Energy efficient R&D investment and Aggregate Energy Demand: Evidence from OECD Countries *

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Abstract

This paper present a different perspective in the debate on energy efficiency and energy demand by classifying the impact of efficiency measures into direct and indirect effect (rebound effect). It examines the potential direct effect of energy efficient R&D capital on energy demand. Irrespective of the "rebound effect" associated with energy efficiency, it is possible to have a negative direct effect from efficiency measures. Using a sample of OECD countries, we find evidence in support of negative own-R&D capital elasticity with respect to energy demand. Further, we find evidence of heterogeneity in the predicted impact of energy efficient R&D capital, with the USA having the largest accumulated reduction in energy demand and Portugal with the smallest. Overall, our empirical results suggest a reasonable reduction in energy demand and associated CO_2 emissions from an increase in energy efficient R&D investment base on the direct effect and this varies across the countries.

Keywords: Efficiency Policy, Energy Demand, Heterogeneity, R&D capital, Spillovers

JEL Classification: C33; Q41; Q49.

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1. Introduction

After the commencement of the Kyoto protocol in 2005, there has been increasing attention by policy makers, academia and firms across various countries, especially industrialized countries on a share burden in meeting the targets set by the Kyoto protocol and their respective national and regional block's targets. Despite the global awareness on the negative consequences of CO_2 emissions, global CO_2 emissions still increased to 35.3 Gigatonnes in 2013, a 0.7 Gigatonne higher than the 2012 figure (about 2% increase in 2013 relative to 2012). The three top ranked emitters in 2013 accounts for 55% of global CO_2 emission, and are China (29%), United States (15%) and the European Union (EU28) (11%). In 2011, OECD countries contributed 38% of global CO_2 emissions and energy combustions accounts for close to 99% of the emissions (IEA, 2013). On individual country level, China is the leading CO_2 emitting country, followed closely by USA, while India occupies the third sport in absolute values (IEA, 2013).

Arguably, one potential channel to reducing the negative impact of energy on the environment is through energy efficiency. However, this is true if the benefits from efficiency measures are taxed and invest in R&D that can produce new technologies that will enable a shift away from fossil based energy. This type of policy mix will reduce or eliminate the potential rebound effect associated with efficiency measures. A potential channel to increase energy efficiency is through research and development (R&D). In most, if not all energy policy packages for OECD countries, there is a great element or requirement for energy efficiency and hence increasing expenditure in energy efficient related R&D's. Energy efficient R&D is therefore seen as a crucial channel among policy makers, at least in decoupling energy use from GDP growth and consequently reducing global CO_2 emissions in general, if combine with a well design tax scheme. For instance the OECD countries that are members of the European Union (EU), under the 20/20/20 directive are required to contribute their respective national targets to reducing energy use by 20% via energy efficiency measures by the year 2020.Such a policy calls for energy efficient R&D investment and other measures that could influence energy efficiency among member countries.

There is however very little empirical studies that examine the potential contribution from energy efficiency measures on aggregate energy demand in general, particularly energy efficient R&D investment on aggregate energy demand, at least for OECD countries. Most of the studies on R&D are rather based on its impact on output via Griliches (1979) type of analysis that focus on a knowledge production within a more general production theory framework, Hall et al. (2009) provides a recent review of the literature in this area. The few studies based on energy for instance Metcalf and Hassett (1999), which measures energy savings from home improvement investment, Geller et al. (2006) reviews energy intensity trends for major OECD countries from 1973 to 2002, assessing how much of the declining trend is due to energy efficiency and what share is attributable to structural change, Gillingham et al. (2006) provides estimates for cumulative savings from energy efficiency policies for the USA, Aroonruengsawat et al. (2012) examined the impact of building codes on electricity consumption at the household level for the USA[1]. Others tend to focus on assessing programs that identify and promote energy-efficient products as in Webber et al. (2000), while Meyers et al. (2003) focus on energy efficiency standards for appliances on energy and environmental impacts for the USA among others. Given the few empirical evidence on the impact of energy efficient R&D investment on energy demand couple with the increasing interest among policy makers on the possible contribution of energy efficiency in at least decoupling energy use from economic growth, there is the need to provide more empirical evidence on the potential impacts, especially from energy efficient R&D investment for inform policy formulation.

The objective of this paper is to address the following key questions; what is the "own"-energy efficient R&D capital elasticity if the usual imposition of the additive separability assumption in the empirical literature to enable the identification of "own/private" R&D elasticity from spillover[2] effect is wrong? What is the potential contribution of energy efficient R&D investment on aggregate energy demand reduction if spillover effects are excluded? Is there a diminishing return to energy efficient R&D investment? Which countries in the sample are likely to benefit more from a policy that increase energy efficient R&D investment? Answers to these questions are very important to clearly understand the dynamics between energy demand and R&D investment in energy

[1] Others studies on the impact of efficiency measures such as building codes on electricity consumption includes; Bion and William (1991), Costa and Kahn(2011), Jocobsen and Kotchen(2013).

[2] A transfer of knowledge from one actor to another in which the receiving actor does not pay for the full cost of accessing and the use of such knowledge. It therefore involves unintentional knowledge transfer from one actor to another.

efficiency in order to inform policy designs focusing on such issues. In answering these questions we focus on the direct effect of energy efficient R&D capital. We classify the effect of energy efficient R&D capital on energy demand into two-the direct effect and the indirect effect (rebound effect). The idea for the classification is to enable us focus on only the direct effect.

Our paper makes the following contribution to the literature. First it provide the first empirical evidence to the best our knowledge on R&D capital elasticity with respect to aggregate energy demand for a sample of OECD countries without imposing the a priori additive separability assumption between “own”- energy efficient R&D capital elasticity and spillover effect as well as other unobserved common factors that could conflate the elasticity estimate for the energy efficient R&D capital (henceforth called own R&D capital). It also provide the policy effect of an increase in energy efficient R&D investment on energy demand across the countries, which will highlight the countries that are likely to achieve the greatest reduction in energy demand from such a policy which is likely to be very informative for policy makers.

The key finding from this study include the following; that when no efforts are made to correctly account for spillover effects and other unobserved common factors, the “own” R&D capital elasticity and its associated private return is bias upwards, implying that the linear separability assumption usually imposed for the identification of R&D capital might be wrong. Further, the results provided evidence of a negative impact of R&D capital on energy demand, with a higher cumulated impact from the USA in the sampled countries, while Portugal has the least impact. However based on percentage contribution of an increase in energy efficient R&D investment on percentage reduction in energy demand, Portugal is top ranked and USA the least ranked among the countries in the sample.

The rest of the paper is organized as follows. Section 2 presents the theoretical background of the study, the econometric model and data is presented in Section 3. Section 4 discussed the results, while section 5 presents the conclusion of the study.

2. Theoretical background

The general background on economic analysis on energy efficiency issues usually stem from cost-minimization/ utility or profit maximization behavior of households and firms.

The general idea on energy efficiency is what it represents, since energy is not an end in itself but rather the services it provides for instance heating, lighting, motion among others. It is therefore important to conceptualized energy as an input into the production of energy services and as a consequence, energy efficiency can generally be define as energy services per unit of energy input. Based on this we can use the production theory framework to derive and understand energy efficiency. In the production theory perspective, capital and energy are the inputs into the production of energy services (Gillingham et al., 2009). In this framework, energy efficiency is located at the point of tangency between an isoquant (that specify a given level of energy service) and ratio of prices between capita and energy. However investment in new capital in the quest to improve energy service per unit of energy input involves comparing the current and future returns from the investment to the cost. This makes relative prices (capital and energy) to depend on the cost of capital incurred in energy service improvement, the discount rate that links the current and future cost and returns on energy efficient investment, future energy prices, and equipment utilization.

Achieving significant improvement in capital and energy using equipment performance in terms of energy use depend almost exclusively on technological development, which is greatly influence by R&D activities. There is large literature on knowledge development and its impact on output, influenced by Griliches (1979) seminar paper that incorporated a knowledge production function into a standard Cobb-Douglas production function. In this framework, output depends on capital and labor inputs in addition to knowledge capital, precisely R&D capital. The unique feature of knowledge capital (non-excludability and non-rivalry) as noted by Arrow (1962), makes it difficult to estimate precisely "own"-knowledge capital elasticity. This is because of the inherent spillover effects associated with knowledge capital and the difficulty associated in quantifying spillovers. In the applied literature, researchers generally impose linear separability assumption on Griliches's type of production function to enable estimation of "own" –knowledge capital elasticity (as well as private return to knowledge capital) or a set-up in which an attempt is made to quantify spillover effect via ad-hoc weights. The weights are constructed based on the relative interaction of actors (industries, countries etc.). Given the difficult in separating spillover effects from "own"-knowledge effect, makes it more important to try to estimate own-R&D capital by methods that are able to eliminate the potential spillover effect in the estimation process.

In the energy literature, most of the studies on energy efficiency tend to focus more on either behavioral inefficiencies in energy demand or market failures and the appropriate policy design to correct these inefficiencies and market failures. This has led to many studies looking at the so call "rebound effect" with less studies looking at the direct effect of knowledge capital on energy demand, especially the energy savings potentials of investment in knowledge accumulation that result in energy efficient capital and direct effect of that on energy savings or potential energy savings.

3. Empirical approach and the Data

Formally we specify the basic empirical model as:

$$\begin{aligned} &e_{it} = \beta_1 p_{it} + \beta_2 y_{it} + \beta_3 hhd_{it} + \beta_4 R\&Dcap_{it} + u_{it} \\ &i = 1,.....,N = Countries, t = 1,....,T = Time\ period \end{aligned} \tag{1}$$

Where the variables are in natural logs and e_{it} is aggregate energy consumption per capita, p_{it} is the energy price, y_{it} is real income per capita, hhd_{it} is heating degree days, $R\&Dcap_{it}$ is energy efficient R&D capital and u_{it} is a composite term that includes a random error, country fixed effects and possibly unobserved common factors. The above model is a variant to the model used in Ryan and Ploure (2009), Filippini and Hunt (2011), Karimu and Brännlund (2013), in the sense that it also included energy efficiency policy variable in the form of energy efficient R&D capital similar to the model used by Aroonruengsawat et al. (2012). The theoretical background for the above models is from the utility framework as done in Karimu and Brännlund (2013).

Move over, in order to appropriately estimate the own R&D capital elasticity, we apply an econometric modelling approach based on the "unobserved common factor framework" that will enable stripping off potential unobserved factors including spillovers on the estimated parameters of interest. The approach is briefly presented below, in which for easy exposition we restrict to a model with one explanatory variable – a simplify version of equation (1) is presented as follows:

$$e_{it} = \beta_i x_{it} + u_{it} \tag{2}$$

$$u_{it} = \alpha_{1i} + \varphi_i f_t + \varepsilon_{it} \tag{3}$$

$$x_{it} = \alpha_{2i} + \rho_i f_t^s + \lambda_i g_t + \upsilon_{it} \tag{4}$$

Where x_{it} is the explanatory variable, u_{it} is a composite term that is composed of country fixed effects (α_{1i}), unobserved common factors (f_t) and a random error term (ε_{it}). The explanatory variable (x_{it}) is also driven by unobserved common factors (g_t and f_t^s, a subset of f_t that also affect x_{it}) and a stochastic error term (υ_{it}). Whereas φ_i, ρ_i and λ_i are the factor loading parameters that vary across panel units. The overlap of common factors in Eq.(3) and (4) creates endogeneity problems that render the identification of β_i very difficult in the usual panel estimators such as fixed effects, dynamic GMM estimators and variant of them that are not design within the context of unobserved common factor framework as described above. The estimators that are design to accommodate this type of endogeneity are the common correlated mean group (CCEMG) and augmented mean group (AMG) estimators proposed by Pesaran (2006) and Eberhardt and Teal (2010), respectively. The intuition is that, it is assumed latent processes drive both the dependent variable via equation (3) and the explanatory variable via equation (4) with possible different strength via φ_i, ρ_i and λ_i. If on average the factor loading parameters are zero, then the usual panel data estimators such as fixed effect, dynamic panel estimators and variants of them produce consistent and unbiased estimator for the parameter β if the assumption that $\beta_i = \beta$ is true. However, if on average the factor loading parameters are not zero, then the usual panel estimators will be biased and inconsistent as shown in Eberhardt et al. (2013). We can generalize equation (1) to a multivariate case if we assume that x_{it} is a vector of explanatory variables and β_i is a vector of parameters corresponding to the vector of regressors. The expression as in Eq. (2) to (4) is estimated for each panel unit and the average panel coefficient for x_{it} is calculated as $N^{-1}\sum_{i=1}^{N}\beta_i = \beta$, hence given a long time period we can have estimates for each panel unit as well as the average over all the panel units to assess if the parameters vary across countries. In specific reference to this study, e_{it} denote aggregate per capita energy consumption, the vector x_{it} comprises energy price, real income, heating degrees days and energy efficient R&D capital.

The econometric strategy is to apply a non-heterogeneous panel estimator (fixed effect model) and three variants of the heterogeneous estimators – Pesaran and Smith (1995) mean group (MG), Pesaran (2006) CCMG and the Eberhardt and Teal (2010) AMG estimator, where the last two heterogeneous estimators are based on the unobserved common factor framework described above. Further, we assess the different estimators on how each fit the data generation process based on diagnostic testing to choose the best model among them, and base our analysis and policy implications on the chosen estimator, details on the three heterogeneous estimators is presented in the appendix.

Each of the three heterogeneous estimators differs in their modelling approach. Whereas the MG-estimator is designed in a way that allows for heterogeneity in parameters across the panel units, it however does not account for possible common unobservable factors. The AMG and CCMG estimators on the other hand account for common unobservable factors in addition to allowing for heterogeneity in the parameters. The above framework is therefore the appropriate approach that will help answer the key questions that the paper intends to answer as enumerated in the introduction. These heterogeneous estimators relative to the homogeneous estimators (e.g., the fixed effect estimator) are able to address the following. First, they relax the constant parameter assumption in a sense that they allow for variability in the parameters across the panel units. Second, both the AMG and CCMG estimators also accounts for cross sectional dependence (effects of common unobservable factors, such as energy/oil crisis, global financial crisis, spillover effects of improvement in technology, etc.) and hence account for possible spillover effects which allows for estimating the own R&D capital elasticity by stripping-off the possible confounding effects from spillovers akin to the work by Eberhardt et al. (2013).

This is particularly important for our study, since our focus is on estimating the own R&D capital elasticity and in the obscene of an approach that can reliably estimate social returns (spillovers), it becomes handy to apply this approach that strip-off potentially all the effects of spillover in addition to other unobservable factors from the estimates. Lastly, both the AMG and CCMG estimators, relaxes the constant effects of common shocks such as global recession by allowing these factors to vary across country via factor loading approach unlike the conventional technique of using time dummies to try and capture unobservable that are assumed to affect all panel units albeit with the same “strength”.

Data

The consumption, price and income data series for this paper were all taken from Adeyemi et al. (2010), Karimu and Brännlund (2013) - an annual data set for a panel of OECD countries covering the period 1960 to 2006; however we limited the coverage for this paper to the period 1980 to 2006. The reason for this limitation is that, the data on our interest variable (energy efficient R&D expenditures) starts from 1974 but to be able to calculate R&D capital from the expenditure series, we used the first 6 years to build the R&D capital that takes effect from 1980 (how this is done is explain below). The variables comprise of aggregate energy consumption (E) for each country expressed in thousand tons of oil equivalent (ktoe), GDP (Y) in billions of 2,000 US$ using PPP for the entire period and the real energy price index (P) at 2,000 US dollars. Both Y and E are converted into per capita terms by dividing each country's Y and E by their respective populations. We used heating degree days to proxy for the effects of climate on energy demand and the data were retrieved from Eurostat - Statistical Office of the European Union site for all the countries except that of the USA, which was taken from National Oceanic and Atmospheric Administration (NOAA).

Data on energy efficient R&D expenditures are retrieved from the International Energy Agency (IEA) energy technology RD&D statistics for OECD countries. These expenditures are used to calculate the R&D capital, constructed by applying the perpetual inventory model, in which R&D capital is derived as:

$$R\&Dcap_{it} = (1-\delta)R\&Dcap_{it-1} + R\&D_{it} \tag{5}$$

Where R&D denotes real R&D expenditures, δ is the depreciation rate which we follow previous literature (Hall, 2007 and Eberhardt et al., 2013) and assume a 12% rate. The initial capital stock is calculated as:

$$R\&Dcap_{i1} = \frac{R\&D_{i0}}{\delta + g_i} \tag{6}$$

where $R\&Dcap_{i1}$ is the initial capital, g_i is the country specific growth rate, which we used the first 6 years of the observed R&D expenditures to compute. The calculated R&D capital calculated via equation (5) to (6) revealed variations across the sampled countries based on the boxplot presented in figure1. The country with the least median value is Portugal (16.78 express in logarithms) and the U.S has the highest median value (21.66). The countries with the highest R&D capital in the sample include; Sweden, UK, Netherland, Italy and the US, however these values are not in per capita terms. From the boxplot, one can identify few countries with potential outliers for the R&D capital series, in a whole, these few outliers are due to the usual periodic increases in energy efficient R&D expenditures in these countries and not due to errors. Further, given the estimation methodology, these outliers will not significantly influence the parameter estimates and hence likely not to bias the estimates.

The boxplot in figure A2 in the appendix indicate some variability for each of the other variables in our data set across the sampled countries. Both the heating degree day's series and energy consumption per capita series have the highest variation relative to real price and income series. The Countries in the study are: Austria, Belgium, Denmark, France, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the USA.

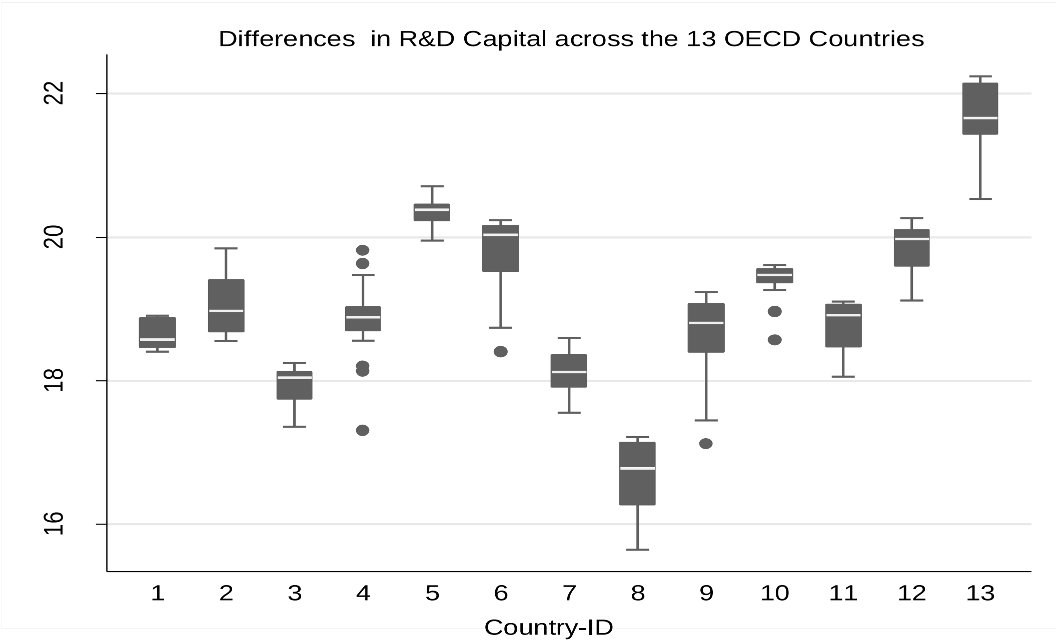

Figure 1: Boxplot showing the variability of the median value for R&D capital across 13 OECD countries. (*Note: the Country-ID, 1=Austria, 2=Belgium, 3= Denmark, 4=France, 5=Italy,6=Netherland,7=Norway,8=Portugal, 9=Spain, 10=Sweden,11=Switzerland, 12=UK, 13=USA*)

4. Results

Table 1 shows the results from cross-sectional dependence test based on the raw series. The results indicate each of the series in our data could not pass the null hypothesis of cross-sectional independence, implying that each of the data series are correlated across panel units and therefore the econometric strategy should incorporate this into the estimation process, in order to reduce the potential problem of producing bias estimates.

This first step in our estimation strategy therefore means that both the AMG and CCMG estimators are likely to be the best estimators for this study as they are purposely design to handle data with cross sectional dependence/common factors. We also tested for the time series properties of the data, specifically unit root test, which show evidence of $I(1)$[3] as presented in Table A1 in the appendix. However to be sure the estimators based on the common factor frame work are appropriate relative to say fixed effect model in fitting the data generating process, we also estimated a fixed effect model and used various diagnostic tests of the residuals to assess which of the models fit the data generating process (DGP). Specifically we estimated four different estimators – fixed effect, MG, AMG and CCMG.

Table 1: Cross sectional dependence test

Variable	CD-test	*P*-value	Correlation
e	28.17	0.000	0.614
p	24.97	0.000	0.544
y	44.94	0.000	0.979
R&Dcap	5.72	0.000	0.125
hhd	29.54	0.000	0.644

Notes: Under the null hypothesis of Cross-section independence CD ~ N (0, 1), R&Dcap and hhd denotes R&D capital and heating degree days, respectively.

The results for each of the four estimators indicated above is presented in Table 2 and reveal that the estimates from the homogeneous fixed effect model are bigger in magnitude relative to the heterogeneous estimators (except the estimates for heating degree days) and this is particularly evident for our interest variable – R&D capital. Another observation from the results is that, the estimated coefficient for R&D capital is approximately the same across the three heterogeneous models. Further, each of the estimators indicates a negative own R&D capital elasticity, implying a negative response of aggregate energy demand to energy efficient R&D capital. The estimated value is statistically significant at the 5% for all except the CCMG model. Additionally, all the estimates from the four estimators have the expected signs from theory.

[3] Two different panel unit root tests are implemented, specifically Pesaran (2007) CIPS test that allows for heterogeneity as well as cross-sectional dependency and Maddala and Wu Panel Unit Root test that does not allow for cross-sectional dependence in the testing procedure. Details on the CIPS unit root test specification are in Pesaran (2007). We also tested for cointegration and the results are reported in Table A1 in the appendix.

In discriminating between the estimators, we relied on the models diagnostics, especially if the models residuals pass the cross sectional independence test (Pesaran, 2006 CD-test) and are stationary – $I(0)$. The diagnostic test results as reported in Table 2, favor both the AMG and CCMG models. Their respective residuals are stationary implying non-spurious regression and also pass the CD-test at the 5% level. While the MG model is also non-spurious, it however fails the CD-test. The FE model's residuals follow an I (1) process and also fails the CD-test. The diagnostic tests therefore provide strong support for the heterogeneous models relative to the fixed effect model. We can conclude that, the estimates from the fixed effect model are bias upward due to failing to correctly model common factor effects. More importantly, given the nature of R&D with inherent spillovers, it is impossible to precisely estimate private R&D elasticity from non-common factor models such as a fixed effect model.

Both the AMG and the CCMG models have approximately the same level of performance based on the two diagnostic tests, however we decided to based our discussion on the estimates from the AMG model on the grounds that it produces a significant income variable that is also within range of values usually found in the literature, whereas in the case of the CCMG the income estimate is statistically not differ rent from zero at the 5% level of significance, which intuitively does not make sense, since income is a key variable that influence energy demand and even on the evolution of energy use from pre-industrial error to modern economic systems of production and consumption (Stern and Kander, 2012).

The AMG estimates shows that price elasticity is rather low but consistent with findings from previous studies such as Adeyemi and Broadstock, 2009; Karimu and Brännlund, 2013; Welsch, 1989. This implies less response to prices across the sample countries which can be due to many things including high income levels which make price increases less painful for the average person within these countries. It could also be the case that, overtime, the average stock of appliances and equipment that relies on the use of energy services has increased and couple with the wealth effect, consumers and producers are becoming less and less responsive to price increases and also because of less available substitutes for energy which tend to make energy more of a necessity in the modern economy.

Table 2: Regression Results

	FE	MG	AMG	CCMG
p	-0.251**	-0.125***	-0.120***	-0.158**
	(0.098)	(0.035)	(0.034)	(0.073)
y	0.906**	0.593***	0.537***	0.265
	(0.413)	(0.095)	(0.106)	(0.170)
R&Dcap	-0.087***	-0.041**	-0.034**	-0.036
	(0.025)	(0.020)	(0.016)	(0.032)
hhd	0.036	0.224***	0.123**	0.123***
	(0.023)	(0.035)	(0.044)	(0.033)
Trend	yes	yes	yes	yes
Constant	14.27	-0.959	-0.561	-0.158
	(12.391)	(0.769)	(0.698)	(1.077)
Diagnostics				
CD-test	2.44	2.28	-1.61	-1.83
	[0.015]	[0.022]	[0.108]	[0.067]
Integration	$I(1)$	$I(0)$	$I(0)$	$I(0)$
N	351	351	351	351

Note: Standard errors in parentheses (robust standard errors), * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, CD-test is the cross-sectional dependence test base on Pesaran (2004) test for the Null of cross-sectional independent residuals, N is the number of observations, hhd is the heating degree days and R&Dcap denote R&D capital. Numbers in square bracket are the *p*-values for CD-test.

The estimated income elasticity have the expected sign and significant but low in magnitude compare to some of estimates from previous studies (Fillipini and Hunt, 2011; Atkinson and Manning, 1995) but consistent with the estimates from Adeyemi and Broadstock, 2009 and Welsch, 1989. The implication is that, people on average demand more energy as their income level rises. The estimated hhd elasticity is positive and significant, which shows that outside temperatures below which heating is required tend to increase energy demand. Further, the estimated R&D capital elasticity is -0.03 and significant at the 5% level.

Next we calculate the effect of the share of R&D capital on energy demand by using the average estimated elasticity ($N^{-1}\sum_{i=1}^{N}\beta_{4,\mathrm{i}}$) multiple by the R&D capital. This can be interpreted as the predicted effect of R&D capital on energy demand based on the AMG model, which will give us the share predicted impact of R&D capital for each of the countries in our sample. The average impact of R&D capital across the countries in our sample as reported in figure A1 in the appendix range from approximately 15% to 20% (cumulated over 1980 to 2006). The US is the country that has the largest energy savings (predicted) from R&D investments, whilst Portugal has the least savings. This shows that policies targeting energy efficiency investments are having the intended effects (reduced energy demand). However the effects are relatively modest given that the values are the averages over the period 1980 – 2006, implying an annual reduction of approximately 1%. This smaller contribution to energy savings from energy efficient investment means that we need to combine energy efficiency policies with other policies such as taxes to have a reasonable reduction in energy demand and consequently on CO_2 reduction.

Policy implications of R&D investment

In assessing the effect of a given change in energy efficient R&D investment on energy demand, we follow the approach implemented in Davis and Killian (2011) by expressing the percentage reduction in energy demand from an x million US$ increase in energy efficiency R&D investment evaluated at a chosen base of R&D capital (taken as the volume-weighted mean of R&D capital at 2006), this is formulated as

$$N^{-1}\sum_{i=1}^{N}\hat{\beta}_{4,\mathrm{i}}\left(\frac{x}{R\,\&\,Dcap_i}\right)*100,$$

where $N^{-1}\sum_{i=1}^{N}\hat{\beta}_{4,\mathrm{i}}$ is the estimated average R&D capital elasticity, R&Dcap is the base for the evaluation of the change which is the volume-weighted mean in year 2006.To demonstrate this policy effect of an increase in energy efficient R&D investment, we consider a 100 million US$ increased in R&D investment, however the choice of size of the investment is irrelevant. The key idea is to show the likely percentage change in energy demand from a given increase in energy efficient R&D investment in order to assess the likely efficacy of energy efficient policy/policies related to energy efficient capital. Table 3 present these effects for each of the countries in the data set and show varied differences in energy demand response to the policy. Portugal stands out with the highest (34.8%) reduction in energy demand from a 100 million US$ increased in R&D investment, while the USA has the least reduction (0.08%). This complement the results on predicted energy savings from energy efficient R&D investment in the sense that the country with the least savings from 1960 to 2006 tends to have the highest reduction in energy demand from a policy that will increase energy efficient R&D investment relative to a country/countries that has/have the highest savings. This is in line with the economic principle of diminishing returns (in this case to R&D investment). The reduction in energy demand is minimal for countries such as Netherland, Italy, France and the UK. This result indicates significant heterogeneity in the impact of an increase in R&D investment in energy efficiency policy.

Table 3: The effects of 100 million US$ increase in R&D investment in energy efficiency on energy demand.

Country	Austria	Belgium	Denmark	France	Italy	Netherland	Norway
%Energy Reduction	-3.34	-2.62	-5.08	-0.84	-0.69	-0.67	-8.09

Country	Portigal	Spain	Sweden	Switzerland	UK	USA
%Energy Reduction	-34.8	-4.13	-1.19	-1.98	-0.79	-0.08

Table 4: Carbon dioxide emission reduction from 100 million US$ increase in energy efficient R&D investment.

Country	Austria	Belgium	Denmark	France	Italy	Netherland	Norway
%CO_2 Reduction	-1.28	-1.0	-1.94	-0.32	-0.26	-0.26	-3.10

Country	Portigal	Spain	Sweden	Switzerland	UK	USA
%CO_2 Reduction	-13.32	-1.58	-0.46	-0.76	-0.30	-0.03

Further we extended the above policy analysis to carbon reduction from the effect of energy efficient R&D investment and this is done via using the energy reduction from the policy as presented in Table 3 and the conversion rate (0.3827 from OECD countries in 2010) of energy to CO_2 emission. The carbon dioxide reduction from this is reported in Table 4 and show CO_2 reduction that vary from 0.03% for the USA to 13.3% for Portugal.

Robustness Analysis

As a robustness check on our key results reported in Table 2, we also relax the static structure for each of the three heterogeneous estimators by applying a dynamic model. The result for this analysis is reported in Table A2 in the appendix. Generally, there is no significant difference in the size of the long-run estimates from both the dynamic and static model based on the AMG and MG estimators, especially on our variable of interest (R&D capital). The CCEMG estimates tend to vary greatly between static and dynamic version of the model for the variable of interest, however none of dynamic long-run estimates for R&D capital is statistically significant at the 5% level.

6. Conclusion

The main objective of this study is to examine the impact of energy efficient R&D investment on aggregate energy demand for OECD countries, the possible differences in the impact across the countries in the sample and how this translate to CO_2 emission reduction across the countries.

Our analysis implemented both homogeneous and heterogeneous panel estimators with different estimation assumption. The estimators that are based on the unobserved common factor framework allow for both heterogeneity in the parameters and unobserved common factors. This approach (unobserved common factor models) enables a "proper" estimation of the own-R&D capital elasticity. The reason for focusing on the "private/own" elasticity rather than the social or both is because the current econometric methods do not provide accurate way/s to precisely estimate the spillover effect, the component that accounts for the difference between "private/own" and "social" elasticity, hence the choice of the unobserved common factor framework to help strip-off all the unobserved common factors including spillovers in order to at least estimate the "private" elasticity more precisely.

Our key result indicate a negative "own" R&D capital elasticity which is however small in our preferred model relative to estimates based on the fixed effect model, which we argue that the difference between the fixed effect estimates and AMG estimates is due to the inability of the fixed effect model to strip-off spillover effects as well as not allowing for possible heterogeneity in the parameter estimates. This conclusion is based on the diagnostic test that indicates non-stationarity in the residuals from the fixed effect model and the inability to deal with cross-sectional dependency. The poor diagnostics from the fixed effect model, specifically the inability to correct for cross-section dependence provide evidence to support the argument that the additive separability assumption usually imposed to enable estimating private elasticity and return to R&D capital is likely inappropriate as indicated in Eberhardt et al.(2013). This result is in line with those from Eberhardt et al. (2013) albeit with different application (production in Eberhardt et al. and energy demand in our study), time frame and countries in the sample.

Further, our result indicate that a policy of increasing energy efficient R&D investment result in reduction in aggregate energy demand that varies significantly across the sampled countries from a relatively low change for the USA to a high change for Portugal, which we argue is due to a relatively high investment in energy efficient R&D capital in the USA relative to Portugal, such that an additional increase in such investments tend to contribute less and less to the total impact in the USA than it does in Portugal. This argument is supported by the higher cumulated (1980-2006) predicted impact of energy efficient R&D capital on energy demand of approximately -20% for the USA relative to -15% for Portugal.

Our analysis shed light on the impact of energy efficient R&D capital on energy demand which can be important for policies focusing on energy efficiency measures in reducing energy demand, where the focus of the policy is on energy efficient R&D investment. It also highlight the importance of spillover effects and other unobserved common factors in influencing the estimates if we only rely on the separability assumption for identification of "private/own" R&D capital elasticity and return as usually done in the literature on knowledge production. It also shows that while energy efficiency measures are important, we need other measures to complement efficiency measures to achieve sizeable reduction in energy demand and the associated CO_2 reduction.

Irrespective of the evidence of a negative effect of energy efficient R&D capital, it is important to stress that this is only the direct effect. It is possible that the indirect effect of energy efficient R&D capital could be negative as a result of the rebound effect via lower energy prices. As a consequence, the total effect from energy efficient R&D investment on energy demand could as well be positive depending on which of the effects dominates (the direct or the indirect effect). This study only focused on the direct effect. Further it is important to recognize that, promoting only efficiency measures without implementing other measures such as taxes and regulation might not lead to a significant reduction in CO_2 emissions if the goal is to reduce CO_2 emissions.

References

Adeyemi,O.I., and Broadstock, D.C. (2009). "Underlying consumer preferences and their contribution to energy demand." OPEC Energy Rev. 33 (3): 198–204.

Adeyemi, O. I., Broadstock, D. C., Chitnis, M., Hunt, L. C., and Judge, G. (2010). "Asymmetric Price Responses and the Underlying Energy Demand Trend: Are they Substitutes or Complements? Evidence from Modelling OECD Aggregate Energy Demand." Energy Economics 32(5): 1157-1164.

Aroonruengsawat, A., Auffhammer, M., and Sanstad, A.H. (2012). "The impact of state level building codes on residential electricity consumption." Energy Journal, 33(1): 31-52.

Arrow, K. (1962). Economic Welfare and the Allocation of Resources for Inventions, in R. Nelson (ed.), The Rate and Direction of Inventive Activity, Princeton, NJ: Princeton University Press.

Bion, H., and William, P., (1991). Better Building Codes through Energy Efficiency. Washington, D.C.: Alliance to Save Energy

Costa, D., and Matthew, K. (2011). Electricity Consumption and Durable Housing: Understanding Cohort Effects. NBER Working Paper 16732.

Davis, L.W., and Killian, L. (2011). "Estimating the effect of a gasoline tax on carbon emissions." J. Appl. Econometrics 26(7): 1187–1214.

Eberhardt, M., Teal, F. (2010). Productivity analysis in global manufacturing production. Economics Series Working Papers, 515. University of Oxford, Department of Economics.

Eberhardt, M., Helmers, C., Strauss, H. (2013). "Do spillovers matter when estimating private returns to R&D?" Rev. Econ. Stat. 95(2): 436–448

Geller, H., Harrington, P., Levine, M.D., Rosenfeld, A.H., and Tanishima, S. (2006). "Policies for Increasing Energy Efficiency: Thirty Years of Experience in OECD Countries." Energy Policy 34(5):556–573.

Gillingham, K., Newell, R., and Palmer, K. (2006). "Energy Efficiency Policies; A Retrospective Examination." Annual Review of Environment and Resources (31):161-192.

Griliches, Z. (1979). "Issues in Assessing the Contribution of Research and Development to Productivity Growth." Bell Journal of Economics 10:92–116.

Hall, B.H., Jacques, M., and Pierre, M. (2009). Measuring the Returns to R&D, NBER working paper 15622.

Jacobsen, G. and M.J. Kotchen. (2013). "Are Building Codes Effective at Saving Energy? Evidence from Residential Billing Data in Florida." The Review of Economics and Statistics 95(1):34-49.

Karimu, A. and Brännlund, R. (2013). "Functional forms and aggregate energy demand elasticities: A nonparametric approach for 17 OECD Countries." Energy Economics 36:19–27.

Metcalf, G.E. and Hassett, K.A. (1999). "Measuring the Energy Savings from Home Improvement Investments: Evidence from Monthly Billing Data." The Review of Economics and Statistics 81(3):516-528.

Meyers S, McMahon, J.E, McNeil, M., and Liu, X. (2003). "Impacts of U.S. federal energy efficiency standards for residential appliances." Energy 28:755–67.

Filippini, M. and Hunt, L. C. (2011). "Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach." The Energy Journal, 32(2): 59-80.

Pesaran, M. H., and Smith, R.P. (1995). "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels." Journal of Econometrics 68: 79–113.

Pesaran, M. H. (2006). "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure" Econometrica 74(4):967-1012.

Pesaran, M. H. (2007). "A simple panel unit root test in the presence of cross section dependence." Journal of Applied Econometrics 22: 265-312.

Ryan, D.L.and Ploure, A. (2009). Empirical modeling of energy demand. In: Evans, J., Hunt, L.C.(Eds.), International Handbook on the Economics of Energy. Edward Elgar, Cheltenham, U.K.

NOAA, 2012 http://www.ncdc.noaa.gov/cag/time-series/us

Stern D. I. and Kander, A. (2012). "The role of energy in the industrial revolution and modern economic growth." Energy Journal 33(3):127-154.

Webber, C.A., Brown, R.E., and Koomey, J.G. (2000). "Savings estimates for the ENERGY STAR voluntary labeling program." Energy Policy 28:1137–49.

Welsch, H. (1989). "The reliability of aggregate demand functions: an application of statistical specification error tests." Energy Economics 11: 285–292.

Appendix

Abrief account of the heterogeneous estimators:

Suppose we have two set of variables, y_{it} the dependent variable and an explanatory variable, x_{it}, which are related via the expression:

$$\begin{aligned} y_{it} &= \beta_i x_{it} + u_{it} \\ u_{it} &= \alpha_{1i} + \varphi_i f_t + \varepsilon_{it} \\ x_{it} &= \alpha_{2i} + \rho_i f_t^s + \lambda_i g_t + \upsilon_{it} \end{aligned} \qquad \text{A1}$$

Where u_{it} is a composite term that comprises both unobserved common factors (f_t ,a country fixed effects, α_{1i}) and a random error term, ε_{it}. Further, x_{it} is also influence by unobserved common factors (f_t^s, g_t).

The Pesaran (1995) mean group estimator (MG) allows for heterogeneity in the β_i but assumes cross-section independence, as a consequence, the MG estimator is implimented by estimating N country regression as follows:

$$\begin{aligned} y_{it} &= \alpha_i + \beta_i x_{it} + \sigma_i \, t + \varepsilon_{it} \\ \hat{\beta}_{MG} &= N^{-1} \sum_{i=1}^{N} \hat{\beta}_i \end{aligned} \qquad \text{A2}$$

Where t is a linear trend to capture unobserved factors that are time-invariant and by construction, the MG estimator allows for parameters to vary or differ across panel units (countries in this study).

The Pesaran (2006) common correlated mean group (CCEMG) estimator, unlike the MG estimator, does not assume cross-section independence. It however allows for heterogeneity in the parameters as does in the MG estimator. The CCEMG accounts for cross-section dependence via cross-section average of both the dependent ($\bar{y}_{it}$) and explanatory variable ($\bar{x}_{it}$) as additional covariates as follows:

$$\begin{aligned} y_{it} &= \alpha_i + \beta_i x_{it} + \tau_1 \bar{y}_{it} + \tau_2 \bar{x}_{it} + \varepsilon_{it} \\ \hat{\beta}_{CCEMG} &= N^{-1} \sum_{i=1}^{N} \hat{\beta}_i \end{aligned} \qquad \text{A3}$$

where the cross-section averages ($\bar{y}_{it}, \bar{x}_{it}$) are to account for the unobserved common factors (f_t^s, $f_{t,} g_t$).

The augmented mean group estimator (AMG) is a variant of the CCEMG estimator that accounts for both heterogeneous parameters and cross-section dependency. The cross-section dependency is accounted for by the inclusion of a "common dynamic effect" in the country specific regressions (Eberhardt and Teal, 2010). The estimation is done in two stages, where the first stage is to obtain the common dynamic variable which is included in the second stage as an additional covariate to account for the "common dynamic effect". The two stages can be express as:

$$stage(1) \qquad \Delta y_{it} = \beta \Delta x_{it} + \sum_{k=2}^{T} c_k \Delta D_k + \Delta \varepsilon_{it} \qquad \hat{c}_k \equiv \hat{\mu}_t \qquad \text{A4}$$

$$stage(2) \qquad y_{it} = \alpha_i + \beta_i x_{it} + \pi_i \hat{\mu}_t + \sigma_i t + \varepsilon_{it} \qquad \hat{\beta}_{AMG} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_i \qquad \text{A5}$$

where the first stage is based on first difference (FD)-OLS regression with $T-1$ first difference year dummies denoted by ΔD_k to get the estimated common dynamic variable ($\hat{\mu}_t$). The estimated common dynamic variable is included in the second stage regression to capture the effects of potential unobserved common factors.

Table A1: Unit root and cointegrating test for each of the series

Unit root test

Variable	lags	CIPS	p-value	MW	p-value
e	0	-0.094	0.463	67.741	0.000
e	1	-0.884	0.188	71.779	0.000
Δe	0	-9.084	0.000	174.845	0.000
Δe	1	-3.798	0.000	148.238	0.000
y	0	1.778	0.962	13.187	0.982
y	1	-0.103	0.459	61.226	0.000
Δy	0	-4.667	0.000	75.268	0.000
Δy	1	-3.867	0.000	79.598	0.000
p	0	-0.012	0.495	1.861	1.000
p	1	0.335	0.631	4.296	1.000
Δp	0	-8.380	0.000	173.744	0.000
Δp	1	-3.581	0.000	106.775	0.000
hhd	0	-7.759	0.000	132.857	0.000
hhd	1	-0.661	0.254	71.276	0.000
Δhhd	0	-15.895	0.000	462.704	0.000
Δhhd	1	-4.413	0.000	169.058	0.000
R&Dcap	0	1.917	0.972	109.976	0.000
R&Dcap	1	2.565	0.995	100.009	0.000
Δ R&Dcap	0	-7.741	0.000	203.677	0.000
Δ R&Dcap	1	-1.135	0.128	48.850	0.004

The null hypothesis is that of a unit root, the Pesaran (2007) CIPS test allows cross-sectional dependency in the testing procedure, while Maddala and Wu (MW) Panel Unit Root test does not allow for cross-sectional dependence. The first difference (change) is denoted by Δ and the numbers in parenthesis are the *P*-values for the unit root test statistic.

Cointegration test (pedroni residual base cointegration)

Test Stats	Panel	Group
υ	0.676	.
ρ	1.195	2.137
t	-2.422	-3.915
ADF	-2.071	-1.944

All test statistics are distributed N (0, 1), under a null of no cointegration, and diverge to negative infinity. There are two groups of the test statistics –panel and group. The group statistics average over the individual country test statistics, while the panel statistics pool the test statistics over the time dimension. The ρ and t are nonparametric test statistics, while ADF and υ are parametric statistics. The estimations for the seven test statistics (υ , ρ , t , ADF) are done with the inclusion of common time dummies to correct for potential simple cross-sectional dependence.

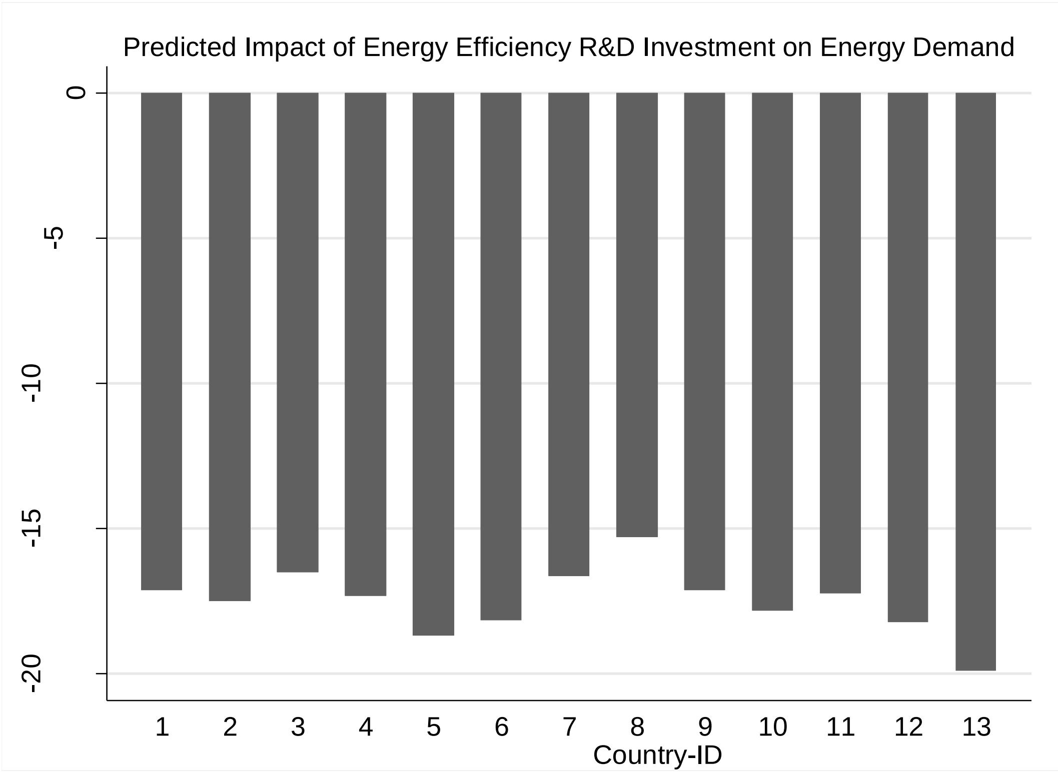

Figure A1: Predicted impact (cumulated over 1980-2006) of Eneregy Efficiency R&D investment on energy demand for 13 OECD countreis.

Note: the Country-ID, 1=Austria, 2=Belgium, 3= Denmark, 4=France, 5=Italy,6=Netherland, 7=Norway,8=Portugal, 9=Spain, 10=Sweden,11=Switzerland, 12=UK, 13=USA

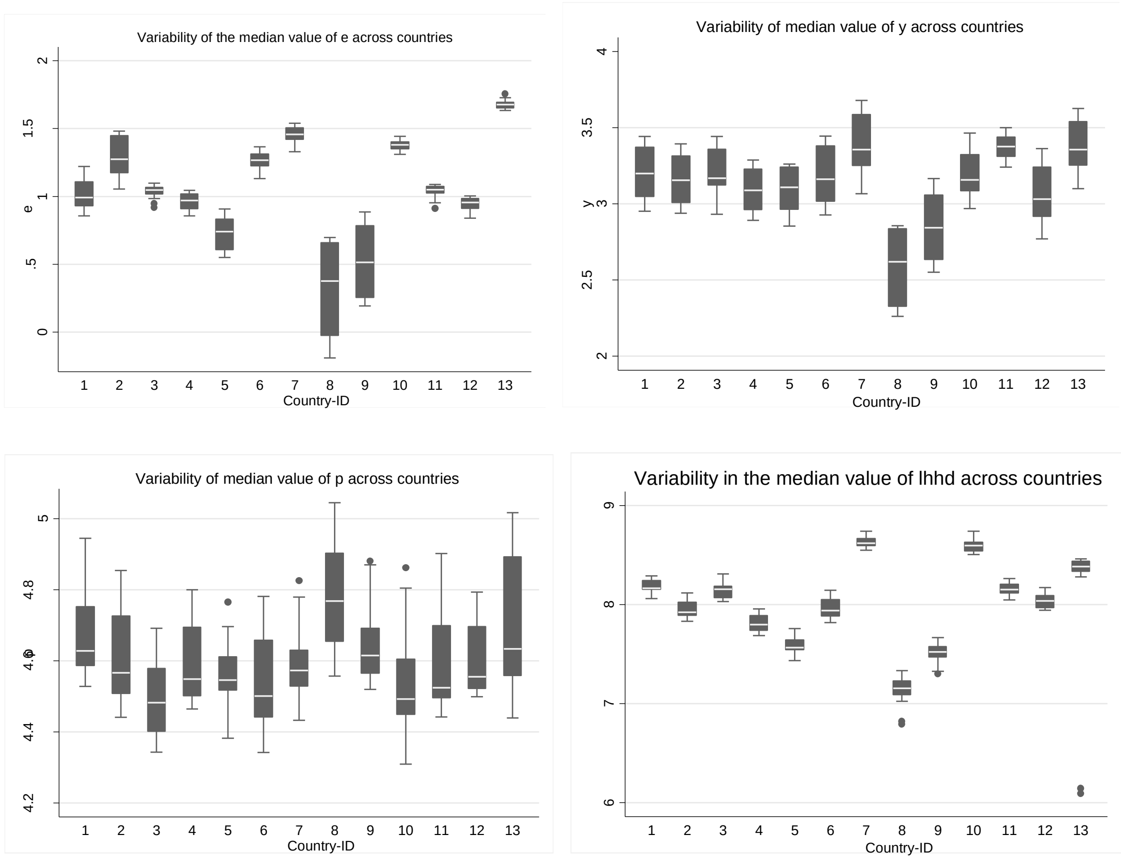

Figure A2: Boxplot showing the variability of the median value for energy consumption(e), income(y), price (p) and heating degree days (hhd) across 13 OECD countries.

Note: the Country-ID, 1=Austria, 2=Belgium, 3= Denmark, 4=France, 5=Italy,6=Netherland, 7=Norway,8=Portugal, 9=Spain, 10=Sweden,11=Switzerland, 12=UK, 13=USA

Table A2: Heterogeneous estimates (dynamic) and respective long-run elasticity

	MG	AMG	CCEMG
e lag	0.180*	0.177**	0.158*
	(0.095)	(0.071)	(0.096)
p	-0.0817**	-0.110***	-0.131**
	(0.033)	(0.030)	(0.059)
p lag	-0.068***	-0.061***	-0.108
	(0.026)	(0.023)	(0.077)
y	0.518***	0.526***	0.697**
	(0.125)	(0.138)	(0.253)
y lag	-0.124	0.048	0.139
	(0.128)	(0.088)	(0.197)
lnrndstock	-0.024	-0.024	-0.002
	(0.023)	(0.015)	(0.044)
lhhd	0.247***	0.136**	0.098**
	(0.017)	(0.048)	(0.040)
Trend	yes	yes	yes
Const	-0.656***	-0.615	-0.194
	(0.093)	(0.431)	(1.269)
Diagnostics			
CD-test	1.22	-1.19	-2.01
	[0.224]	[0.232]	[0.045]
Integration	*I*(0)	*I*(0)	*I*(0)
N	338	338	338

Note: Standard errors in parentheses (robust standard errors), * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, CD-test is the cross-sectional dependence test base on Pesaran (2004) test for the Null of cross-sectional independent residuals and N is the number of observations, hhd is the heating degree days and R&Dcap denote R&D capital. Numbers in square bracket are the *p*-values for CD-test.

Long-run eslasticity estimates

	MG	AMG	CCMG
p	-0.182***	-0.207***	-0.283**
	(0.055)	(0.049)	(0.119)
y	0.481**	0.698***	0.993**
	(0.226)	(0.206)	(0.397)
R&Dcap	-0.029	-0.029	-0.002
	(0.028)	(0.018)	(0.052)
hhd	0.301***	0.165***	0.116**
	(0.040)	(0.060)	(0.049)