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CEPE Working Paper No. 68
Oktober 2009

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

CEPE
Zurichbergstrasse 18 (ZUE E)
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Abstract

This paper attempts to estimate a panel 'frontier' whole economy aggregate energy demand function for 29 countries over the period 1978 to 2006 using stochastic frontier analysis (SFA). Consequently, unlike standard energy demand econometric estimation, the energy efficiency of each country is also modelled and it is argued that this represents a measure of the underlying efficiency for each country over time, as well as the relative efficiency across the 29 OECD countries. This shows that energy intensity is not necessarily a good indicator of energy efficiency, whereas by controlling for a range of economic and other factors, the measure of energy efficiency obtained via this approach is. This is, as far as is known, the first attempt to model energy demand and efficiency in this way and it is arguably particularly relevant in a world dominated by environmental concerns with the subsequent need to conserve energy and/or use it as efficiently as possible. Moreover, the results show that although for a number of countries the change in energy intensity over time might give a reasonable indication of efficiency improvements; this is not always the case. Therefore, unless this analysis is undertaken, it is not possible to know whether the energy intensity of a country is a good proxy for energy efficiency or not. Hence, it is argued that this analysis should be undertaken to avoid potentially misleading advice to policy makers.

JEL: D, D2, Q, Q4, Q5.

Keywords: Energy demand; OECD; efficiency and frontier analysis; energy efficiency.

Acknowledgements

We are grateful to Olutomi Adeyemi for his assistance with the data collection. A preliminary version of the paper was presented at the 2nd International workshop on Empirical Methods in Energy Economics (Jasper, Canada, 2009) and we are grateful to the discussant, Denise Young and other participants for their very helpful comments and suggestions. A revised version of the paper was presented at the 10th IAEE European conference (Vienna, Austria, 2009) and we thank participants for their additional comments and suggestions. The authors are, of course, responsible for all errors and omissions.

1 Introduction

During the last 20 years, there has been considerable debate within energy policy about the possible contribution from an improvement in energy efficiency and on the effectiveness of ecological tax reforms in the alleviation of the greenhouse effect and in the decrease of the dependency on fossil fuels. In order to design and implement effective energy policy instruments to promote an efficient and parsimonious utilization of energy, it is necessary to have information on energy demand price and income elasticities in addition to sound indicators of energy efficiency.

In practical energy policy analysis, the typical indicator used is energy intensity, defined as the ratio of energy consumption to GDP. This is highlighted by a report from the International Energy Agency (IEA, 2009) on the Energy Efficiency Policies in the G8, which states that since the 1970s many countries have promoted energy efficiency improvements, which is illustrated by the decline in energy intensity. The report goes on to say that "Energy intensity is the amount of energy used per unit of activity. It is commonly calculated as the ratio of energy use to GDP. *Energy intensity is often taken as a proxy for energy efficiency, although this is not entirely accurate* since changes in energy intensity are a function of changes in several factors including the structure of the economy and energy efficiency" (our emphasis, p. 15). This highlights the weakness of this simple aggregate energy consumption to GDP ratio in that it does not measure the level of 'underlying energy efficiency' that characterizes an economy; hence, it is difficult to make conclusions for energy policy based upon this simple measure.

In this paper, an alternative way to estimate the economy-wide level of energy efficiency is proposed, by drawing on different strands of the energy economics research literature; in particular, frontier estimation and energy demand modelling. An energy demand frontier function is therefore estimated in order to attempt to isolate 'underlying energy efficiency', by explicitly controlling for income and price effects, country specific effects, climate effects and a common Underling Energy Demand Trend (the UEDT, capturing both 'exogenous' technical progress and other exogenous factors). Hence, it allows for the impact of 'endogenous' technical progress' through the price effect and 'exogenous' technical progress through the UEDT.

The aim is to analyse economy wide energy efficiency; hence, the estimated model introduced below is for aggregate energy consumption for the whole economy. Economy wide aggregate energy demand is derived from the demand for energy services such as heat, illumination, cooked food, hot water, transport services, manufacturing processes, etc. To produce the desired services it is generally necessary to use a combination of energy fuels and capital equipment such as household appliances, cars, insulated walls, machinery, etc. This implies that the demand for energy is influenced by the level of energy efficiency of the equipment and, generally, of the production process. For instance, some relatively new equipment and production processes are able to provide the same level of services and products using less energy than old equipment. This comes from research and development that improves the thermodynamic efficiency of appliances and the capital stock, as well as production processes – there is a technical improvement. Of course, in reality, apart from the technological and economic factors there are a range of exogenous institutional and regulatory factors that are important in explaining the level of energy consumption, furthermore, these exogenous changes are unlikely to impact in a consistent rate over time. Hence, it is important that the UEDT is specified in such a way that it is 'non-linear' and could increase and/or decrease over the estimation period as advocated by Hunt et al. (2003a,b). Therefore, given a panel data set is used this is achieved by time dummies as proposed by Griffin and Schulman (2005) and Adeyemi and Hunt (2007).

In order to try to tease out these different influences, a general energy demand relationship found in the standard energy demand modelling literature, relating energy consumption to economic activity and the real energy price, is utilised for the estimation of an aggregate energy demand function for a panel of OECD countries. Moreover, in order to control for other important factors that vary across countries and hence can affect a country's energy demand, some variables related to climate, size, and structure of the economy are introduced in the model. Thus the framework adopted here attempts to isolate the 'underlying energy efficiency' for each country after controlling for income, price, climate effects, technical progress and other exogenous factors, as well effects due to difference in area size and in the structure of the economy. The estimated model therefore isolates the level of underlying energy efficiency, defined with respect to a benchmark, e.g. a best practice economy in the use of energy by estimation a 'common energy demand' function across countries, with homogenous income and price elasticities, and responses to other factors, plus a homogenous UEDT. This is seen as important, given the need to isolate the different underlying energy efficiency across the countries.[1] Consequently, once these effects are adequately controlled for, it allows for the estimation of the underlying energy efficiency for each country showing i) how efficiency has changed over the estimation period and ii) the differences in efficiency across the panel of countries.

[1] The UEDT includes exogenous technical progress and it could be argued that even though technologies are available to each country they are not necessarily installed at the same rate; however, it is assumed that this results from different behaviour across countries and reflects 'inefficiency' across countries; hence, it is captured by the different (in)efficiency terms for all countries.

The paper is organized as follows. The next section, discusses the rationale and specification of the energy demand frontier function, with the data and econometric specification introduced in Section 3. The results of the estimation are presented in Section 4, with a summary and conclusion in the final section.

2 An aggregate frontier energy demand model

Given the discussion above, it is assumed that there exists an aggregate energy demand relationship for a panel of OECD countries, as follows:

$$E_{it} = E(P_{it}, Y_{it}, C_i, A_i, ISH_{it}, SSH_{it}, D_t, EF_{it}) \qquad (1)$$

where E_{it} is aggregate energy consumption per capita, Y_{it} is GDP per capita, P_{it} is the real price of energy, C_i is climate, A_i is the area size, ISH_{it} is the share of value added of the industrial sector and SSH_{it} is the share of value added for the service sector all for country *i* in year *t*. Further, D_t is a series of time dummy variables representing the UEDT that captures the common impact of important unmeasured exogenous factors that influence all countries simultaneously, e.g. general expectations of changes in international oil price, general changes in awareness of climate change, and exogenous change in the technology. Finally, EF_{it} is the level of 'underlying energy efficiency' of the appliance and capital equipment used in an economy. This could incorporate a number of factors that will differ across countries, including different government regulations as well as different social behaviours, norms, lifestyles and values. Hence, a low level of underlying energy efficiency implies an inefficient use of energy (i.e. 'waste energy'), so that in this situation, awareness for energy conservation could be increased in order to reach the 'optimal' energy demand function. Nevertheless, from an empirical perspective, when using OECD aggregate energy data, the aggregate level of energy efficiency of the capital equipment and of the production processes is not observed directly. Therefore, this underlying energy efficiency indicator has to be estimated. Consequently, in order to estimate this economy-wide level of underlying energy efficiency (EF_{it}) and identify the best practice economy in term of energy utilization, the stochastic frontier function approach introduced by Aigner et al. (1977) is used.[2]

The stochastic frontier function has generally been used in production theory to measure, using an econometric approach, the economic performance of production processes. The central concept of the frontier approach is that in general the function gives the maximum or minimum level of an economic indicator attainable by an economic agent. For a production function, the frontier gives the maximum level of output attainable by a firm for any given level of inputs. In the case of an aggregate energy demand function, used here, the frontier gives the minimum level of energy necessary for an economy to produce any given level of energy services. In principle, the aim here is to apply the frontier function concept in order to estimate the baseline energy demand, which is the frontier that reflects the demand of the countries that use high efficient equipment and production process. This frontier approach allows the possibility to identify if a country is, or is not, on the frontier. Moreover, if a country is not on the frontier, the distance from the frontier measures the level of energy consumption above the baseline demand, e.g. the level of energy inefficiency.

The approach used in this study is therefore based on the assumption that the level of the economy-wide energy efficiency can be approximated by a one-sided non-negative term, so

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[2] Of course, the frontier function approach suggested by Aigner et al. (1977) has been developed within the neoclassical production theory. The main goal of this literature has been to estimate production and cost frontier in order to identify the level of productive inefficiency (allocative and technical inefficiency). In this study, the neoclassical production theory is discarded and instead the concept of a stochastic frontier within the empirical approach traditionally used in the estimation of economy-wide energy demand function is employed. Of course, behind the concept of underlying energy inefficiency developed here, there is still a 'production process'.

that a panel log-log functional form of Equation (1) adopting the stochastic frontier function approach proposed by Aigner et al. (1977) can be specified as follows:

$$e_{it} = \alpha + \alpha^{y} y_{it} + \alpha^{p} p_{it} + \delta_{t} D_{t} + \alpha^{C} DC_{i} + \alpha^{a} a_{i} + \alpha^{I} ISH_{it} \alpha^{S} SSH_{it} + v_{it} + u_{it} \qquad (2)$$

where e_{it} is the natural logarithm of aggregate energy consumption per capita (E_{it}), y_{it} is the natural logarithm of GDP per capita (Y_{it}), p_{it} is the natural logarithm of the real price of energy (P_{it}), DC_i is a cold climate dummy variable, a_i is the natural logarithm of the area size of a country measured in squared km (A_i), ISH_{it} is the share of value added of the industrial sector, SSH_{it} is the share of value added for the service sector and D_t is a series of time dummy variables. Furthermore, the error term in Equation (2) is composed of two independent parts. The first part, v_{it}, is a symmetric disturbance capturing the effect of noise and as usual is assumed to be normally distributed. The second part, u_{it}, which represents the underlying energy level of efficiency EF_{it} in equation (1) is interpreted as an indicator of the inefficient use of energy, e.g. the 'waste energy'. It is a one-sided non-negative random disturbance term that can vary over time, assumed to follow a half-normal distribution.[3] An improvement in the energy efficiency of the equipment or on the use of energy through a new production process will increase the level of energy efficiency of a country. The impact of technological, organisational, and social innovation in the production and consumption of energy services on the energy demand is therefore captured in several ways: the time dummy variables, the indicator of energy efficiency and through the price effect.[4]

[3] It could be argued that this is a strong assumption for *EF*, but it does allow the 'identification' of the efficiency for each country separately.

[4] In this model specification, we are assuming that the price effect is symmetric. Gately and Huntington (2002), amongst others, discuss the possibility of specifying a demand model with asymmetric price effects and some

In summary, Equation (2) is estimated in order to estimate underlying energy efficiency for each country in the sample. The data and the econometric specification of the estimated equations are discussed in the next section.

3. Data and econometric specification

The study is based on an unbalanced panel data set for a sample of 29 OECD countries (i = 1, …, 29)[5] over the period 1978 to 2006 (t = 1978-2006). This data set is based on information taken from the International Energy Agency (IEA) database "World Energy Statistics and Balances of OECD Countries" available at www.iea.org and from the general OECD database "Country profile Statistics".

E is each country's per capita aggregate energy consumption in tonnes of oil equivalent (toe), Y is each country's per capita GDP in thousand US2000$PPP, and P is each country's index of real energy prices (2000=100). The climate dummy variable, DC, indicates whether a country belongs to those characterized by a cold climate (according to the Köppen-Geiger climate classification[6]) and A is the area size of a country is measured in squared kilometres. Finally, the value added of the industrial and service sectors is measured as percentage of GDP (ISH and SSH). Descriptive statistics of the key variables are presented in Table 1.

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experimentation with asymmetric prices was undertaken here, however, the model did not fit the data well. Future research will investigate this further.

[5] Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, the UK, and the US. For some countries, information on the share of the industrial and service sector in the economy are only available for the years after 1990. For this reason the data set is unbalanced.

[6] See for a discussion of this classification Peel et al. (2007).

Table 1: Descriptive statistics

Variable Description	Name	Mean	Std. Dev.	Minimum	Maximum
Energy consumption per capita (toe/capita)	**E**	2.99	1.58	0.58	9.49
GDP per capita (1000 US2000$PPP/capita)	**Y**	20.63	8.44	4.19	63.36
Real Price of energy (2000=100)	**P**	99.65	16.42	53.56	170.30
Area size in km^2	**A**	1269850	2786260	2590	9984670
Share of industrial sector in % of GDP	**ISH**	25.22	4.99	9.40	40.40
Share of service sector in % of GDP	**SSH**	20.95	5.52	8.20	48.50
Climate Dummy	**DC**	0.45	0.50	0	1

From the econometric specification perspective, the literature on the estimation of stochastic frontier models using panel data needs to be considered. The first use of panel data in stochastic frontier models goes back to Pitt and Lee (1981) who interpreted the panel data random effects as inefficiency rather than heterogeneity.[7] A major shortcoming of these models is that any unobserved, time-invariant, group-specific heterogeneity is considered as inefficiency. In order to solve this problem using panel data, Greene (2005a and 2005b) proposed to extend the SFA model in its original form (Aigner, et al., 1977) by adding a fixed or random individual effect in the model.[8] It should be noted that these models produce efficiency estimates that do not include the persistent inefficiencies that might remain more or less constant over time. To the extent that there are certain sources of energy efficiency that result in time-invariant excess energy consumption, the estimates of these models provide relatively high levels of energy efficiency. For this reason, this study uses the original approach proposed by Aigner, et al. (1977) so that fixed or random individual effects proposed by Greene (2005a and 2005b) are not included in the model. Of course, by not considering the individual effects in the econometric specification, it could result in the so-called 'unobserved

[7] Schmidt and Sickles (1984) and Battese and Coelli (1992) presented variations of this model.

[8] For a successful application of these models in network industries, see Farsi, et al. (2006) and Farsi, et al. (2005).

variables bias'; e.g. a situation where correlation between observables and unobservables could bias some coefficients of the explanatory variables. However, by introducing several explanatory variables such as the climate, the area size, and some variables on the structure of the economy it is possible to reduce this problem. In fact, the estimated coefficients of the demand frontier function presented in the next section are very similar to those obtained by estimating equation (2) by using a random or a fixed effects approach. [9] The econometric approach used in this paper therefore has the advantage that it includes in the inefficiency term the persistent inefficiencies that might remain more or less constant over time as well the inefficiencies that vary over time.

Table 2 provides a summary of the model specification and a description of the stochastic terms included in the model.

Table 2: Econometric specification of the model employed

Model	*Random error* ε_{it}	*Level of efficiency* u_{it}
TRE (ML)	$\varepsilon_{it} = v_{it} + u_{it}$ $u_{it} \sim \text{iid}\, N^{+}(0,\sigma_u^2)$ $v_{it} \sim \text{iid}\, N(0,\sigma_v^2)$	$E(u_{it} \mid \varepsilon_{it})$

The country's efficiency is estimated using the conditional mean of the efficiency term $E[u_{it} | u_{it} + v_{it}]$, proposed by Jondrow et al. (1982). The level of energy efficiency can be expressed in the following way:

$$EF_{it} = \frac{E_{it}^F}{E_{it}} = \exp(-\hat{u}_{it}) \quad (3)$$

where E_{it} is the observed energy consumption per capita and E_{it}^F is the frontier or minimum demand of the i^{th} country in time t. An energy efficiency score of one indicates a country on

[9] In a preliminary analysis, a version of equation (2) using the true random effects model was also estimated. As expected, the obtained level of energy efficiency were very high (average level of efficiency higher than 90%).

the frontier (100% efficient), while non-frontier countries, e.g. countries characterized by a level of energy efficiency lower than 100%, receive scores below one. This therefore gives the measure of underlying energy efficiency estimated below.[10]

In summary, Equation (2) is estimated and Equation (3) used to estimate the efficiency scores for each country for each year. The results from the estimation are given in the next section.

4. Estimation results

The estimation results for frontier energy demand model, Equation (2), are given in Table 3. This shows that the estimated coefficients and *lambda* have the expected signs and are statistically significant.[11]

Table 3: Estimated coefficients (*t*-values in parentheses)

Constant	-1.916 (-6.93)
α^y	0.900 (38.98)
α^p	-0.275 (-4.77)
α^C	0.227 (12.29)
α^a	0.021 (3.44)
α^l	0.017 (9.08)
α^s	0.029 (11.51)
Time dummies	Yes
Lamda (λ)	2.762 (8.71)

[10] This is in contrast to the alternative indicator of energy inefficiency given by the exponential of u_{it}. In this case, a value of 0.2 indicates a level of energy inefficiency of 20%.

[11] Lambda (λ) gives information on the relative contribution of u_{it} and v_{it} on the decomposed error term ε_{it} and shows that in this case, the one-sided error component is relatively large.

For the variables in logarithmic form, the estimated coefficients can be directly interpreted as elasticities. The estimated income elasticity and the estimated own price elasticity are about 0.9 and -0.3 respectively, both not out of line with previous estimates. The estimated area elasticity is about 0.02 indicating that a 10% larger country will demand 0.5% more energy. The climate variable, DC, also appears to have an important influence on a country's energy demand; with countries characterized by a cold climate experiencing a higher consumption of energy. Similarly, larger shares of a country's industrial and service sectors will also increase energy consumption. The time dummies, as a group, are significant and, as expected, the overall the trend in their coefficients is negative as shown in Figure 1; however, they do not fall continually over the estimation period, reflecting the 'non-linear' impact of technical progress and other exogenous variables.

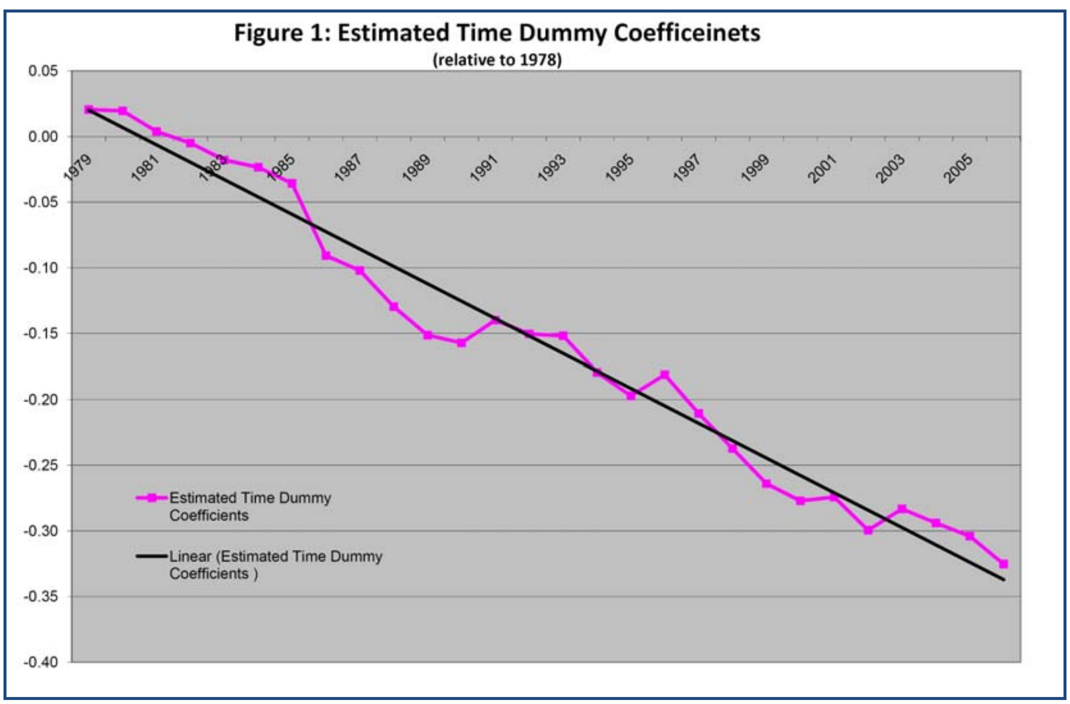


Table 4: Energy efficiency scores

min	0.522
max	0.951
mean	0.781
median	0.797
st.dev.	0.117

Table 4 provides descriptive statistics for the overall underlying energy efficiency estimates of the countries obtained from the econometric estimation, showing that the mean average efficiency is estimated to be about 78% (median 80%) nonetheless, as expected, there is a fair degree of variation around the average. Table 5 presents the average energy efficiency score for every country for three sub periods of the estimation period considered in the analysis and over the whole period and Figure 2 shows that the estimated underlying energy efficiency scores for each country over the estimation period relative to energy intensity. It should be noted that, although presented individually for each country, the estimated efficiencies of each country should not be taken as the precise position of each country given the stochastic technique used in estimation. However, they do give a good relative indication of a country's change in efficiency over time and a country's relative position vis-à-vis other countries.

Bearing this in mind, Table 5 and Figure 2 show that the estimated underlying energy efficiency generally increased over the estimation period for some countries, such as Australia, Canada, Denmark, Germany, Luxembourg, Netherlands, Norway, Sweden, the UK, and the USA. Whereas for some countries the opposite is the case, with the estimated underlying energy efficiency generally decreasing, such as Greece, Italy, Mexico, New Zealand, Portugal, Spain and Turkey. Figure 2 also illustrates that the estimated underlying energy efficiency would appear to be negatively correlated with energy intensity for most countries (i.e. the level of energy intensity decreases with an increase of the level of energy efficiency), but with some exceptions (discussed further below). This is to be expected in one sense. However, if this technique were to be a useful tool for teasing out underlying energy efficiency then a perfect, or even near perfect, negative correlation would not be expected since all the useful information would be contained in the standard energy to GDP ratio.

Table 5: Average energy efficiency scores over time

	1978 – 1987	1988 – 1997	1998 – 2006	Whole Period
Australia	0.768	0.783	0.806	0.785
Austria	0.865	0.894	0.888	0.882
Belgium	0.666	0.682	0.622	0.658
Canada	0.583	0.608	0.645	0.608
Czech Rep	n/a	0.678	0.695	0.687
Denmark	0.849	0.909	0.916	0.891
Finland	0.581	0.584	0.612	0.591
France	0.856	0.888	0.876	0.873
Germany	0.844	0.931	0.944	0.905
Greece	0.911	0.838	0.755	0.838
Hungary	n/a	0.742	0.823	0.788
Ireland	0.628	0.725	0.902	0.747
Italy	0.937	0.931	0.908	0.926
Japan	0.880	0.890	0.863	0.878
Korea	0.820	0.833	0.753	0.804
Luxembourg	0.561	0.632	0.719	0.635
Mexico	0.902	0.902	0.869	0.892
Netherlands	0.612	0.681	0.701	0.663
New Zealand	0.740	0.706	0.652	0.707
Norway	0.790	0.802	0.864	0.817
Poland	n/a	0.571	0.740	0.673
Portugal	0.882	0.813	0.696	0.800
Slovak Rep.	n/a	0.594	0.637	0.622
Spain	0.934	0.871	0.770	0.861
Sweden	0.723	0.774	0.813	0.768
Switzerland	n/a	0.931	0.933	0.932
Turkey	0.880	0.800	0.718	0.802
UK	0.842	0.859	0.893	0.864
USA	0.545	0.642	0.720	0.633

Note: n/a represents the situation where the average is not available over the sub-period.
Due to the unbalanced panel, some averages are calculated over a slightly shorter period than indicated.

Figure 2: Comparison of Estimated Underlying Energy Efficiency with Energy Intensity

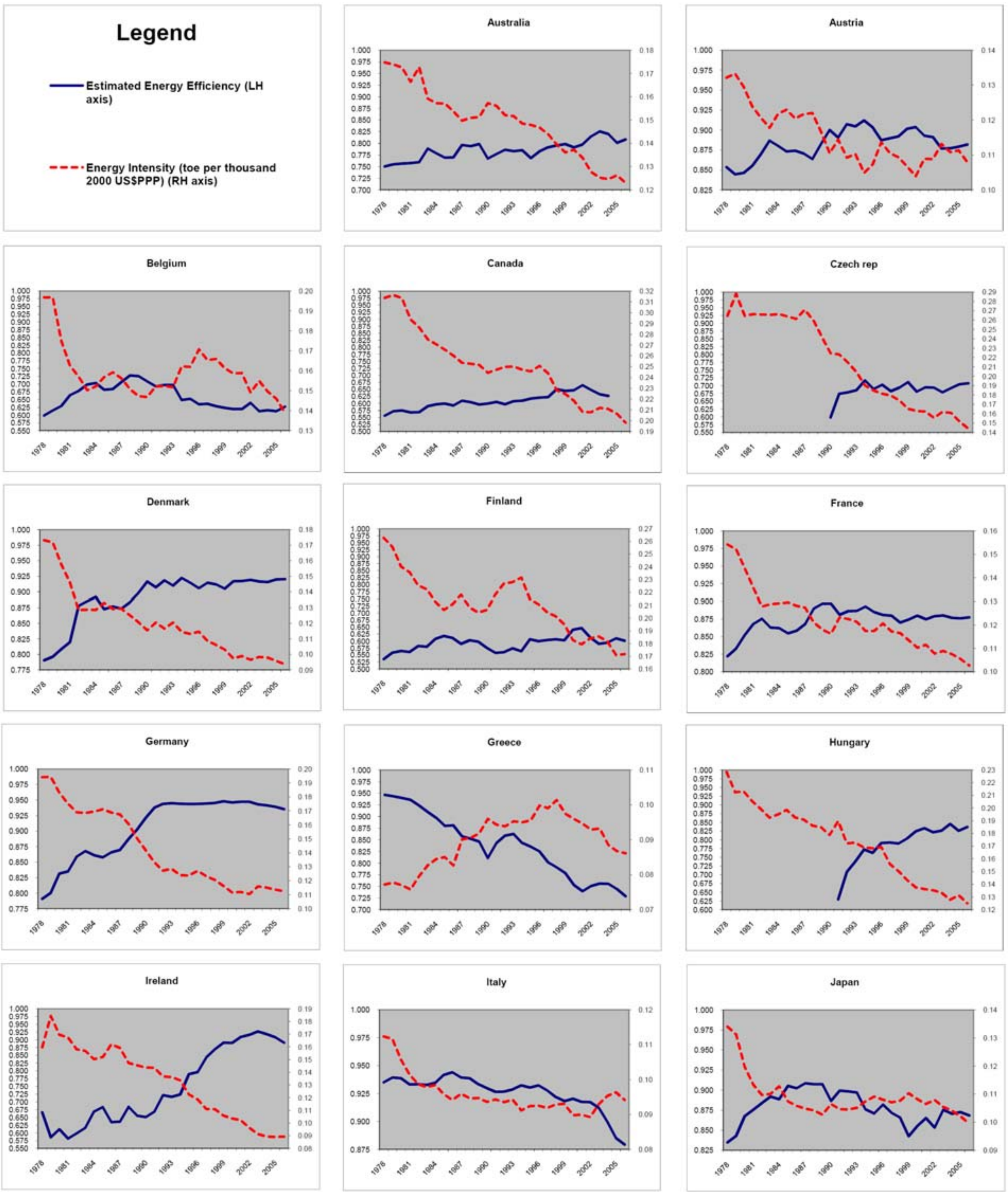
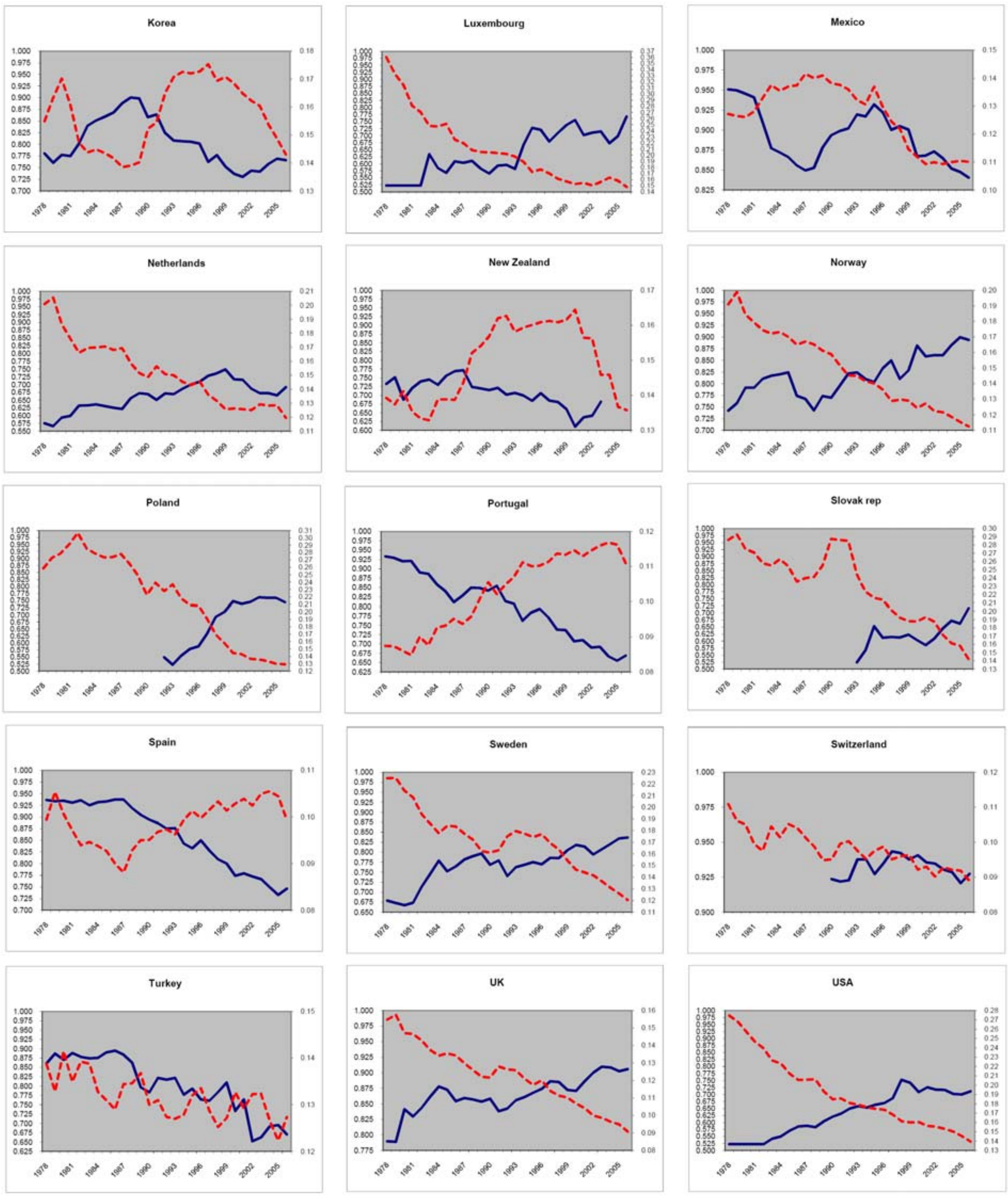


Figure 2: Continued



This is confirmed, given the average correlation coefficient between the estimated underlying energy efficiency and energy intensity across all countries is -0.68. Within this, there is a relatively high negative correlation for some countries, such as Australia, Austria, Canada, Denmark, Germany, Hungary, Ireland, Luxembourg, Netherlands, Norway, Poland, Portugal, the Slovak Republic, Sweden, the UK and the USA; whereas for some countries the (negative) correlation is somewhat less, such as Belgium, the Czech Republic, Greece, Japan, Korea, New Zealand, and Switzerland. Furthermore, for Italy, Mexico, and Turkey, there appears to be a positive relationship between the energy to GDP ratio and estimated energy efficiency. This suggests that for some countries energy intensity is a reasonable proxy for energy efficiency, whereas for others it is a very poor proxy. Hence, unless the analysis undertaken here is conducted it is arguably not possible to identify for which countries energy intensity is a good proxy and for which it is a poor proxy.

Turning to the differences in estimated energy efficiency scores across the panel of countries in the sample it can be seen from Table 5 that there is some difference over the whole sample period. Finland, Canada, the Slovak Republic, the USA, and Luxembourg are the estimated five least efficient countries, with Switzerland, Italy, Germany, Mexico, and Denmark the estimated five most efficient countries.[12] This is further shown in Figure 3, with the countries re-ordered from the most efficient to the least efficient. However, although Italy is estimated to be one of the most energy efficient countries over time its level of efficiency has been generally declining, despite a general fall in energy intensity. This highlights that energy intensity in this case gives a poor indication of Italy's change in energy efficiency over time.

[12] However, it should be noted that, given the unbalanced panel used in estimation, the figures for the Slovak Republic and Switzerland are over a much shorter period.

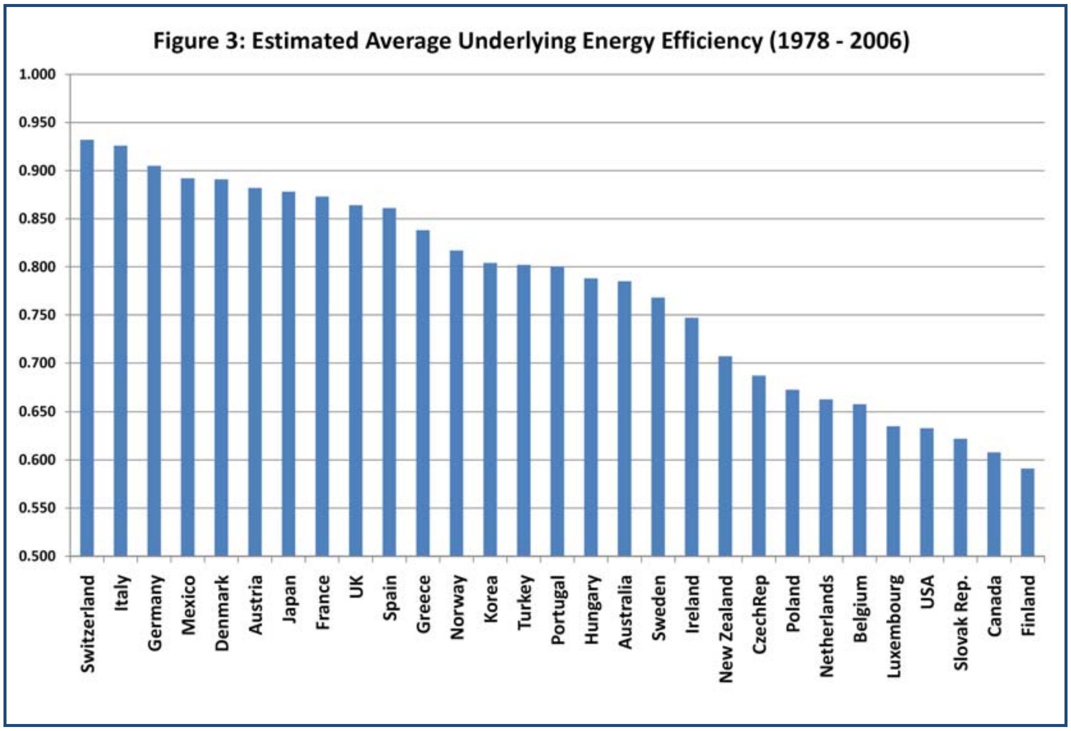
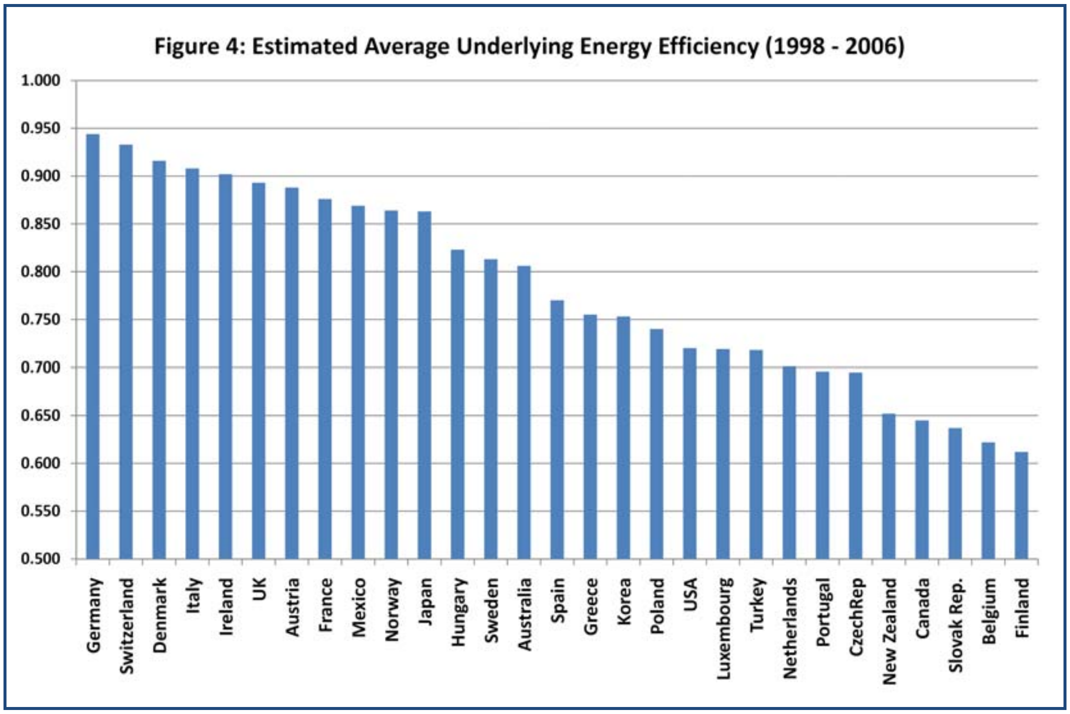


Figure 3: Estimated Average Underlying Energy Efficiency (1978 - 2006)

Countries will, however, have improved (or deteriorated) at different rates; hence, Figure 4 gives the ordered data for the latter period only, 1998-2006. This shows that the ordering does change, with the five least efficient countries being Finland, Belgium, the Slovak Republic, Canada and New Zealand and the five most efficient countries being Germany, Switzerland, Denmark, Italy and Ireland. Furthermore, as shown in Table 6, and illustrated when comparing Figure 4 and Figure 5, it can be seen that although there is generally a negative relationship between the rankings of the estimated underlying energy efficiency and energy intensity there is not a one to one correspondence. For example, according to the measure of energy intensity over the period 1998-2006, Germany is ranked 12th, whereas it is estimated to be the most efficient over the period; suggesting that Germany is relatively more energy efficient than the simple energy intensity measure would suggest. Conversely, Greece and Portugal are ranked 1st and 12th respectively in terms of energy intensity but are only ranked 16th and 23rd respectively in terms of underlying energy efficiency; suggesting that

Greece and Portugal are somewhat less energy efficient than the simple energy intensity measure suggest.



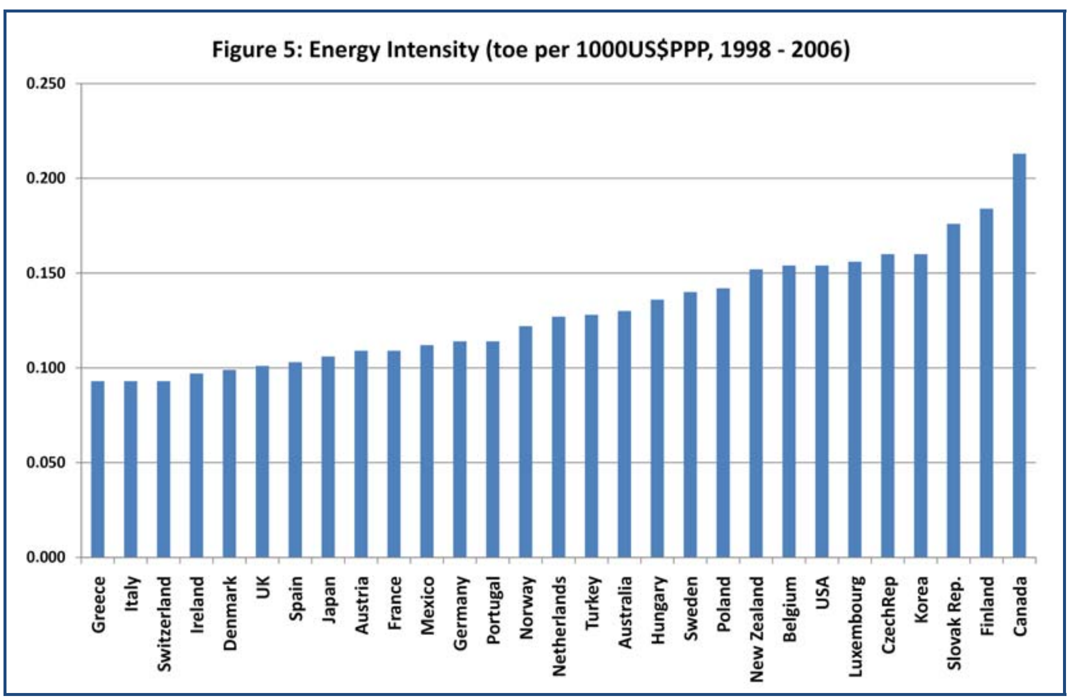


Table 6: Comparison of the Rankings for Estimated Underlying Energy Efficiency and Energy Intensity (1998-2006)

	Estimated Underlying Energy Efficiency (symmetric model)		***Energy Intensity (Energy GDP ratio, toe per 1000 US2000$PPP)***	
	Level	*Rank*	*Level*	*Rank*
Australia	0.806	14	0.130	17
Austria	0.888	7	0.109	9
Belgium	0.622	28	0.154	22
Canada	0.645	26	0.213	29
Czech Rep	0.695	24	0.160	25
Denmark	0.916	3	0.099	5
Finland	0.612	29	0.184	28
France	0.876	8	0.109	9
Germany	0.944	1	0.114	12
Greece	0.755	16	0.093	1
Hungary	0.823	12	0.136	18
Ireland	0.902	5	0.097	4
Italy	0.908	4	0.093	1
Japan	0.863	11	0.106	8
Korea	0.753	17	0.160	25
Luxembourg	0.719	20	0.156	24
Mexico	0.869	9	0.112	11
Netherlands	0.701	22	0.127	15
New Zealand	0.652	25	0.152	21
Norway	0.864	10	0.122	14
Poland	0.740	18	0.142	20
Portugal	0.696	23	0.114	12
Slovak Rep.	0.637	27	0.176	27
Spain	0.770	15	0.103	7
Sweden	0.813	13	0.140	19
Switzerland	0.933	2	0.093	1
Turkey	0.718	21	0.128	16
UK	0.893	6	0.101	6
USA	0.720	19	0.154	22

Note: A rank of 29 for underlying energy efficiency represents the least efficient country by this measure, whereas a rank of 1 represents the most efficient country. A rank of 29 for energy intensity represents the most energy intensity country whereas a rank of 1 represents the least energy intensive country.

5. Summary and Conclusion

This research is a fresh attempt to isolate core energy efficiency for a panel of 29 OECD countries, opposed to relying on the simple energy to GDP ratio – or energy intensity.

By combining the approaches taken in energy demand modelling and frontier analysis, a measure of the 'underlying energy efficiency' for each country is estimated. This approach has not, as far is known, been attempted before. The energy demand specification controls for income, price, climate country specific effects, area, industrial structure, and a underlying energy demand trend in order to obtain a measure of 'efficiency' – in a similar way to previous work on cost and production estimation – thus giving a measure of underlying energy efficiency (reflecting the relative inefficient use of energy, i.e. 'waste energy').

The estimates for the core energy efficiency using this approach show that although for a number of countries the change in energy intensity might give a reasonable indication of efficiency improvements; this is not always the case both over time and across countries - Italy and Greece being prime examples. For Italy, energy intensity declines over the estimation period suggesting an improvement in energy efficiency, whereas the estimated underlying energy efficiency falls over the period.[13] For Greece, energy intensity suggests that it is the most efficient country over the latter period covered by the data, whereas the estimated underlying energy efficiency suggests otherwise. Therefore, unless the analysis advocated here is undertaken, it is not possible to know whether the energy intensity of a country is a good proxy for energy efficiency or not. Hence, it is argued that this analysis should be undertaken in order to give policy makers an additional indicator other than the rather naïve measure of energy intensity in order to try to avoid potentially misleading policy conclusions.

[13] Although it still remains relatively one of the most efficient countries.

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