at 10%, 5% and 1% respectively.

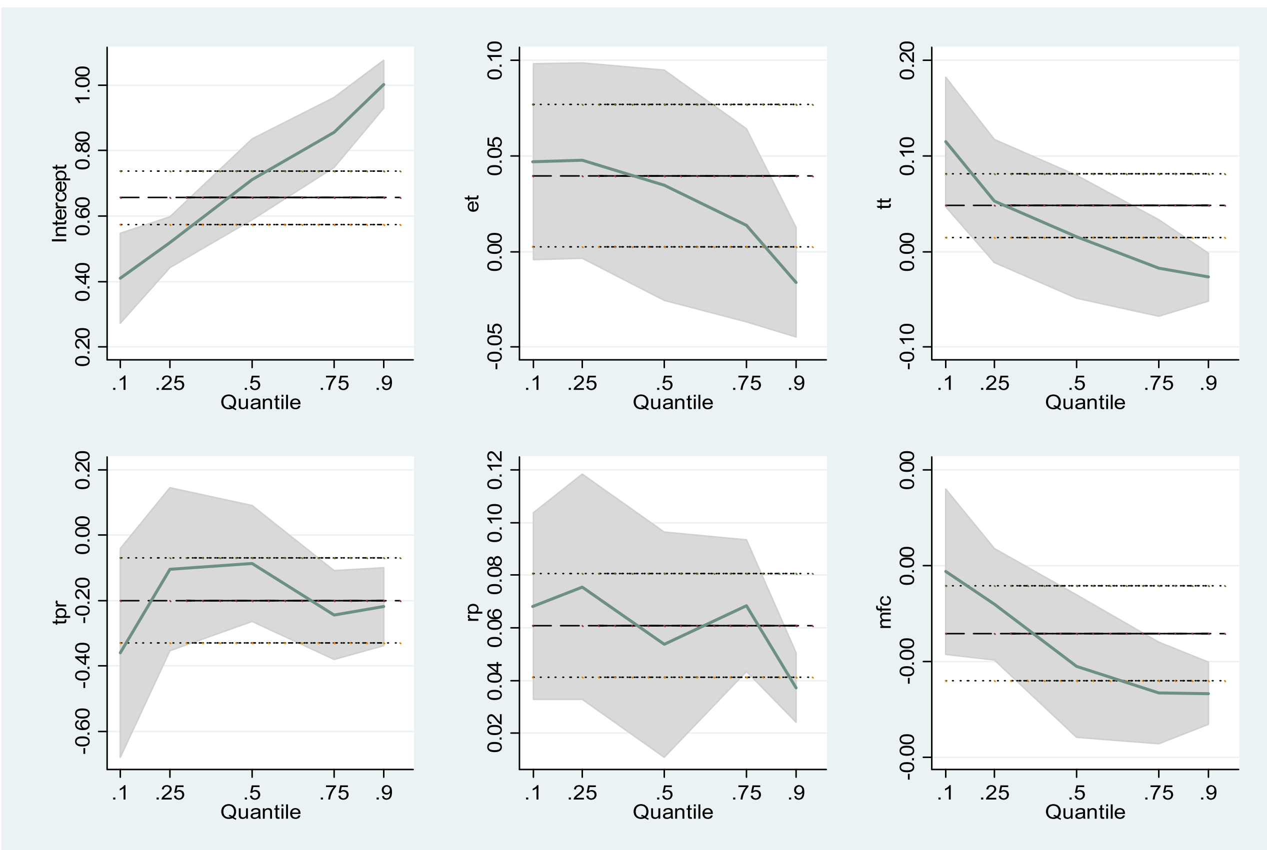

Fig. 5. Results of OLS and Quantile Regression – Variable Returns-to-Scale.
Note: Intercept is the constant; et stands for energy taxes; tt for transport taxes; tpr stands for taxes on pollution/resources; rp for resources productivity; and mtc for domestic material consumption. Horizontal black line represents OLS estimates with blue "shadow" representing 95% confidence intervals. The trended line represents quantile regression estimates for VRS.

Fig. 5 allows a visual appreciation of the quantile regression results. Following Azevedo (2004), one can view how each covariate's effects vary across quantiles and contrast them with the OLS robust estimates. According to Baum (2013) the graph illustrates how the effects of each regressor vary over quantiles, and how the magnitude of the effects at various quantiles differ considerably from OLS coefficients, even in terms of the confidence intervals around each coefficient.

Our results, in both VRS and CRS versions, show that for the lowest quantiles of the conditional scores of efficiency distribution, the coefficients on experience are very low, being close to zero. However, as we move up the conditional distribution, the coefficient rises significantly, especially at the extreme upper quantiles.

Fig. 6 presents a plot of quantile regression results but using CRS. Horizontal lines in both figures represent OLS estimates, whereas the grey interval is the 95% confidence interval and the green line stands for the quantile regression estimates. Taxes on pol-

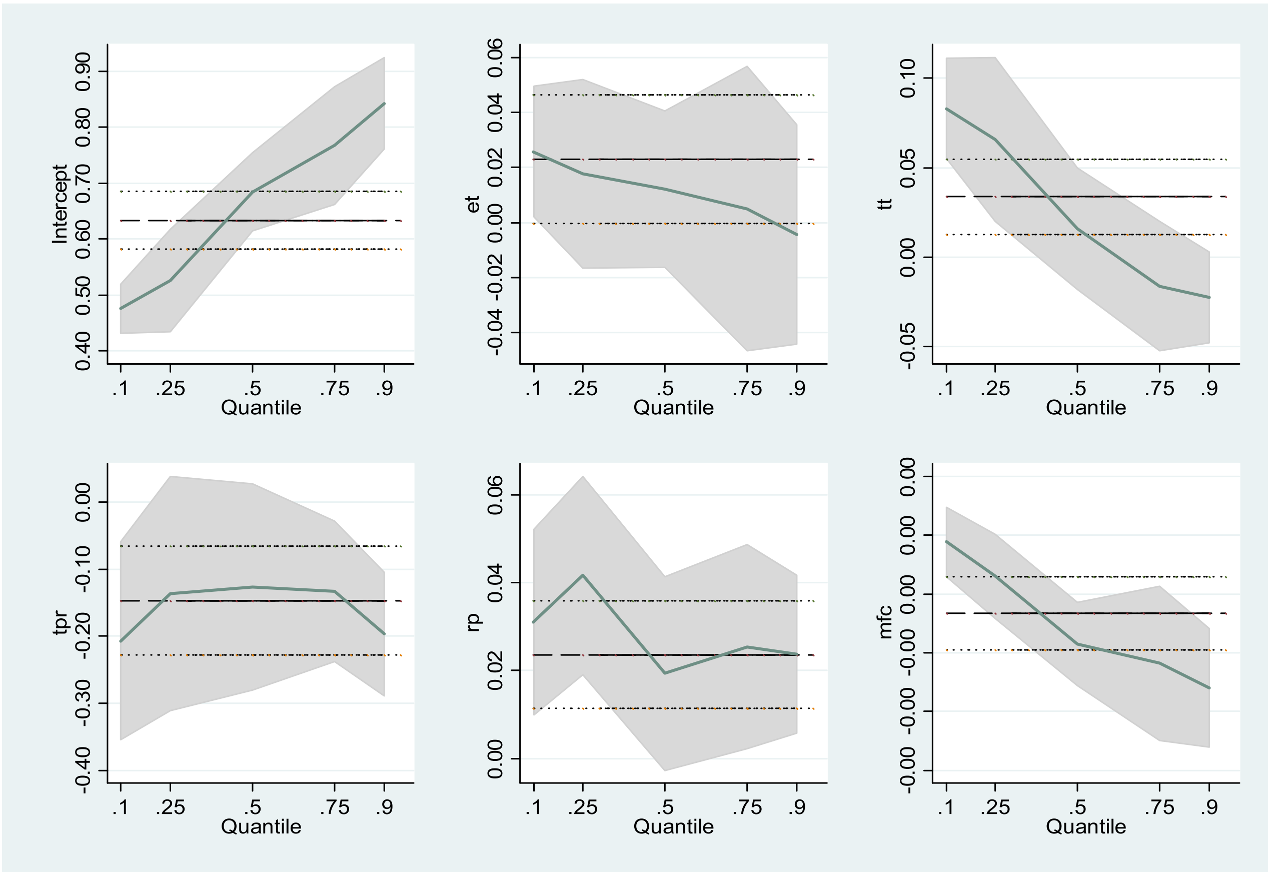

Fig. 6. Results of OLS and Quantile Regression – Constant Returns-to-Scale.
Note: Intercept is the constant; et stands for energy taxes; tt for transport taxes; tpr stands for taxes on pollution/resources; rp for resources productivity; and mtc for domestic material consumption. Horizontal black line represents OLS estimates with blue "shadow" representing 95% confidence intervals. The trended line represents quantile regression estimates for CRS.

lution/resources exert a negative and significant influence at the lowest quantile and at the two highest quantiles, using both VRS and CRS. Also in both, resources productivity exerts a positive and significant influence in all considered quantiles (except at quantile 0.50 in CRS). This means that countries eco-efficiency scores are determined by its high taxes on pollution/resources, which coincides also with those that have higher resources productivity. On the other hand, the positive and significant sign of energy and transport taxes at lowest quantiles means that countries with low eco-efficiency scores have higher taxes. By opposition, transport taxes have a negative, significant and similar (in both VRS and CRS) impact in countries with higher technical eco-efficiency (0.90 quantile) scores, which pay more transport taxes and taxes on pollution/resources than should be reasonable. Moreover, energy taxes seem to have higher impact over low eco-efficiency score countries.

For median quantile (0.50) and above, domestic material consumption is found to be significant and negative, meaning that average (0.5) and high eco-efficiency countries score is determined by lower domestic material consumption, keeping all the rest constant and more noticed in the DEA-VRS model version.

5. Discussion

The long-term objective of current European environmental policies is that the overall environmental impact of all major sectors of the economy should be significantly reduced, and resource efficiency increased. The large differences in resource-efficiency performance amongst countries—and the fact that the same half-a-dozen countries have remained at the bottom of resource efficiency rankings since 2000—indicates opportunities for improvements and actions (EEA's report SOE, 2015). Natural resources underpin economic and social development, and over-consumption of these resources has resulted in environmental degradation and economic losses.

Improving the resource efficiency of European economies and societies is essential, and this objective has been on the European environmental policy agenda for more than a decade (EC, 2005, 2008, 2011). As Zhou et al. (2014) state, for instance, a productive entity may have more than one abatement strategies and different groups of productive entities may face different degrees of environmental regulations. In addition, since the marginal abatement cost for a productive entity is dependent upon its abatement level, the derivation of a curve for shadow prices would provide valuable approximation to marginal abatement cost curve. As such, there could be differences with respect to taxation, resources productivity or even DMC able to explain the eco-efficiency ranking among European countries, which we tried to analyze.

Given the heterogeneity across Europe and the reality results stated previously, some reflections need to be done. Namely, with respect to the different intensity levels in the mix of fossil energy resources, the capacity of existing renewable energy power plants, energy consumption and production and also economic growth. Moreover, it is necessary in eco-efficiency analysis to include other variables like energy taxes, transport taxes, pollution/resources taxes, account for resources productivity and domestic material consumption (among others). We included these in order to see if these can mitigate or are able to explain the simultaneous changes in economic growth and CO_2 emissions intensities.

Eco-efficiency estimates for these European countries demonstrate that changes in labour productivity, capital productivity, and the weight of fossil energy and the share of renewable energy in GDP might give reasonable joint indications of economic and environmental improvements, or better in terms of the performance of the output ratio GDP per GHG emissions. Relevant conclusions might be taken from Tables 1, 2, A2 and A3 where it was evident that some countries performed well between 2001 and 2012 while others did not. For example, considering DEA-VRS model we see that Hungary increased its performance by about 26.8%, Ireland in about 54%, Latvia with a modest 10.5%, while Slovenia in 19.6%. Portugal saw its eco-efficiency score improve in about 23.9% (from 0.753 in 2001–0.933 in 2012). However, not in all countries we might observe a good performance. In Bulgaria the performance level decreased in 33.2%, in Luxembourg in about 21.4%, in Poland 24.7%, in Romania 20.6% and Spain in about 9%. Although the technical eco-efficiency indicator provides the overall outcome for the economic and environmental efficiency of the joint use of capital, labour, and both renewable and non-renewable energy sources, it is still important to see which factors lay behind the good or bad performance of European countries in terms of eco-efficiency rankings.

Countries betting on renewable energy efficiently, substituting in a gradual way fossil energy like Hungary and Ireland, considered to have lower energy intensity or with a good performance in terms of energy intensity, also had a greater potential to move closer to efficiency levels of one (European Commission, 2014; Robaina-Alves et al., 2015). Investment in renewable energy undertaken by some countries, especially after the Kyoto Protocol, also differentiates that kind of "good behavior" because these countries initiatives to reduce emissions were noticed in the level of eco-efficiency of some countries.

In the present work, taxes, domestic material consumption and resources productivity were the factors used in quantile regressions to try to explain eco-efficiency rankings. We observe that taxes over pollution/resources exert a higher influence over the ranking placement of production per unit of emissions. Resources productivity shows to have a positive and significant influence for almost all considered quantiles, meaning independently of the country technical eco-efficiency level. Considering the initial hypothesis formulated, results point for distorting effects of taxes over eco-efficiency scores, more evidenced by transport taxes whose effect is positive in lower efficient countries being negative for those more highly efficient. In the meanwhile, the positive effect of resources productivity is observed through the results attained. As such, results point that economic output and human well-being shall continue to increase in parallel with increasing resource use and slower environmental impact. With time, these should brought into decline, allowing to sustain resource use, whereas delivering ecosystem products able to withstand sustainable economic development.

The reality of the different levels of eco-efficiency in European countries might show the importance of measuring eco-efficiency, whose aim provides an important indicator to investigate sustainability performance in Europe under the background of energy saving and emissions reduction. In accordance with Canton and Lindén (2010), subsidies might be an incentive for firms to invest in renewables resources and benefit from similar return rates as conventional energy sources. Following the authors, the goal is to compensate for the relatively high costs of such energy sources as compared to other fossil fuels. As renewables development occurs, we should expect further technology development, thus reducing costs over time and render them competitive in the long run.

In 2009, the Commission's Third Energy Package introduced a set of Directives and Regulations to further consolidate and open up the Internal Energy Market. Besides, being broadly adopted, these reforms have been implemented to varying degrees across Member States (European Commission, 2014). The worst performance observed in some countries might be attributed to remaining lobbies and renewable sources generation costs, which remain higher than that of conventional technologies. This effect, when combined with protectionism policies into the energy production sector, increases the use of non-renewable sources, despite their effective promotion from public policies and their recent increase in EU until 2011 (European Commission, 2014).

Subsidies were necessary to respond to some market failures like positive externalities of renewables such as avoided greenhouse gas emissions and pollution, huge fixed investment costs, contribution to technological progress and decreased generation costs in the longer run (European Commission, 2014).

With respect to the factors able to explain eco-efficiency scores, resources productivity positive and significant influence independently of the country technical and pure technical eco-efficiency level means that these should be a bet and a useful incentive in terms of technology improvement. If countries eco-efficiency scores are determined by its high taxes on pollution/resources this may induce a substitution for subsidies provided and mean that countries will exert more effort in terms of eco-efficiency improvements to reduce additional costs. Moreover, if eco-efficiency countries score is determined by lower domestic material consumption and this provides an assessment of the absolute level of the use of resources, and allows distinguishing consumption driven by domestic demand from consumption driven by the export market, denoting apparent consumption and not final consumption, this means that countries should use resources in a more efficient way. As such, sustainable development should be a maximum in countries if these are intended to improve their eco-efficiency ratings. In fact, other variables might be used in an attempt to explain countries efficiency scores and these might provide even more policy indications about how could countries improve in these sense.

6. Conclusions

The study was intended to analyze the eco-efficiency of 26 European countries, in a comparative way, through a ranking, and the evolution of this efficiency between 2001 and 2012. Additionally, we wanted to identify the determinants of the estimated efficiency scores.

The technical eco-efficiency rankings were identified using DEA-VRS and DEA-CRS models. In a second stage, we relied upon quantile regression analysis using taxes, resources productivity and domestic material consumption as possible explanatory variables for eco-efficiency rankings.

Results seem to indicate that taxes have higher effects over scores than do resources productivity and domestic materials consumption. Among taxes, energy taxes and transport taxes are those, which exert lower influence. Countries with high eco-efficiency scores have higher taxes on pollution/resources, playing a negative influence and countries inside low eco-efficiency scores suffer a positive influence of both energy and transport taxes. Those countries placed at higher efficiency scores have a negative and significant impact from transport taxes, meaning that these tend to lower eco-efficiency scores for more eco-efficient countries. As such, policy makers should revise transport taxes effects in these countries turning transport taxes dependent over eco-efficiency rankings through time and promote their lowering whenever the country reaches a desirable eco-efficiency ranking.

Results in both VRS and CRS versions point for the fact that for the lowest quantiles of the conditional scores efficiency distribution coefficients have a tendency to be lower. As such, despite the efforts taken by European countries, in terms of the impact of environmental taxes over GDP, these could be barely recognized by the energy producer behavior at least those placed at the lowest EE quantiles. Using constant versus variable returns to scale evidences some estimation differences, although results may be generalized. Countries with low eco-efficiency are also those with higher taxes. Therefore, countries eco-efficiency scores are determined by its high taxes over pollution/resources and high eco-efficiency countries score is determined by lower domestic material consumption.

To sum up, our results confirm the initially stated hypothesis provided that environmental tax revenues cause distorting effects in eco-efficient countries. In addition, resources productivity and domestic material consumption are able to positively and negatively explain eco-efficiency scores, respectively, as initially predicted. The different and distorting tax effects provide valuable and reliable information's for policy making, turning evident the need to adjust taxes as a country places itself in higher eco-efficiency rankings in an effort to compensate those which are more careful with respect to sustainable economic development. This would encourage the other to follow different paths and as such fulfill the goals of the EU with respect to environmental goals.

This work may even be improved by exploring other variables capable to explain eco-efficiency scores in EU-26 and by determining the degree of influence exerted by each of the variables included in the model. Thus far, taxes results exploration provide valuable policy implications for the future and should aware policy makers for policies settlement in this respect. It could as well be extended by increasing the analysis period and by including more countries into the sample, provided the present data availability limitations.

Acknowledgements

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Appendix A.

Table A1
Eco-Efficiency obtained through DEA (VRS and CRS) – some descriptive statistics.

	Mean		Standard Deviation		Minimum		Maximum	
	VRS	CRS	VRS	CRS	VRS CRS	C	VRS	CRS
2001	0,7861	0,6815	0,1178	0,0879	0,5407	0,4843	0,9527	0,8472
2002	0,8258	0,7278	0,0793	0,0768	0,6127	0,5399	0,9351	0,8740
2003	0,8062	0,7084	0,1093	0,0839	0,4886	0,4842	0,9581	0,8769
2004	0,7984	0,7104	0,1193	0,0885	0,4217	0,4539	0,9598	0,8902
2005	0,8061	0,7166	0,1159	0,0763	0,4388	0,4844	0,9647	0,8680
2006	0,8036	0,7152	0,1274	0,0762	0,4123	0,4848	0,9689	0,8586
2007	0,7769	0,7043	0,1523	0,0766	0,3563	0,4758	0,9776	0,8343
2008	0,7703	0,7045	0,1835	0,0809	0,2957	0,4543	1,0000	0,8297
2009	0,7528	0,6872	0,1757	0,0888	0,3447	0,4587	1,0000	0,8361
2010	0,7977	0,7115	0,1347	0,0852	0,4997	0,5318	0,9665	0,8469
2011	0,7848	0,6994	0,1506	0,0877	0,4012	0,4842	0,9774	0,8670
2012	0,7615	0,6783	0,1751	0,0997	0,3358	0,4099	0,9893	0,8196

Table A2
Rankings of Eco-Efficiency in European Countries established by the DEA estimator with Variable Returns-to-Scale.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Austria	11	23	16	14	9	9	7	6	7	9	10	10
Belgium	14	10	10	9	14	17	13	12	11	13	17	12
Bulgaria	10	9	11	17	16	20	18	18	24	24	23	23
Cyprus	3	2	2	2	2	2	3	1	4	8	11	7
Czech Republic	25	25	25	25	25	25	25	24	25	25	25	25
Denmark	13	14	14	19	15	13	21	21	16	17	14	13
Estonia	26	26	26	26	26	26	26	26	26	26	26	26
Finland	20	17	20	21	20	14	19	17	15	20	20	19
France	6	5	5	5	6	8	8	9	10	10	6	9
Germany	24	16	18	18	19	19	17	16	19	19	19	22
Greece	21	22	24	24	24	22	23	25	22	22	22	18
Hungary	17	12	12	10	8	6	2	2	5	6	7	4
Ireland	23	24	22	22	22	24	22	19	17	15	4	1
Italy	12	13	13	16	18	18	16	15	14	16	16	15
Latvia	5	6	4	4	3	7	9	8	3	1	1	2
Lithuania	7	8	7	8	10	11	15	20	18	7	13	14
Luxembourg	8	7	9	11	11	10	11	5	6	11	15	21
Netherlands	9	11	8	7	7	5	6	7	8	5	5	11
Poland	22	18	21	20	21	21	20	22	23	23	24	24
Portugal	19	20	19	12	12	15	10	10	12	12	8	8
Romania	4	3	6	6	4	4	5	14	20	18	21	16
Slovakia	16	21	17	13	17	16	12	11	9	4	12	17
Slovenia	15	15	15	15	13	12	14	13	13	14	9	6
Spain	18	19	23	23	23	23	24	23	21	21	18	20
Sweden	1	1	1	1	1	1	1	3	1	2	3	3
United Kingdom	2	4	3	3	5	3	4	4	2	3	2	5

Table A3
Rankings of Eco-Efficiency in European Countries established by the DEA estimator with Constant Returns-to-Scale.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Austria	14	11	9	11	7	10	8	8	5	7	7	9
Belgium	11	13	11	12	18	20	16	16	14	19	18	18
Bulgaria	7	15	14	18	21	21	21	22	24	23	23	23
Cyprus	5	2	2	2	2	5	6	4	6	9	12	8
Czech Republic	25	25	25	25	25	25	25	25	25	25	25	25
Denmark	12	16	13	16	13	11	18	15	13	16	16	17
Estonia	26	26	26	26	26	26	26	26	26	26	26	26
Finland	20	18	18	21	19	16	19	17	17	20	20	15
France	8	7	7	6	4	7	4	5	10	15	15	10
Germany	18	20	20	20	16	19	20	20	18	18	19	22
Greece	22	19	23	23	24	22	23	24	22	22	22	19
Hungary	16	14	15	13	8	6	2	2	4	6	4	1
Ireland	23	22	24	24	22	24	22	21	20	11	6	5
Italy	10	10	17	19	20	15	15	12	15	12	13	11
Latvia	4	4	5	4	3	3	3	3	1	1	1	2
Lithuania	6	9	8	7	9	8	10	14	11	4	9	13
Luxembourg	9	8	12	14	14	17	14	18	19	17	21	21
Netherlands	15	12	10	10	15	14	13	11	9	8	10	14
Poland	24	24	22	22	23	23	24	23	23	24	24	24
Portugal	19	21	19	9	10	13	7	6	7	10	5	6
Romania	3	3	6	8	6	4	12	13	16	13	14	12
Slovakia	17	23	21	17	11	12	11	10	8	5	11	20
Slovenia	13	17	16	15	12	9	9	9	12	14	8	7
Spain	21	6	3	5	17	18	17	19	21	21	17	16
Sweden	1	1	1	1	1	1	1	1	3	3	3	3
United Kingdom	2	5	4	3	5	2	5	7	2	2	2	4

Table A4
Technical Efficiency and Pure technical efficiency computed by periods and country.

	TE – CRS Model			PTE – VRS Model		
EU-Country	2001–2004	2005–2008	2009–2012	2001–2004	2005–2008	2009–2012
Austria	0.7242	0.7555	0.7527	0.8021	0.8864	0.8625
Belgium	0.7230	0.6917	0.6784	0.8403	0.8295	0.8037
Bulgaria	0.7187	0.6597	0.5027	0.8399	0.7406	0.5431
Cyprus	0.8050	0.7864	0.7434	0.9220	0.9592	0.9095
Czech Rep	0.5504	0.5384	0.4608	0.5844	0.5615	0.4909
Denmark	0.7059	0.7163	0.6893	0.8165	0.8006	0.7683
Estonia	0.4784	0.4245	0.4441	0.5394	0.5499	0.5364
Finland	0.6697	0.6912	0.6657	0.7597	0.7438	0.7201
France	0.7639	0.7805	0.7147	0.8957	0.8905	0.8501
Germany	0.6728	0.6791	0.6588	0.7884	0.7490	0.6874
Greece	0.6360	0.6269	0.6293	0.6859	0.6756	0.6914
Hungary	0.7056	0.7800	0.7966	0.8280	0.9323	0.9243
Ireland	0.6022	0.6487	0.7356	0.6998	0.7218	0.8728
Italy	0.7088	0.7032	0.6998	0.8286	0.7857	0.7740
Latvia	0.8001	0.7942	0.8379	0.9042	0.8964	0.9819
Lithuania	0.7557	0.7344	0.7262	0.8740	0.8151	0.8038
Luxembourg	0.7305	0.7008	0.6572	0.8664	0.8824	0.8122
Netherlands	0.7232	0.7147	0.7196	0.8690	0.8980	0.8597
Poland	0.6283	0.6392	0.5707	0.7303	0.7012	0.6719
Portugal	0.6853	0.7536	0.7606	0.7908	0.8493	0.8695
Romania	0.7818	0.7412	0.6952	0.8964	0.8772	0.7505
Slovakia	0.6678	0.7347	0.7258	0.7899	0.8235	0.8161
Slovenia	0.6986	0.7455	0.7257	0.8124	0.8184	0.8538
Spain	0.7257	0.6891	0.6510	0.7926	0.7697	0.7581
Sweden	0.8719	0.8476	0.8099	0.9514	0.9779	0.9749
United Kingd	0.8017	0.7834	0.8138	0.9130	0.9334	0.9709

Note: TE – Technical efficiency; CRS – Constant returns to scale; PTE – Pure technical efficiency; VRS – Variable returns to scale.

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