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Underlying Energy Efficiency in the US

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ABSTRACT

The promotion of US energy efficiency policy is seen as a very important activity. Generally, the level of energy efficiency of a country or state is approximated by energy intensity, commonly calculated as the ratio of energy use to GDP. However, energy intensity is not an accurate proxy for energy efficiency given that changes in energy intensity are a function of changes in several factors including the structure of the economy, climate, efficiency in the use of resources, behaviour, and technical change. The aim of this paper is to measure persistent and transient underlying energy efficiency for the whole economy of 49 states in the US using a stochastic frontier energy demand approach. A total US energy demand frontier function is estimated using panel data for 49 states over the period 1995 to 2009 using two panel data models: the Mundlak version of the random effects model (which estimates the persistent part of the underlying energy efficiency) and the true random effects model (which estimates the transient part of the underlying energy efficiency). The analysis confirms that energy intensity is not a good indicator of underlying energy efficiency whereas, by controlling for a range of economic and other factors, the measure of persistent underlying energy efficiency obtained via the approach adopted here is. Moreover, the estimates show that although for some states EI might give a reasonable indication of a state's relative UEE this is not the case for all states, California being a prime example.

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

Key Words: US total energy demand; efficiency and frontier analysis;
persistent and transient underlying energy efficiency.

Underlying Energy Efficiency in the US [#]

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1 Introduction

The promotion of energy efficiency policies is seen as a major strand of energy policy, in the US and across the globe given the need to reduce greenhouse gas emissions and maintain security of energy supply. It is therefore vital that in the US the *true* relative energy efficiency across the different states is clearly measured. However, generally a state's energy efficiency is approximated by energy intensity – commonly calculated as the ratio of energy use to GDP (or approximated by energy productivity – the inverse of the energy intensity).[1] Nonetheless, these two indicators, energy intensity and energy productivity, are not good proxies for energy efficiency, because changes in both indicators are a function of changes in several factors including the structure of the economy, the level

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[1] As discussed in Patterson (1996) and Bhattacharyya (2011), the energy economics literature generally uses definitions of energy efficiency based on the simple ratio of output to energy consumption, where the output and inputs can be measured in energy/thermodynamic units, physical units, or economic monetary units; although, generally the hybrid measure using the ratio of economic to thermodynamic units is favoured.

of production, climate, the level of efficiency in the use of resources and technical change. For example, EC (2000, p. 3) recognises that “Changes in energy intensity for final energy consumption are a first and rough estimate indicator for changes in energy efficiency” and the US Energy Information Agency come to a similar conclusion.[2] Therefore, a decrease in energy intensity or an increase in energy productivity of a state does not necessarily imply that the efficiency in the use of energy in the state has increased.

Given the problems with the proxy measures, different approaches have been proposed in the academic literature that attempt to identify the change in the *true* level of efficiency in the use of energy at the aggregate economy level.[3] One approach, proposed by Bossanyi (1979) and Myers and Nakamura (1978) is based upon Index Decomposition Analysis (IDA). This makes use of several types of index numbers and is achieved by decomposing the changes in energy intensity into the change in fuel mix, the change in the structure of the economy and, what they regard as, the actual change in energy efficiency.[4] Moreover, some studies using IDA, propose an additional step of the empirical analysis to identify, using an econometric approach, the determinants of the variation over time and across regions of energy intensity. For instance, Metcalf (2008) decomposed US state aggregate

[2] This problem in the measurement of energy efficiency is discussed by the EIA at: www.eia.gov/emeu/efficiency/measure_discussion.htm.

[3] There are also bottom up approaches used by energy professionals to estimate the level of energy efficiency. For example, EPRI (2009) applies a bottom-up methodology that is based on equipment stock turnover and the adoption of efficiency measures for energy at the technology and end-use levels within different US sectors and McKinsey (2009) who undertook a detailed analysis of the potential for improved efficiency in energy use by the US non-transport sector.

[4] See Boyd and Roop (2004) and Ang (2006) for a general discussion and application of this method and www1.eere.energy.gov/ba/pba/intensityindicators/ for an example related to the introduction by the US Department of Energy of an Energy Intensive Index using the decomposition approach that attempts to separate the difference factors that affect energy efficiency from non-efficiency factors.

energy intensity for the period 1970-2001 and attempted econometrically to identify the determinants of the changes in intensity, efficiency, and activity indexes.[5]

Another approach is based on the concept of productive efficiency introduced by Farrell (1957) and used for estimating production, cost, distance or input demand frontier functions. From the economics point of view it is important to produce energy services in an efficient way; that is, by minimising the amount of inputs used in the production of a given energy service, by choosing the combination of inputs that minimise the production cost and by adopting the least cost technology. A reduction in energy consumption for the production of energy services can come about by an improvement of the level of the efficiency in the use of inputs (productive efficiency), by an adoption of a new energy saving technology or by both processes. A theoretical explanation of this approach was originally introduced by Huntington (1994) and developed in Evans et al. (2013), with Zhou and Ang (2008) and Filippini and Hunt (2011) attempting empirical applications. These empirical applications use frontier analysis methods developed in applied production theory. They recognise that, in order to analyse the level of (energy) efficiency, it is important to base the analysis on a theoretical framework that regards energy as an input into a production function for producing an energy service (such as heating and lighting). It is therefore believed that this latter approach, which is advocated in this paper, is more suitable for performing an economic analysis of energy efficiency given its theoretical foundation in the microeconomics of production, whereas arguably other approaches are regarded as being rather *ad hoc*. It is therefore believed that from the microeconomic point of view, the term *energy efficiency* (hereafter EE) is imprecise with *energy intensity*

[5] Several papers have followed Metcalf (2008) in attempting to analyse the determinants of energy intensity, such as Jimenez and Mercado (2014).

(hereafter EI) a poor proxy; consequently, the term *underlying energy efficiency* (hereafter UEE) within the context of the production theory is introduced.

Frontier analysis can be undertaken by estimating *either* a parametric *or* a non-parametric best practice frontier for the use of energy, where the level of EE is computed as the difference between the actual energy use and the predicted energy use at the frontier. Zhou and Ang (2008) is an example of the non-parametric approach, where the EE performance of 21 OECD countries over 5 years (1997-2001) is measured using a Data Envelopment Analysis (DEA) model. Alternatively, Filippini and Hunt (2011) is an example of the parametric approach,[6] where they estimate a frontier whole economy aggregate energy demand function for 29 OECD countries over the period 1978 to 2006 using Stochastic Frontier Analysis (SFA).[7]

This paper therefore builds on Filippini and Hunt (2011 and 2012) by attempting to measure the efficiency of energy use for the whole economy of 49 states in the US.[8] An aggregate energy demand frontier function is estimated using a parametric approach in order to isolate a specific measure of EE by explicitly controlling for income and price effects, population, climate, household size, the structure of the economy and the

[6] Examples of the use of parametric frontier analysis at the disaggregate level are Buck and Young (2007) who measured the level of EE of a sample of Canadian commercial buildings and Boyd (2008) who estimated an energy use frontier function for a sample of wet corn milling plants.

[7] Both approaches – *parametric and non-parametric* – have advantages and disadvantages but neither one has emerged as dominant, at least in the scientific community. In terms of the parametric approach adopted here, an important advantage is the possibility, using panel data, to use econometric methods that allow for the consideration of unobserved heterogeneity variables and allow, at the same time, for errors in the variables and outliers.

[8] The reason for the use of only 49 states is explained below.

underlying energy demand trend (UEDT).[9] This is seen as important, given the need to isolate the *true* EE across the different states. This paper attempts therefore to unpick exactly what is meant by the term EE and re-couch it in terms of productive economic efficiency and inefficiency. The focus being on where consumers of energy and energy services are away from their economically optimal position on the isoquant (i.e. they are inefficient) and from this develop a measure of the UEE based on economic principles. Furthermore, using different frontier models for panel data enables the estimation of the persistent, as well the transient, UEE for the US states.

The paper is organised as follows. The next section presents and discusses the rationale and specification of the energy demand frontier function. Section 3 illustrates the data and econometric specification. 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

Energy is a derived demand, emanating from the demand for an energy service. A state's total aggregate energy demand is therefore a demand derived from the demand for several energy services used in an economy, all of which are produced by combining capital, energy and labour. Consequently, in this context, aggregate total energy demand can be

[9] The UEDT attempts to capture exogenous technical progress and other exogenous factors, such as changes in environmental pressures and regulations, changes in standards, and the general changes in tastes and behaviour (Hunt, et al. 2003a and 2003b). Moreover, it could be argued that even though technologies are available to each state they are not necessarily installed at the same rate; however, it is assumed that this results from different behaviour across states and reflects inefficiency across states; hence, it is captured by the different (in)efficiency terms for all states.

interpreted as a state's input demand function. Therefore, following Filippini and Hunt (2011) it is assumed that there exists an aggregate energy demand relationship for a panel of states of the US, as follows:[10]

$$E_{it} = E(P_{it,}, Y_{it}, POP_{it}, HDD_{it}, CDD_{it}, HS_{it}, SHI_{it}, SHS_{t}, A_{i}, UEDT_{t,} UEE_{it}) \quad (1)$$

where E_{it} is aggregate energy consumption, Y_{it} is GDP, P_{it} is the real price of energy, POP_{it} is population, HDD_{it} are the heating degree days, CDD_{it} are the cooling degree days, HS_{it} is the household size, SHI_{it} is the share of value added of the industrial sector, and SHS_{it} is the share of value added for the service sector;[11] all for state *i* in year *t*. A_i is the geographical area size of each state, $UEDT_t$ reflects a common UEDT across states capturing both exogenous technical progress and other exogenous factors. UEE_{it} is the unobserved level of UEE for state *i* in year *t*. Hence, a low level of UEE 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. Of course, an inefficient use of energy implies productive inefficiency, i.e. a non-optimal use of all inputs, not only of the energy input. Nevertheless, from an empirical perspective, the aggregate level of UEE is not observed directly, but instead this indicator has to be estimated. Consequently, in order to estimate a state's level of UEE and identify the best practice state in terms of

[10] It is recognised that some analysts and researchers would prefer a more disaggregated approach. Nonetheless, the analysis of aggregate energy used here is consistent with numerous previous academic studies that have attempted to analyse aggregate energy consumption as well reports and studies by energy agencies and policy makers such as the International Energy Agency (see, for example, IEA, 2009).

[11] Although these two share variables vary both over time and across states, the variation over time is small relative to the variation across states, thus primarily controlling for the different economic structures across the states but with a small allowance for the change in these relativities over time.

energy utilization, the stochastic frontier function approach introduced by Aigner et al. (1977) is used.

An aggregate input demand frontier function gives the minimum level of input used by an economy for any given level of output; hence, the difference between the observed input and the cost-minimizing input demand represents both technically as well as allocative inefficiency.[12] In the case of an aggregate total energy demand function, used here, the frontier gives the minimum level of energy consumption necessary for a state to produce any given level of energy services. This frontier approach allows the possibility to identify if a state is, or is not, on the frontier. Moreover, if a state 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 underlying energy inefficiency.[13]

The approach used in this study is therefore based on the assumption that the level of underlying energy inefficiency of the total sector can be approximated by a one-sided non-negative term, so 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:

$$\begin{aligned} e_{it} = {} & \alpha + \alpha^{p} p_{it} + \alpha^{y} y_{it} + \alpha^{pop} pop_{it} + \alpha^{hs} hs_{it} + \alpha^{hdd} hdd_{it} + \alpha^{cdd} cdd_{it} + \alpha^{SHI} SHI_{it} \\ & + \alpha^{SHS} SHS_{it} + \alpha^{a} a_{i} + \alpha^{t} t + v_{it} + u_{it} \end{aligned} \tag{2}$$

[12] Furthermore, it is worth noting that for input demand functions derived from a Cobb-Douglas production function that is homothetic, as discussed in Schmidt and Lovell (1979), a percentage increase of the level of the productive efficiency implies a reduction of the use of each input by the same percentage. For instance, given a production process that uses capital and energy, if the level of the productive efficiency increases by 10% then the level of efficiency in the use of energy and in the use of capital will also increase by 10%. In this framework, the estimated UEE directly measures the energy saving due to an improvement of the level of the productive efficiency.

[13] As discussed in the context of an input demand function derived from a Cobb-Douglas production function as in the case here, the increase of the level of productive efficiency corresponds to the increase in the efficient the use of energy.

where e_{it} is the natural logarithm of aggregate energy consumption (E_{it}), p_{it} is the natural logarithm of the real price of energy (P_{it}), y_{it} is the natural logarithm of GDP (Y_{it}), pop_{it} is the natural logarithm of population (POP_{it}), hdd_{it} is the natural logarithm of the heating degree days (HDD_{it}), cdd_{it} is the natural logarithm of the cooling degree days (CDD_{it}), hs_{it} is the natural logarithm of the household size (HS_{it}), a_i is the natural logarithm of the area size (A_i), and t is a time trend that proxies the UEDT.[14] SHI_{it}, and SHS_{it} are as defined above. 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 reflects the level of UEE_{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.[15] A more efficient use of energy will increase a state's UEE. The impact of technological and organizational innovation in the production and consumption of energy services on energy demand is therefore captured in a number of ways, including though the price term and the time trend. For instance, a rise in energy prices with a negative price elasticity and a negative coefficient of the time trend both suggest that energy saving technologies would be adopted over time, thus allowing

[14] Kumbhakar and Lovell (2000) note that the inclusion of a time trend as a regressor in a frontier model as a proxy for technical progress can frequently cause problems in estimation. One possible reason being the difficulty in disentangling the separate effects of technical change and productive efficiency change when both vary over time. An alternative approach is to include yearly time dummies or, if the number of years is high, time dummy variables that consist of two years rather than one. Although ideally time dummies are preferred in order to capture any possible non-linearity of the UEDT, here in order to reduce the number of parameters to be estimated a time trend was chosen. However, as a robustness check, the models were also estimated with some time dummies and there were no discernible differences in the estimated parameters.

[15] It could be argued that this is a strong assumption for *UEE*, but it does allow the identification of the efficiency for each state separately. This is a standard assumption used in the production frontier literature; see Kumbhakar and Lovell (2000, p. 148) for a discussion.

states to decrease, *ceteris paribus*, their energy consumption. The model specification therefore allows on one side for states to modify their energy demand by adopting new energy saving technologies and on the other side by improving the level of efficiency in the use of energy (and the other inputs).

In summary, Equation (2) is estimated in order to estimate UEE for each state 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 a balanced US panel data set for a sample of 49 states ($i = 1, \ldots, 49$) over the period 1995 to 2009. For the purposes of this paper attention is restricted to the contiguous states (i.e. Alaska and Hawaii are excluded), whereas the District of Columbia is included and considered as a separate 'state'. The data set is based on information from the US Energy Information Administration (EIA) database called States Energy Data System, from the US Department of Commerce, the US Census Bureau and the National Climatic Data Center at NOAA.

E_{it} is each state's aggregate total energy consumption for each year in trillion BTUs, Y_{it} is each state's real GDP for each year in thousand US 2010$, P_{it} is each state's real energy price for each year in per million BTUs 2010$. Total energy consumption figures and prices are from the EIA. Population (POP_{it}) and GDP are from the Bureau of Economic Analysis of the US Census Bureau. The heating and cooling degree days (HDD_{it} and

CDD_{it}) are obtained from the National Climatic Data Center at NOAA. [16] The data on area size (A_i) and household size, the number of people per household (HS_{it}) is collected from the U.S. Census Bureau. Descriptive statistics of the key variables are presented in Table 1.

There are a number of different SFA model specifications using panel data that could be considered suitable for the task at hand.[17] These include the basic models for panel data: the pooled model (PM); the random effects model (REM); the true fixed effects model (TFEM); and the true random effects model (TREM). Furthermore, as shown by Farsi et al. (2005) and by Filippini and Hunt (2012) it is possible to estimate some of these models using an adjustment introduced by Mundlak (1978) in order to account for the econometric problem of unobserved heterogeneity bias; such as, the Mundlak adjusted pooled model (MPM) and the Mundlak adjusted random effects model (MREM). This adjustment attempts to separate the unobserved variables from inefficiency. Moreover, within this suite of models, some (such as the REM and the MREM) attempt to provide information on the persistent (time-invariant) part of inefficiency, whereas others (such as the TFEM and the TREM) attempt to provide information on the transient (time-varying) part of inefficiency.[18]

[16] See http://www.ncdc.noaa.gov/.

[17] For a general presentation of these models, see Greene (2008) and Farsi and Filippini (2009).

[18] It is worth noting that some recently proposed complex econometric approaches attempt to control for unobserved heterogeneity bias in order to obtain, from the same model, information on persistent and transient inefficiency (see, for example, Tsionas and Kumbhakar, 2014 and Colombi et al., 2014). There is also an approach proposed by Filippini and Greene (2014), which is relatively straightforward, but at the time of writing, it is still in an implementation and testing phase.

Table 1: Descriptive statistics

Variable Description	Name	Mean 1995-1999	Mean 2000-2004	Mean 2005-2009	Minimum 1995-1999	Minimum 2000-2004	Minimum 2005-2009	Maximum 1995-1999	Maximum 2000-2004	Maximum 2005-2009
Energy consumption *(Trillion Btu)*	***E***	1,407.59	1,448.07	1,451.07	97.82	100.57	91.53	9,681.71	9,682.49	9,304.70
GDP *(Million 2010US$)*	***Y***	227,075	257,897	285,964	19,878	21,946	24,469	1,545,226	1,753,963	1,924,790
Real price of energy *(per million Btus 2010$)*	***P***	11.95	13.57	18.90	7.22	8.38	11.98	18.21	19.47	29.20
Household size *(number of people per house)*	***HS***	2.40	2.33	2.29	1.98	1.93	1.89	2.99	2.90	2.88
Population *(1000)*	***POP***	5,527	5,831	6,107	485	493	506	33,499	35,630	36,961
Heating degree days *(base: 65F)*	***HDD***	5,141	5,124	5,144	558	624	555	10,754	9,302	9,990
Cooling degree days *(base: 65F)*	***CDD***	1,102	1,113	1,141	156	128	173	3,870	3,668	3,650
Share of industrial sector (%)	***SHI***	17.77	14.83	14.49	0.41	0.35	0.22	34.96	31.16	40.99
Share of service sector (%)	***SHS***	80.28	83.62	83.90	62.86	66.87	57.79	99.59	99.65	99.78
Area *(square miles)*	***A***	63,717			61			268,820		

All these models have their relative advantages and disadvantages and the choice of model is not straightforward, it depends upon the goal of the exercise and the type of data and variables that are available. The PM is the SFA model in its original form proposed by Aigner, et al. (1977) and adapted for panel data by Pitt and Lee (1981). This model does not exploit the possibility given by panel data to control for unobserved heterogeneity variables that are constant over time. Therefore, the unobserved heterogeneity bias can be a serious problem in this model. On the contrary, the REM introduced by Pitt and Lee (1981) interprets the typical panel data individual random effects as inefficiency rather than unobserved heterogeneity as in the traditional literature on panel data econometric methods.[19] The level of efficiency estimated with the REM does not vary over time. Therefore, this model arguably provides information on the persistent part of efficiency in the use of energy. One problem with the REM is that any unobserved, time-invariant, group-specific heterogeneity is considered as inefficiency and the level of efficiency does not vary over time. However, as shown in Farsi et al. (2005), the application of Mundlak's adjustment to the REM frontier framework decreases the bias in inefficiency estimates by separating inefficiency from unobserved heterogeneity. This separation of inefficiency from unobserved heterogeneity is based on the assumption that the effects of unobserved time invariant state characteristics are captured by the coefficients of the group mean of the explanatory variables of the Mundlak adjustment equation.

Greene (2005a and 2005b) proposed the TFEM and the TREM whereby the PM is extended by adding fixed and random individual effects respectively. The TFEM and the TREM are able to distinguish time invariant unobserved heterogeneity from the time varying level of efficiency component (the transient part). However, in these models any time-invariant or persistent component of inefficiency is completely absorbed in the state-specific constant terms. Therefore, in contexts characterized by persistent inefficient use of energy determined for instance by the presence in a country of old houses or of an urban planning system that does not minimize the travel time, this provides relatively high levels of estimated transient part of the UEE.

Given this discussion, the MREM is seen as the appropriate approach to estimate the persistent part of the level of UEE, and the TREM the appropriate approach to estimate the transient part of the level of UEE. Consequently, in order to obtain estimates of both the

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

persistent and transient parts of the inefficiency for the 49 states in the US these two separate models the MREM and the TREM are estimated here and the two estimated values of inefficiency are interpreted accordingly.[20] Of course, because the two models are measuring a different component of the level of energy efficiency, it is not expected to obtain similar rankings from these models. Table 2 summarizes the two models.

Table 2: Econometric specifications of the stochastic cost frontier

	MREM	**TREM**
State effects α_i	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$	$iid\ (0, \sigma_\alpha^2)$
Random error ε_{it}	$\varepsilon_{it} = \delta_i + v_{it}$ $\delta_i \sim N^+(0, \sigma_\delta^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$
Inefficiency	$E(\delta_i \text{ I } v_{it})$	$E(u_{it} \text{ I } v_{it})$

After Equation (2) is estimated, it is possible to estimate a state's efficiency using the conditional mean of the efficiency term $E[u_{it}|u_{it}+v_{it}]$, proposed by Jondrow et al. (1982) and the level of UEE can be expressed by:

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

where E_{it} is the observed energy consumption and E_{it}^F is the frontier or minimum demand of the i^{th} state in time t. An UEE score of one indicates a state on the frontier (100% efficient), while non-frontier states, e.g. states characterized by a level of UEE lower than

[20] The TFEM is also an appropriate approach to measure the level of transient inefficiency, thus as a robustness check this model was also estimated and the results are highly correlated with the results obtained with the TREM. Therefore, to avoid confusion by presenting several similar models, it was decided to restrict the analysis to the TREM.

100%, receive scores below one. This therefore gives the measures of UEE estimated below.[21] In summary, Equation (2) is estimated using the MREM and TREM and for each of these, Equation (3) is used to estimate the respective persistent and transient UEE for each state for each year. Moreover, as previously discussed, it is expected that, compared to the estimated persistent UEE, the level of the transient UEE would be relatively high but with a lower variation. The results from the estimation are given in the next section.

4. Estimation results

The estimation results of the frontier energy demand models using the two models discussed above are given in Table 3. Most of the estimated coefficients[22] and *lambda*[23] have the expected signs and are statistically significant at the 10% level and generally, the results obtained in the two models are relatively similar.

The results suggest that US total energy demand is price-inelastic, with the estimated elasticities being statistically significant from zero but relatively low at about -0.1. The results also suggest that US total energy demand is income-inelastic, with an estimated elasticity of about 0.5. For the weather variables, the estimated heating degree day elasticity has the expected sign and is significant, whereas the coefficient of the CDD variable is not significantly different from zero; similarly the AREA coefficient is not

[21] 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%.

[22] Note, most of the estimated coefficients can be regarded as estimated elasticities given the variables are in logarithmic form (the coefficients on the industrial and service share being the exceptions).

[23] 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.

significant in the MREM. The estimated household size elasticities are significant however and, as expected, are negative (both being close to -1) suggesting that an increase of 10% in the household size decreases energy consumption by approximately 10%. This decrease is probably due to economies of scale in the production of some residential energy services; for instance, the size of a fridge is unlikely to vary proportionally with the number of household members.

The estimated coefficient of the share of the industrial sector and of the service sector suggest a negative impact of these two variables on US total energy demand (noting that the reference sector is agricultural and mining). The coefficient of the time trend variable is negative and significant in both models suggesting energy saving technical progress dominates other exogenous factors with an inward shift of the energy demand function over time. Finally, in the MREM half of the included Mundlak terms are significant, (note, that in order to avoid multicollinearity between these mean variables and the original variables, a subset only of the variables are introduced for the Mundlak adjustment).[24]

Table 4 provides descriptive statistics for the overall US UEE estimates for the 49 states obtained from the econometric estimation. As discussed previously, the MREM provides information on the persistent level of inefficiency, whereas the TREM provides information on the transient part of efficiency. Nevertheless, it should be noted that although the persistent UEE estimated by the MREM is time invariant, it does not mean that the model constrains states from using less energy by adopting new technologies over time given the inclusion of the UEDT in the form of a time trend with an estimated negative coefficient.

[24] For the selection of the variables to consider in the Mundlak adjustment equation, a regular fixed and random effects model was estimated and the model specification used in the estimation of the MREM is supported by the results of a Hausman test.

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

	MREM	TREM
Constant	24.3170*** (13.19)	14.4881*** (74.89)
α^{y}	0.4808*** (10.54)	0.4860*** (46.35)
α^{p}	-0.0695*** (-2.70)	-0.0693*** (-4.78)
α^{pop}	0.3701*** (9.45)	0.5168*** (46.58)
α^{hdd}	0.1155** (2.56)	0.0536*** (7.90)
α^{cdd}	0.0096 (0.47)	-0.0019 (-0.43)
α^{hs}	-1.0116*** (-11.10)	-1.0169*** (-33.08)
α^{SHI}	-0.5501** (-2.40)	-0.5599*** (-4.60)
α^{SHS}	-0.5900** (-2.47)	-0.5850*** (-4.75)
α^{a}	-0.0300 (-1.07)	0.0825*** (37.91)
α^{t}	-0.0112*** (-6.58)	-0.0129*** (-17.36)
$Av\text{-}\alpha^{y}$	-0.2722 (-1.55)	
$Av\text{-}\alpha^{p}$	-1.7467*** (-6.40)	
$Av\text{-}\alpha^{pop}$	0.4057** (2.21)	
$Av\text{-}\alpha^{hdd}$	-0.1525*** (-2.60)	
$Av\text{-}\alpha^{hs}$	0.4278 (0.76)	
$Av\text{-}\alpha^{SHS}$	-0.6784 (-1.21)	
State effects	no	yes
Lamda (λ)	4.5506** (2.53)	1.5460*** (9.69)

*** Significant at 0.01 level. **Significant at 0.05 level.
*Significant at 0.10 level.

Table 4: Summary of UEE estimates across all states, 1995-2009

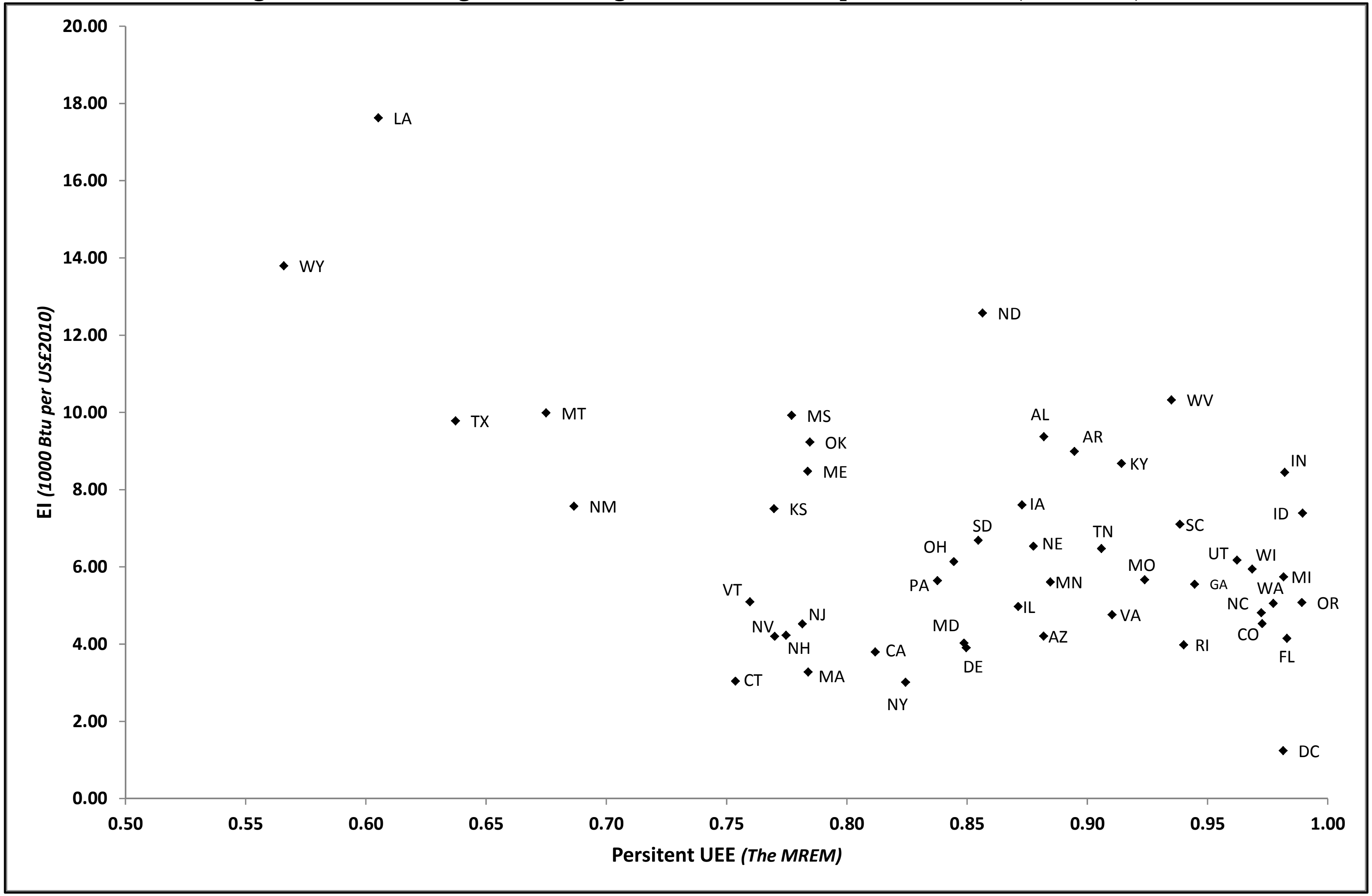
	MREM: Persistent UEE	**TREM: Transient UEE**
Minimum	0.57	0.81
Maximum	0.99	0.99
Mean	0.86	0.96
Median	0.87	0.97
Standard deviation	0.10	0.02
Coefficient of variation	12%	2%

Table 4 shows that, as expected, the estimated persistent part of UEE is greater than the transient part, but the variation in the estimated transient UEE is somewhat lower than the variation in the estimated persistent UEE. This is also highlighted by Table 5, which gives the average estimated UEE from the two models as well as the average energy intensity over the estimation period (along with the state rankings). Hence, for the remainder of this paper the focus is more on the estimated persistent UEE from the MREM.

As discussed in Filippini and Hunt (2011 and 2012) it is expected that estimated UEE would be negatively correlated with EI; thus for most states it is expected that the level of EI decreases with an increase of the estimated level of UEE. However, as Filippini and Hunt (2011) argue, if this technique were to be a useful tool for teasing out the *true* EE then a perfect, or even near perfect, negative correlation would not be expected since all the useful information would be contained in standard EI measures. This proves to be the case with the estimates here, as illustrated in Figure 1 and Table 5; moreover, the correlation coefficients between EI and the estimated average UEE measure from the MREM and the TREM are -0.46 and -0.21 respectively. In addition, there is not a strong correlation between the rankings, with the Spearman rank correlation coefficients between EI and the average UEE measure from the MREM and the TREM being 0.18 and 0.21 respectively.

This is further highlighted in Figure 2 that ranks the states in terms of the estimated persistent UEE and EI and classifies the states into three groups: relatively efficient states; relatively inefficient states; and relatively moderately efficient states. This shows that EI would appear to be a good predictor of a state's relative UEE for some states but a very poor indicator for others. For example, Kansas, Louisiana, Maine, Mississippi, Montana, New Mexico, North Dakota, Ohio, Oklahoma, South Dakota, Texas, and Wyoming are classified as being relatively inefficient states according to the estimated UEE and are states with relatively high levels of EI. At the other end of the spectrum, the District of Columbia and Florida are classified as being relatively efficient states according to the estimated UEE and are states with relatively low levels of EI. However, California, Connecticut, Delaware, Massachusetts, Maryland, New Hampshire, New York and Nevada are classified as being relatively inefficient states according to the estimated UEE but are states with relatively low high levels of EI. And Idaho, Indiana, Michigan, Utah and Wisconsin are classified as being relatively efficient states according to the estimated UEE but are states with relatively low levels of EI.

Figure 1: Scatter diagram of average EI and estimated persistent UEE (1995-2009)

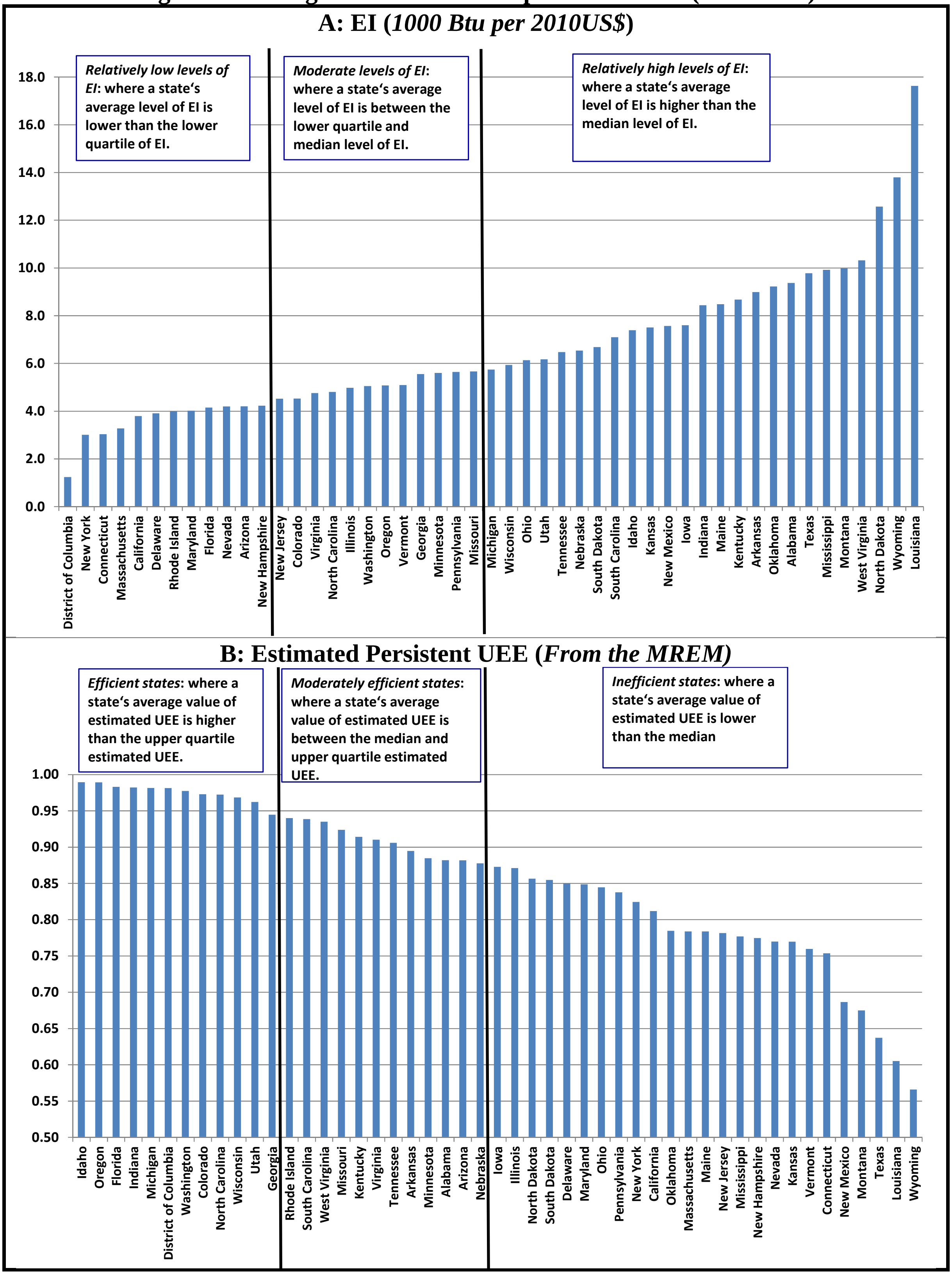


Note: State codes are given in Table 5.

Table 5: Average EI and UEE Estimates with rankings (1995-2009)

States	State Code	EI (1000 Btu per 2010US$)		Persistent UEE (The MREM)		Transient UEE (The TREM)	
		Ratio	Rank	Score	Rank	Score	Rank
Alabama	AL	9.3703	42	0.8820	22	0.9606	29
Arizona	AZ	4.2060	11	0.8819	23	0.9643	6
Arkansas	AR	8.9912	40	0.8947	20	0.9601	30
California	CA	3.7948	5	0.8119	34	0.9630	20
Colorado	CO	4.5277	14	0.9728	8	0.9552	41
Connecticut	CT	3.0392	3	0.7537	44	0.9571	36
Delaware	DE	3.9069	6	0.8497	29	0.9545	44
District of Columbia	DC	1.2381	1	0.9815	6	0.9556	40
Florida	FL	4.1475	9	0.9831	3	0.9660	1
Georgia	GA	5.5524	21	0.9447	12	0.9632	17
Idaho	ID	7.3925	33	0.9896	1	0.9589	32
Illinois	IL	4.9752	17	0.8713	26	0.9639	11
Indiana	IN	8.4436	37	0.9822	4	0.9634	15
Iowa	IA	7.6024	36	0.8729	25	0.9486	48
Kansas	KS	7.5059	34	0.7698	42	0.9621	26
Kentucky	KY	8.6784	39	0.9143	17	0.9631	18
Louisiana	LA	17.6273	49	0.6052	48	0.9501	47
Maine	ME	8.4777	38	0.7838	37	0.9559	39
Maryland	MD	4.0256	8	0.8488	30	0.9643	6
Massachusetts	MA	3.2785	4	0.7839	36	0.9652	2
Michigan	MI	5.7431	25	0.9817	5	0.9646	3
Minnesota	MN	5.6063	22	0.8847	21	0.9641	9
Mississippi	MS	9.9221	44	0.7771	39	0.9634	15
Missouri	MO	5.6639	24	0.9239	16	0.9616	27
Montana	MT	9.9843	45	0.6750	46	0.9563	37
Nebraska	NE	6.5370	30	0.8776	24	0.9560	38
Nevada	NV	4.1976	10	0.7700	41	0.9646	3
New Hampshire	NH	4.2293	12	0.7748	40	0.9584	33
New Jersey	NJ	4.5209	13	0.7815	38	0.9628	23
New Mexico	NM	7.5718	35	0.6866	45	0.9643	6
New York	NY	3.0104	2	0.8245	33	0.9631	18
North Carolina	NC	4.8089	16	0.9724	9	0.9599	31
North Dakota	ND	12.5702	47	0.8565	27	0.9547	43
Ohio	OH	6.1371	27	0.8445	31	0.9644	5
Oklahoma	OK	9.2295	41	0.7847	35	0.9639	11
Oregon	OR	5.0781	19	0.9893	2	0.9613	28
Pennsylvania	PA	5.6407	23	0.8377	32	0.9638	14
Rhode Island	RI	3.9827	7	0.9401	13	0.9506	46
South Carolina	SC	7.1011	32	0.9386	14	0.9630	20
South Dakota	SD	6.6852	31	0.8547	28	0.9386	49
Tennessee	TN	6.4742	29	0.9059	19	0.9639	11
Texas	TX	9.7816	43	0.6373	47	0.9549	42
Utah	UT	6.1701	28	0.9623	11	0.9583	34
Vermont	VT	5.0922	20	0.7597	43	0.9625	24
Virginia	VA	4.7593	15	0.9104	18	0.9629	22
Washington	WA	5.0563	18	0.9774	7	0.9522	45
West Virginia	WV	10.3221	46	0.9350	15	0.9583	34
Wisconsin	WI	5.9417	26	0.9686	10	0.9641	9
Wyoming	WY	13.7955	48	0.5659	49	0.9625	24

Figure 2: Average EI and estimated persistent UEE (1995-2009)



Within these results, it is worth highlighting California, which is found to be relatively inefficient being ranked 34th according to the estimated persistent UEE estimates. This would appear to be at odds with the conventional wisdom of energy efficiency policymakers and professionals who generally regard California as being a highly energy efficient state as well as a number of research papers such as Howrowitz (2007) and Sudarsham (2013). However, the view is normally based on EI or electricity intensity so a direct comparison with the analysis here is difficult if not impossible given the whole premise of the UEE measure estimated here is that analysis based on EI is potentially biased and misleading for policymakers. Thus, the research presented here does not implicitly disagree with some of the previous research such as Howrowitz (2007, p. 93) who argues that "California's energy efficiency programs … have dramatically reduced state electricity intensity" just that there is still more to be done in order for California to increase its UEE and move closer to the energy demand efficient frontier.[25] Moreover, the work here supports the conclusion by Sudarshan (2013, p. 207) who contends that "while indices such as energy intensities … can provide a great deal of insight, they also hide as much as they reveal".

[25] The results presented here would also appear, at first site, to be in disagreement with the rankings provided by ACEEE (2103). However, the ACEEE rankings refer to the degree or intensity of policy makers to *promote* EE not the *actual* EE. Therefore, although California is ranked highly by ACEEE but is classified as being relatively inefficient according to the estimates here it suggests that despite the promotion of such policies California still has some way to go in order to increase its relative UEE.

5. Summary and Conclusion

Building on Filippini and Hunt (2011 and 2012) this research attempts to define and estimate the UEE for 49 US states by combining energy demand modelling and frontier analysis. The energy demand specification controls for income, price, population, household size heating degree days, cooling degree days, the area, the share of the industrial sector, the share of the service sector and a UEDT and is estimated using the MREM and the TREM. These two models are seen as the most appropriate techniques for attempting to uncover the *true* EE of the 49 states; they are seen as superior to the range of other techniques available; moreover, they avoid the problem of unobserved heterogeneity. Therefore, the MREM and the TREM arguably provide robust estimates of each states' persistent and transient UEE respectively.

The estimates show that for some states the simple measure of EI might give a reasonable indication of a state's relative UEE but this is not so for others states, California being a good example. Therefore, unless the analysis advocated here is undertaken, US policy makers are likely to have a misleading picture of the *true* relative EE across the states and thus might make misguided decisions when allocating funds to various states in order to implement EE and conservation measures. Hence, it is argued that this analysis should be undertaken in order to give US policy makers an additional indicator other than the rather naïve measure of EI in order to try to avoid potentially misleading policy conclusions.

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