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US Residential Energy Demand and Energy Efficiency: A Stochastic Demand Frontier Approach

Massimo Filippini and Lester C Hunt

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Enquiries:

***Director of SEEC and Editor of SEEDS*:**
Lester C Hunt
SEEC,
Department of Economics,
University of Surrey,
Guildford GU2 7XH,
UK.

Tel: +44 (0)1483 686956
Fax: +44 (0)1483 689548
Email: L.Hunt@surrey.ac.uk

www.seec.surrey.ac.uk

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ABSTRACT

This paper estimates a US 'frontier' residential aggregate energy demand function using panel data for 48 'states' over the period 1995 to 2006 using stochastic frontier analysis (SFA). Utilizing an econometric energy demand model, the (in) efficiency of each state is modelled and it is argued that this represents a measure of the inefficient use of residential energy in each state (i.e. 'waste energy'). This underlying efficiency for the US is therefore observed for each state as well as the relative efficiency across the states. Moreover, the analysis suggests 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 a novel approach to model residential energy demand and efficiency and it is arguably particularly relevant given current US energy policy discussions related to energy efficiency.

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

Key Words: US residential energy demand; efficiency and frontier analysis; state energy efficiency.

US Residential Energy Demand and Energy Efficiency: A Stochastic Demand Frontier Approach*

Massimo **Filippini** and Lester C **Hunt**

Centre for Energy Policy and Economics (cepe), ETH Zurich
and
Department of Economics, University of Lugano, Switzerland

Massimo.Filippini@usi.ch

Surrey Energy Economics Centre (SEEC) and Research Group on Lifestyles Values and Environment (RESOLVE), Department of Economics, University of Surrey, UK

L.Hunt@surrey.ac.uk

1 Introduction

The promotion of energy efficiency policy is seen as a very important activity by both the International Energy Agency (IEA) and the Energy Information Agency (EIA) (e.g. see IEA, 2009). Moreover, the role of energy efficiency in reducing energy consumption and emissions remains a key policy objective for governments across the globe; and the US is no exception. Since the beginning of the Obama administration, there have been many policy announcements involving energy efficiency in one way or another; you just have to look at the US Department of Energy press web site to see the many different announcements.[1] Nevertheless, it is worth noting that a number of the announcements during the Obama period build upon initiatives from the Bush administration, such as The Energy Efficiency and

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[1] www.energy.gov/news/releases.htm.

Conservation Block Grant (EECCBG); initially put in place in 2007 to help implement energy efficiency and conservation measures.[2] Given its importance, and the many millions of US dollars allocated across the different states it is vital that US policy makers understand, and are able to clearly measure, the relative energy efficiency across the different states. However, generally this is not the case, which is not a new problem; the EIA (1995) report states:

> "Energy efficiency is a vital component of the Nation's energy strategy. One of the Department of Energy's missions are to promote energy efficiency to help the Nation manage its energy resources. *The ability to define and measure energy efficiency is essential to this objective*. In the absence of consistent defensible measures, energy efficiency is a vague, subjective concept that engenders directionless speculation and confusion rather than insightful analysis. ... The task of defining and measuring energy efficiency and creating statistical measures as descriptors is a daunting one." (p. vii, *our emphasis*).

This clearly supports the view above, but the EIA (1995) report goes on to discuss the use of energy intensity as a "measurement indicator of energy efficiency" (p. vii) highlighting that energy intensity and energy efficiency are often used interchangeably; furthermore, energy intensity might not reflect certain factors that would allow energy intensity to approximate energy efficiency accurately. In particular, trends in different measures of energy intensity are generally suggestive of trends in energy efficiency but the trends in energy intensity are likely to be influenced by factors other than just energy efficiency. Moreover, the EIA (1995) report states that

> "it is virtually impossible to remove, or even to consider, all of the behavioral or structural factors that would be necessary to obtain a pure measurement of energy efficiency, however broadly energy efficiency may be defined." (p. vii).

This clearly highlights the problems in trying to measure energy efficiency in general and the use of energy intensity in particular as a proxy for it. Furthermore, given the problems with

[2] www1.eere.energy.gov/wip/eecbg.html.

energy intensity, it shows that there is a need to 'control' for other important factors in order to get 'pure' measure of energy efficiency. This therefore is one of the key aims of this paper with respect to the US residential sector.

The EIA (1995) report goes on to consider the measurement of energy intensity in a number of sectors of the US economy attempting, where possible, to remove the influence of such factors as weather, capacity, and inventory changes that are commonly viewed as not related to changes in energy efficiency. For the residential sector, the EIA (1995) report suggests four energy intensity measures applicable as proxies for energy efficiency: i) million BTUs per building; ii) million BTUs per household; iii) thousand BTUs per square foot; and iv) million BTUs per household member.[3] However, the report suggests that these are imperfect and that "No single energy-intensity indicator for the residential sector stands out as clearly superior to the others. The choice of indicator depends on the questions asked and on data and resource availability" (p. 16).

Some approaches have been proposed in the energy economics literature in order to overcome the problems of some of these simple efficiency indicators; such as Index Decomposition Analysis (IDA) and Frontier Analysis. IDA is basically a bottom-up framework used to create energy efficiency indicators.[4] For instance, the US Department of Energy has introduced an Energy Intensive Index using the decomposition approach that attempts to separate the difference factors that affect energy efficiency from non-efficiency

[3] BTU = British Thermal Unit; the quantity of heat required to raise the temperature of 1 pound of liquid water by 1 degree Fahrenheit at the temperature at which water has its greatest density.

[4] See Boyd and Roop (2004) and Ang (2006) for a general discussion and application of this method.

factors.[5] Whereas frontier analysis is based on the estimation of a parametric, as well as a non-parametric, best practice frontier for the use of energy where the level of energy efficiency is computed as the difference between the actual energy use and the predicted energy use.[6]

As stated above, the aim of this paper is to attempt to construct and measure the 'underlying energy efficiency' for the US residential sector across 48 'states';[7] building on previous work by Filippini and Hunt (2011). This draws upon different strands of the energy economics research literature; in particular, frontier estimation and energy demand modelling. An aggregate energy demand frontier function is estimated in order to isolate the measure of 'underlying energy efficiency'; explicitly controlling for income and price effects, population, household size, weather, types of housing, regional effects, and a common Underling Energy Demand Trend (the UEDT, capturing both 'exogenous' technical progress and other exogenous factors[8]). Furthermore, the UEDT needs to be specified in such a way that it is

[5] See www1.eere.energy.gov/ba/pba/intensityindicators/. It is argued that the new index gives a more accurate representation of intensity change associated with energy efficiency improvement than the simple energy/activity ratios.

[6] Huntington (1994) discusses the relation between energy efficiency and productive efficiency using the production theory framework. Zhoe and Ang (2008) is an example of a non-parametric approach, where the energy efficiency performance of 21 OECD countries over 5 years (1997-2001) is measured using a DEA model. Examples of the use of parametric frontier analysis at the sectoral level are Buck and Young (2007) who measured the level of energy efficiency 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. In addition, Filippini and Hunt (2011) estimate a panel 'frontier' whole economy aggregate energy demand function for 29 OECD countries over the period 1978 to 2006 using parametric stochastic frontier analysis (SFA).

[7] The reason for the use of only 48 states is explained below.

[8] Hence, this method allows for the impact of 'endogenous' technical progress' through the price effect and 'exogenous' technical progress through the UEDT.

'non-linear' and therefore could increase and/or decrease over the estimation period,[9] and given a panel data set is used, this is achieved by the inclusion of time dummies.[10]

In summary, in order to try to uncover these different influences, a general energy demand relationship for US residential energy demand relating energy consumption to economic activity and the real energy price is estimated for a panel of 48 states; but controlling for other important factors that vary across states and hence can affect a states' residential energy demand. This attempts to isolate the 'underlying energy efficiency' for each state. 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 states, 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 underlying energy efficiency across the different states.[11] Consequently, once these effects are controlled for, it allows for the estimation of the underlying energy efficiency for each country showing the differences in efficiency across the panel of states.

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

[9] As advocated by Hunt et al. (2003a and 2003b)

[10] As proposed by Griffin and Schulman (2005) and Adeyemi and Hunt (2007).

[11] The UEDT includes exogenous technical progress of the appliance and building stock and 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.

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

Residential demand for energy is a demand derived from the demand for a warm house, cooked food, hot water, etc., and can be specified using the basic framework of household production theory. According to this theory, households purchase market ‘goods’ that serve as inputs in the production processes, to produce the ‘commodities’ which appear as arguments in the household's utility function. Within the framework of the household production theory, the aggregate residential energy demand is an input demand function.[12]

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

$$E_{it} = E(P_{it}, Y_{it}, POP_{it}, HS_{it}, HDD_{it}, CDD_{it}, SH_{it}, D_t, EF_{it}) \qquad (1)$$

where E_{it} is aggregate residential energy consumption, Y_{it} is real income, P_{it} is the real energy price, POP_{it} is population, HS_{it} is the average house size, HDD_{it} are the heating degree days, CDD_{it} are the cooling degree days, SH_{it} is the share of detached houses for state i in year t. D_t is a series of time dummy variables. Finally, EF_{it} is the level of ‘underlying energy efficiency’ of the US residential sector. This could incorporate a number of factors that will differ across states, including the different technical appliance and capital equipment, different regulations

[12] For a presentation of the household production theory, see Deaton and Muellbauer (1980). See Filippini (1999) and Banfi et al. (2007) for an application of household production theory to energy demand analysis.

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 of energy conservation could be increased in order to reach the 'optimal' energy demand function. Nevertheless, from an empirical perspective, when using US aggregate energy data, the aggregate level of energy efficiency of residential appliances is not observed directly. Therefore, this underlying energy efficiency indicator has to be estimated. Consequently, in order to estimate the residential level of underlying energy efficiency (EF_{it}) and identify the best practice system in term of energy utilization, the stochastic frontier function approach introduced by Aigner et al. (1977) is used.

The stochastic frontier function has generally been used in production theory to measure econometrically 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 an input demand function the frontier gives the minimum level of input used by a firm or a household for any given level of output; hence, the difference between the observed input and the cost-minimizing input demand represents both technically as well allocative inefficiency.[13] In the case of an aggregate residential energy demand function, used here, the frontier gives the minimum level of energy consumption necessary for the residential sector 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 input demand, which is the frontier that reflects the demand of the residential sector of a state that use high efficient equipment and production process. This frontier

[13] See Kumbhakar and Lovell (2000, p. 148) for a discussion on the interpretation of the efficiency in an input demand function.

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 energy inefficiency.

The approach used in this study is therefore based on the assumption that the level of the energy efficiency of the residential 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:

$$e_{it} = \alpha + \alpha^{p} p_{it} + \alpha^{y} y_{it} + \alpha^{pop} pop_{it} + \alpha^{hs} hs_{it} + \alpha^{hdd} hdd_{it} + \alpha^{cdd} cdd_{it} + \alpha^{SH} SH_{it} + \alpha^{t} Dt + v_{it} + u_{it} \quad (2)$$

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 real income (Y_{it}), pop_{it} is the natural logarithm of population (POP_{it}), hs_{it} is the natural logarithm of the number of housing units (HS_{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}) and SH_{it}, and D_t 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 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.[14] An improvement in the energy efficiency of the equipment or on the use of energy through a new production process will

[14] It could be argued that this is a strong assumption for *EF*, 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.

increase the level of energy efficiency of a country. The impact of technological, organizational, 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.

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 a balanced US panel data set for a sample of 48 states ($i = 1, \ldots, 48$) over the period 1995 to 2006 ($t = 1995\text{-}2006$). For the purposes of this paper attention is restricted to the contiguous states (i.e. Alaska and Hawaii are excluded) as is Rhode Island because of incomplete information whereas the District of Columbia is included and considered as a separate 'state'. The data set is based on information taken from the U.S. Energy Information Administration 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 residential energy consumption for each year in trillion BTUs, Y_{it} is each state's real disposable personal income for each year in thousand US 1982\$, P_{it} is each state's real energy price for each year in per million BTUs 1982\$. Residential energy consumption figures and prices are provided by the Energy Information Administration. 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. The typical size of a household (HS_{it}) is obtained by dividing population by the number of housing units, where the latter come from the US Census Bureau. Descriptive statistics of the key variables are presented in Table 1.

Table 1: Descriptive statistics

Variable		Mean	Std. Dev.	Minimum	Maximum
Description	Name				
Energy consumption *(Trillion Btu)*	***E***	227.630	209.64	19.80	915.6
Real disposable personal income *(Mio 1982US$)*	***Y***	588751.3	101167	6072.44	646019
Real Price of energy *(per million Btu)*	***P***	15.29	4.20	7.35	32.50
Population *(1000)*	***POP***	5863	6275	485	36377
Household size *(no. of people per housing unit)*	***HS***	2.35	0.16	1.89	2.99
Heating degree days *(base: 65F)*	***HDD***	5087	1998	555	10745
Cooling degree days *(base: 65F)*	***CDD***	1142	796	128	3870
Share of detached houses	***SH***	62.30	9.74	13.20	74

It is important to discuss the literature on the estimation of stochastic frontier models using panel data, given the econometric specification of the model. This literature identifies at least three models that could be used in this empirical analysis: i) the pooled model (PM hereafter), the stochastic frontier model (SFM) in its original form proposed by Aigner, et al., (1977); ii) the random effects model (REM hereafter) proposed by Pitt and Lee (1981) who interpreted the panel data random effects as inefficiency rather than heterogeneity; and iii) the true random effects model (TREM hereafter) proposed more recently by Greene (2005a and 2005b).[15] A shortcoming of the REM is that any unobserved, time-invariant, group-specific heterogeneity is considered as inefficiency. Moreover, the level of efficiency is not varying over time. In order to solve this problem using panel data, Greene (2005a and 2005b) proposed the TREM by extending the PM by adding a random individual effect.[16] In the TREM the general constant term, *α,* in equation (1), is substituted with a series of state-specific random effects that take into account all unobserved socioeconomic and environmental characteristics that are time-invariant. The TREM is therefore able to distinguish time invariant unobserved heterogeneity from the time varying level of efficiency component. In this way, the TREM arguably overcomes some of the limitations of conventional frontier panel data models (see Greene, 2005a and 2005b); however, it produces 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.

In this study, the PM is used as the reference approach and for comparison purposes, the REM model and the TREM are also estimated. Of course, by not considering the individual effects in the econometric specification of the PM, it could result in the so-called 'unobserved variables bias'; e.g. a situation where correlation between observables and unobservables could

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

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

bias some coefficients of the explanatory variables. However, by introducing several explanatory variables such as the heating and cooling degree days and the household size it is possible to reduce this problem to some extent.[17] Table 2 provides a summary of the model specification and a description of the stochastic terms included in the models.

Table 2: Econometric specifications of the stochastic cost frontier

	PM ***Half-Normal***	**REM** ***Half-Normal***	**TREM** **Half-Normal**
Country-specific component α_i	None	$u_{it} \sim N^+(0, \sigma_u^2)$	$N(0, \sigma_\alpha^2)$
Random error ε_{it}	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$
Level of efficiency	$E(u_{it} \mid u_{it} + v_{it})$	$E(u_{it} \mid \varepsilon_{it})$	$E(u_{it} \mid \alpha_{it} + \varepsilon_{it})$

The state'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:

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

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

[17] A similar approach in estimating an energy demand frontier model for OECD countries has been adopted by Filippini and Hunt (2011).

energy efficiency lower than 100%, receive scores below one. This therefore gives the measure of underlying energy efficiency estimated below.[18]

In summary, Equation (2) is estimated and Equation (3) is used to estimate the efficiency scores for each state for each year. 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 PM, the REM and the TREM are given in Table 3. All estimated coefficients and *lambda*[19] have the expected signs and almost all are statistically significant at the 10% level; the only exceptions being the share of detached houses in the REM. The values of the estimated coefficients for the REM and the TREM are relatively similar, whereas, the values of the estimated coefficients for some variables are different in the REM and TREM from the PM. This difference is probably due to the problem of unobserved heterogeneity mentioned above or to a limited 'within' variability of some explanatory variables.

[18] 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%.

[19] 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.

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

	PM	REM	TREM
Constant	-3.521 (-8.47)	-1.610 (-2.10)	-1.646 (-9.57
α^{y}	0.394 (9.11)	0.166 (3.44)	0.160 (9.75)
α^{p}	-0.066 (-2.18)	-0.108 (-3.71)	-0.128 (-11.83)
α^{pop}	0.640 (14.24)	0.855 (16.53)	0.894 (52.58)
α^{hs}	-1.113 (-15.94)	-0.554 (-5.43)	-0.450 (-15.80)
α^{hdd}	0.374 (23.26)	0.420 (16.43)	0.380 (63.24)
α^{cdd}	0.088 (10.72)	0.050 (2.66)	0.044 (11.97)
α^{SH}	0.004 (8.14)	0.001 (0.20)	0.002 (8.49)
Lamda (λ)	0.853 (7.72)	5.686 (1.71)	1.141 (3.42)

Given that most of the variables are in logarithmic form, the coefficients can be directly interpreted as estimated elasticities. The results suggest that US residential energy demand is price-inelastic, with estimated elasticities of -0.07 -0.11 and -0.13 for the PM, the REM and the TREM respectively. The results also suggest that US residential energy demand is income-inelastic, with an estimated elasticity of 0.39 for the PM but only about 0.16 for the REM and TREM. For weather, the estimated heating degree day elasticities for all three models is about 0.4, whereas the estimated cooling degree day elasticities are rather low; ranging from 0.04 for the TREM to 0.08 for the PM. The estimated coefficient of household size suggests that as family size increases, there is a tendency to use less energy; indicating there are economies of scale with an estimated elasticity of -1.11 for the PM, -0.55 for the REM, and -0.45 for the TREM. Whereas, for the share of detached houses the results suggest that there is only a marginal positive influence on US residential energy demand; the estimated coefficient for the

REM is not significantly different from zero, and although for the PM and the TREM the estimated coefficients are significantly different from zero, they are still rather low being 0.004 and 0.002 respectively.

For the PM the time dummies, as a group, are significant and the overall trend in their coefficients is negative as shown in Figure 1. However, the estimated coefficients do not fall continually over the estimation period, reflecting the 'non-linear' impact of technical progress and other exogenous variables. The estimated coefficients for the REM and the TREM are almost identical to each other, both having a 'similar' pattern to the PM coefficients; nevertheless, they are both around zero reflecting that there are a lot less individual coefficients significantly different from zero for the PM and TREM.

Figure 1: Estimated Time Dummy Coefficients (relative to 19995)

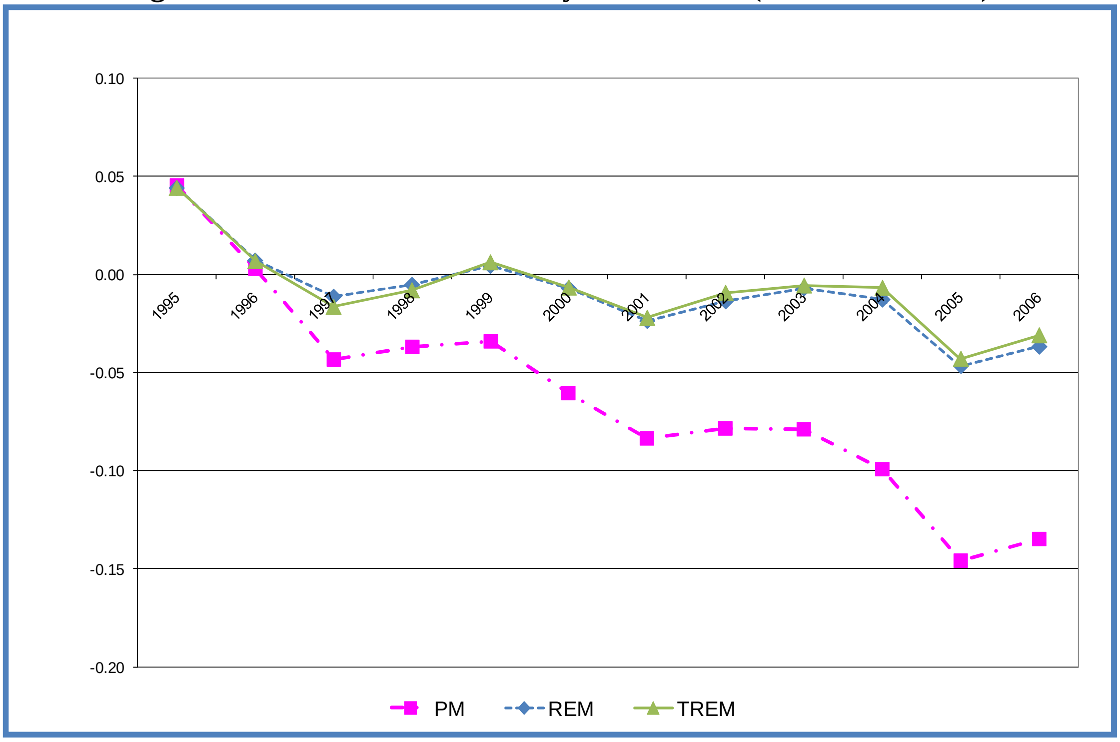


Table 4 provides descriptive statistics for the overall underlying US energy efficiency estimates of the 48 states obtained from the econometric estimation, showing that the estimated mean average efficiency is about 85% to 97% (median 85% to 98%). As discussed above, the TREM generally produces higher average values for the level of efficiency than the other models; probably due to the time-invariant country-specific energy inefficiency being captured by the individual random effects. Therefore, to the extent that there are certain sources of energy inefficiency that result in time-invariant excess energy consumption, the estimates from the TREM arguably provide imprecise estimates resulting in overestimated levels of energy efficiency. There is, therefore, a trade-off in the choice of the most appropriate estimator: the estimated coefficients from a PM could be affected by the so-called unobserved heterogeneity bias, whereas the estimated levels of efficiency obtained using the TREM could be imprecise, because they do not include the persistent inefficiencies that might remain constant over time. Furthermore, the REM suffers from two shortcomings; any unobserved, time-invariant, group-specific heterogeneity is considered as inefficiency and the level of efficiency is not varying over time. Consequently, all further analysis focuses on the results obtained using the PM.[20]

Table 4: Energy efficiency scores

	PM	REM	TREM
min	0.87	0.64	0.91
max	0.98	0.99	0.99
mean	0.95	0.85	0.97
median	0.95	0.85	0.98
st.dev.	0.02	0.08	0.01

[20] It is worth noting, that the correlation coefficient between the level of efficiency obtained using the PM and the REM is (0.73) , the correlation coefficient between the level of efficiency obtained using the PM and the TREM is (0.42) , whereas the correlation coefficient between the level of efficiency obtained using the REM and the TREM is (0.02)

As discussed in Filippini and Hunt (2011) it is expected that the estimated underlying energy efficiency is negatively correlated with energy intensity. Thus for most states it is expected that the level of energy intensity decreases with an increase of the level of energy efficiency, however, as Filippini and Hunt (2011) argue, 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 standard energy intensity measures. This proves to be the case with the estimates here. The overall correlation coefficients between the estimated underlying energy efficiency measure from the PM and the energy intensity measures suggested by the EIA (1995) report being -0.4 for 'energy per capita' and -0.5 for 'energy per building'. Furthermore, the mean correlation coefficient across the 48 states between the estimated underlying energy efficiency and the two intensity measures is -0.6. Thus, as suggested, there appears to be a negative relationship, but it is by no means perfect.

Nevertheless, of vital importance for US policy makers is the relative position across the states and if energy intensity is a good proxy for energy efficiency then would need to be a high (positive) correlation between the rankings of the energy intensity measures and the estimated underlying energy efficiency across the states. However, this is not the case with the Spearman's rank correlation coefficient across the 48 states being 0.4 for 'energy per capita' and 0.5 for 'energy per building. Table 5, Figure 2, and Figure 3 illustrate the rankings and clearly illustrate this relationship.

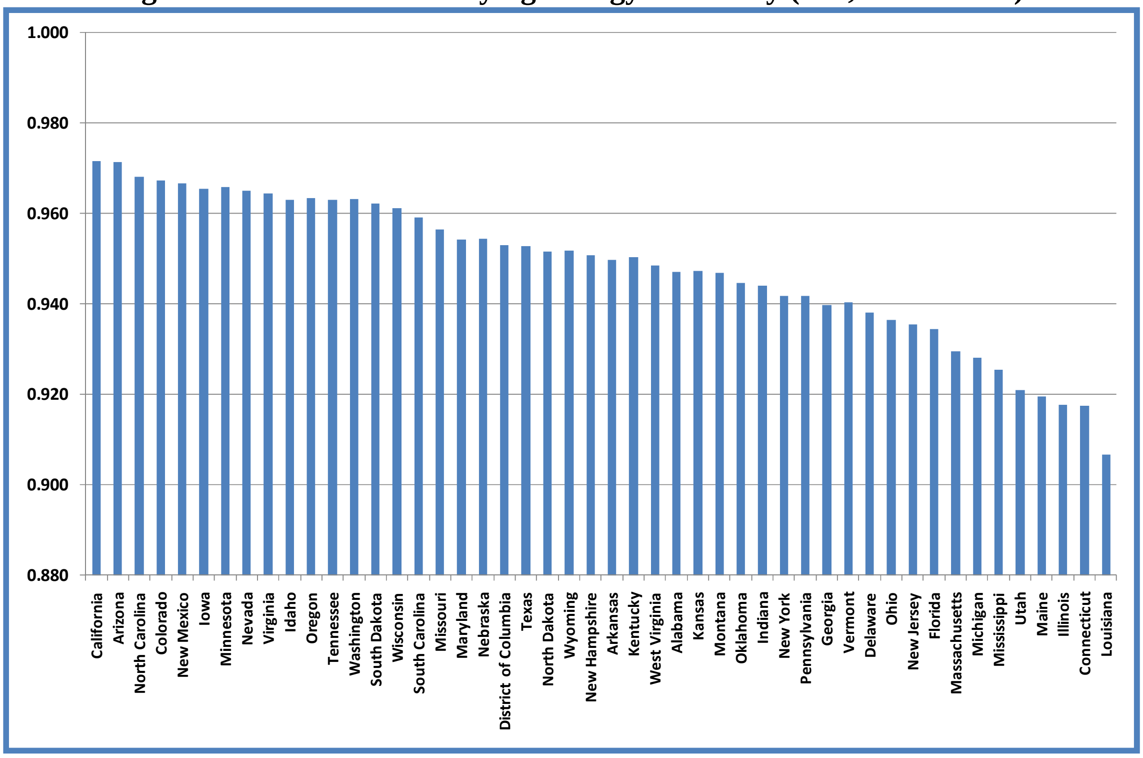
Table 5: Comparison of the Rankings for Estimated Underlying Energy Efficiency (from the PM) and Energy Intensity (1995-2007)

	Estimated Underlying Energy Efficiency		***Energy Intensity 1 (Energy per capita)***		***Energy Intensity 2 (Energy per building)***	
	Level	*Rank*	*Level*	*Rank*	*Level*	*Rank*
Alabama	0.947	28	36.722	14	83.311	11
Arkansas	0.950	25	37.573	15	86.304	14
Arizona	0.971	2	25.837	3	61.553	2
California	0.972	1	25.162	1	69.252	3
Colorado	0.967	4	42.020	24	98.377	25
Connecticut	0.917	47	51.577	44	126.304	46
District of Columbia	0.953	20	40.415	21	84.933	13
Delaware	0.938	37	42.451	25	96.863	23
Florida	0.934	40	25.656	2	55.649	1
Georgia	0.940	35	36.464	12	89.593	17
Iowa	0.966	6	44.219	28	103.778	29
Idaho	0.963	10	38.273	18	93.386	19
Illinois	0.918	46	51.592	45	130.195	48
Indiana	0.944	32	47.477	37	112.154	40
Kansas	0.947	28	46.344	33	108.385	35
Kentucky	0.950	25	40.470	22	93.596	20
Louisiana	0.907	48	33.935	7	81.555	9
Massachusetts	0.929	41	48.428	41	116.997	45
Maryland	0.954	18	39.377	20	97.268	24
Maine	0.919	45	58.892	48	115.466	42
Michigan	0.928	42	54.991	47	127.686	47
Minnesota	0.966	6	48.127	40	112.322	41
Missouri	0.956	17	45.147	30	102.750	28
Mississippi	0.925	43	34.164	8	83.320	12
Montana	0.947	28	45.202	31	101.168	26
North Carolina	0.968	3	35.203	11	79.732	7
North Dakota	0.952	22	50.347	43	108.948	36
Nebraska	0.954	18	47.252	36	110.711	38
New Hampshire	0.951	24	47.488	38	106.235	31
New Jersey	0.936	39	45.714	32	115.739	43
New Mexico	0.967	4	33.667	6	78.951	6
Nevada	0.965	8	34.511	10	82.503	10
New York	0.942	33	43.057	26	106.783	33
Ohio	0.937	38	49.408	42	116.570	44
Oklahoma	0.945	31	41.712	23	94.828	22
Oregon	0.963	10	34.308	9	81.057	8
Pennsylvania	0.942	33	46.953	35	108.958	37
South Carolina	0.959	16	32.849	5	74.680	4
South Dakota	0.962	14	44.450	29	102.245	27
Tennessee	0.963	10	37.713	16	88.024	16
Texas	0.953	20	30.155	4	77.012	5
Utah	0.921	44	38.438	19	112.103	39
Virginia	0.964	9	37.905	17	91.481	18

Vermont	0.940	35	51.661	46	105.923	30
Washington	0.963	10	36.638	13	87.567	15
Wisconsin	0.961	15	46.870	34	107.004	34
West Virginia	0.949	27	43.588	27	94.282	21
Wyoming	0.952	22	47.828	39	106.293	32

Note: A rank of 48 for underlying energy efficiency represents the least efficient state by this measure, whereas a rank of 1 represents the most efficient state. A rank of 48 for energy intensity represents the most energy intensity state whereas a rank of 1 represents the least energy intensive state.

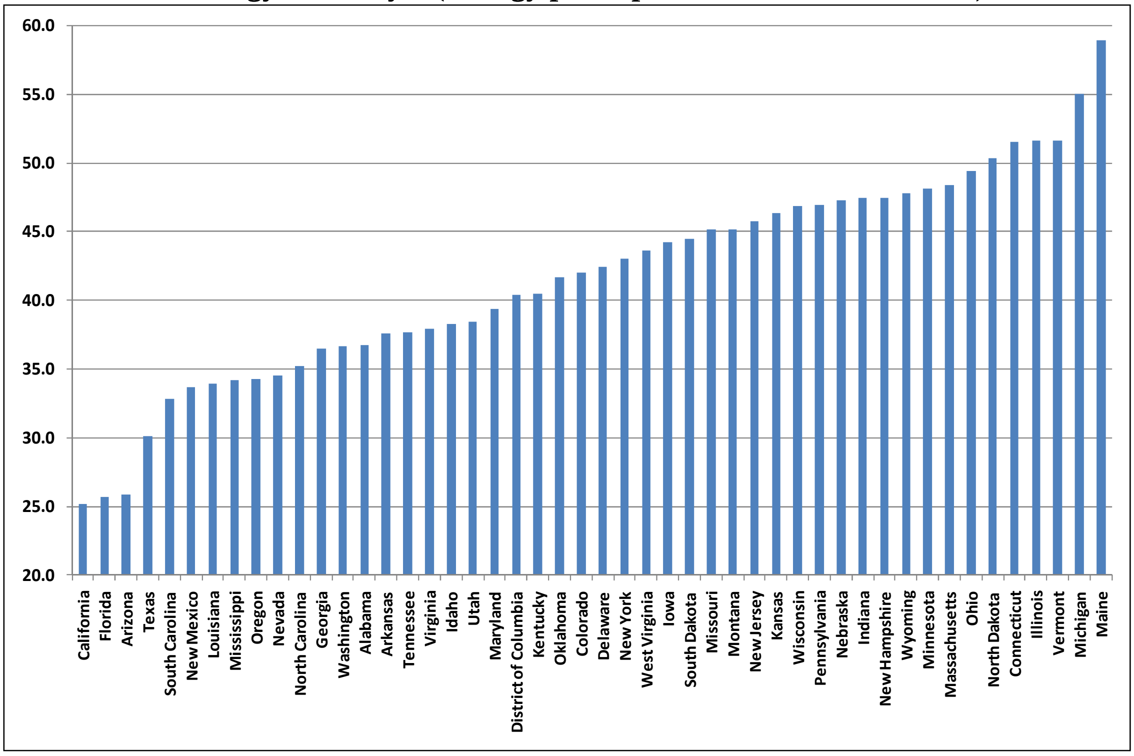
Figure 2: Estimated Underlying Energy Efficiency (PM, 1995 - 2007)



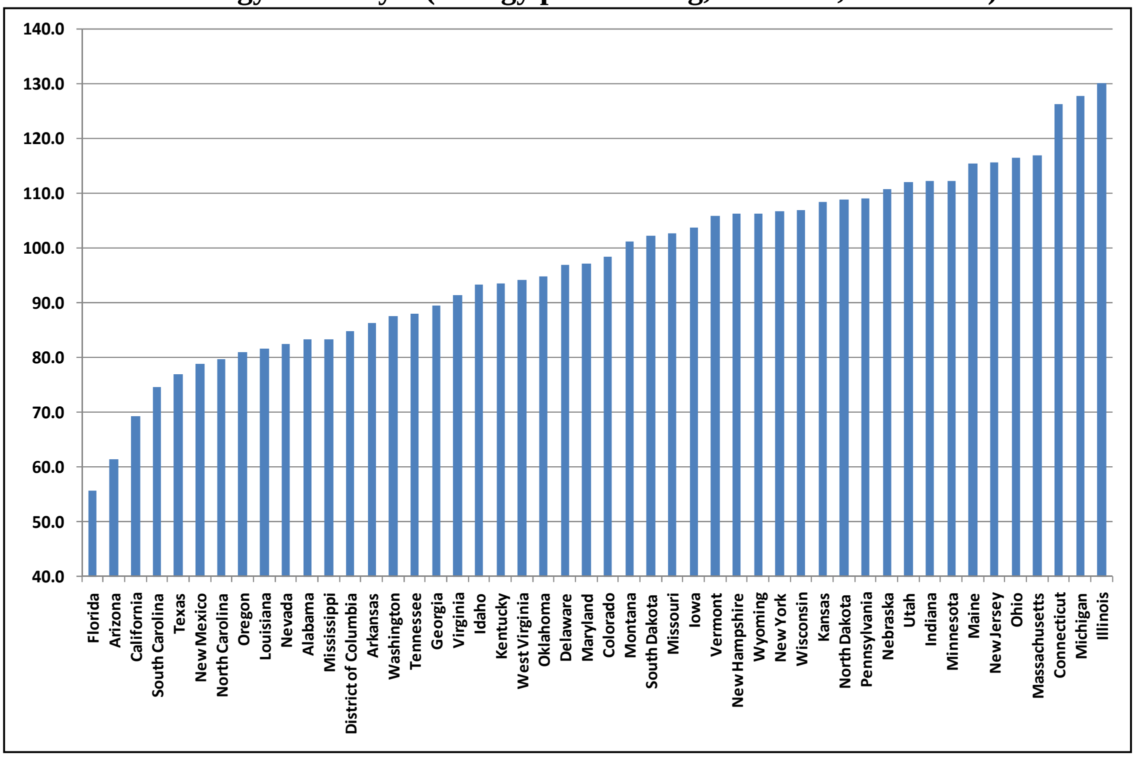
There are some states where the energy intensity measures would appear to be a good predictor of a state's rank of the estimated underlying energy intensity, for both efficient and inefficient states. For example, California is estimated to be the most efficient state according to the analysis above and is the state with the first and third lowest levels of 'energy per capita' and 'energy per building' respectively. Whereas Illinois is estimated to be the 46th most efficient state and is ranked 45th and 48th respectively according to the 'energy per capita' and 'energy per building' measures.

Figure 3: Energy Intensity

a: Energy Intensity 1 (Energy per capita, 1000 Btu, 1995-2007)



b: Energy Intensity 2 (Energy per building, 1000 Btu, 1995-2007)



However, there are also a number of states where the energy intensity measures would appear ***not*** to be a god predictor of a state's rank of the estimated underlying energy intensity, for both efficient and inefficient states. For example, Florida is ranked 2nd and 1st respectively according to the 'energy per capita' and 'energy per building' measures, but is only 40th efficient according to the analysis above. Whereas Minnesota is ranked 40th and 41st respectively according to the 'energy per capita' and 'energy per building' measures, but found to be relatively more efficient according to the analysis above, being ranked 6th.

5. Summary and Conclusion

Building on Filippini and Hunt (2011) this research attempts to isolate core US residential energy efficiency for a panel of 48 states, as opposed to relying on simple measures of energy intensity, such as 'energy per capita' or 'energy per building'. The approach taken combines energy demand modelling and frontier analysis in order to estimate the 'underlying residential energy efficiency' for each state. The energy demand specification controls for income, price, population, the number of housing units, heating degree days, cooling degree days, the share of detached housing, regional effects and an 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 residential energy efficiency.

The estimates for the underlying residential energy efficiency using this approach show that although for a number of states the change in the simple measures of energy intensity might give a reasonable indication of their relative energy efficiency (such as California and

Illinois); this is not always the case (such as Florida and Minnesota). Therefore, unless the analysis advocated here is undertaken, US policy makers are likely to have a misleading picture of the real relative energy efficiency across the states and thus might make misguided decisions when allocated funds to various states in order to implement energy efficiency 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 energy intensity in order to try to avoid potentially misleading policy conclusions.

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Surrey Energy Economics Centre (SEEC)
Department of Economics
University of Surrey
Guildford
Surrey GU2 7XH

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