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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 by the Energy Information Agency (EIA). Generally, the level of energy efficiency of a 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, because 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 and technical change. The aim of this paper is to measure the ‘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 several panel data models: the pooled model; the random effects model; true fixed effects model; the true random effects model; and the Mundlak versions of the pooled and random effects models. The analysis confirms that energy intensity is not a good indicator of energy efficiency; whereas, by controlling for a range of economic and other factors, the measure of ‘underlying energy efficiency’ obtained via the approach adopted here (based on the microeconomic theory of production) is.

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

Keywords: US total energy demand; efficiency and frontier analysis; state energy efficiency.

1 Introduction

For many countries and global energy institutions, the promotion of energy efficiency policies is seen as a major strand of energy policy, given the need to reduce greenhouse gas emissions and maintain security of energy supply. This is true for the US where the promotion of energy efficiency is seen as a very important activity by the Energy Information Agency (EIA). Given this, it is vital that 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 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, two approaches have been proposed in the literature that attempt to identify the change in the 'true' level of efficiency in the use of

[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.

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

energy at the aggregate economy level. The first 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.[3] The second approach, which is advocated in this paper, is based on the microeconomic theory of production and on the estimation of a production, cost, distance or input demand frontier function. A theoretical explanation of this approach was originally introduced by Huntington (1994), with Zhou and Ang (2008) and Filippini and Hunt (2011) attempting empirical applications. Both of these empirical applications use frontier analysis methods developed in applied production theory. They both recognise that, in order to analyse the level of (energy) efficiency, it is important 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 second approach is more suitable for performing an economic analysis of energy efficiency given its theoretical foundation in microeconomic production, whereas arguably the first approach is regarded as being rather 'ad hoc'. As explained later, it is believed that from the microeconomic point of view, the term 'energy efficiency' is imprecise; consequently, the term 'underlying energy efficiency' within the context of the production theory is introduced in Section 2.

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 energy efficiency is computed

[3] 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.

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 energy efficiency 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,[4] 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).[5]

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.[6] An aggregate energy demand frontier function is estimated using a parametric approach in order to isolate a specific measure of energy efficiency by explicitly controlling for income and price effects, population, climate, household density, the structure of the economy and the underlying energy demand trend (UEDT).[7] This is seen as important, given the need to isolate the 'true' energy efficiency' across the different states. This paper attempts therefore to unpick exactly what is meant by the term energy efficiency and re-couch it in

[4] Examples of the use of parametric frontier analysis at the disaggregate 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.

[5] 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.

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

[7] 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.

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 'underlying energy efficiency' based on economic principles (as explained below).

The paper is organised as follows. The next section, presents a discussion on the concept of 'energy efficiency', while section 3 discusses the rationale and specification of the energy demand frontier function. Section 4 illustrates the data and econometric specification. The results of the estimation are presented in Section 5, with a summary and conclusion in the final section.

2. Productive efficiency, 'underlying energy efficiency', and technical change

Energy demand is derived from the demand for energy services. Households and firms combine energy, labour and capital to produce a composite energy service. Therefore, behind the production process of any energy service there is an associated theoretical production function. From an economic perspective, 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 output and by choosing the combination of inputs that minimise the production cost. In this context, two cases can be identified where households or firms are producing an energy service without minimising the use of inputs. The first case is where households or firms employ modern technology but utilize inputs in an inefficient way; i.e. the households or firms do not minimizing the use of energy, labour and capital in the production of an energy service – the input energy is therefore used in an inefficient way. The second case, assuming the same input prices, is where households or firms use an obsolete technology that does not allow them to minimize the quantity of energy, labour and capital and, therefore, to minimize the cost for the production of an energy service[8] – so again the input energy is used in an inefficient way. In both cases, the level of energy used to produce a predefined level of energy services could be reduced; i.e. they are both characterized by a situation of 'waste' of energy.

The discussion above suggests that 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, by an adoption of a new energy saving technology or by both processes. While an increase in energy productivity (or fall in energy intensity) can also come about by both these processes but ***also*** by the change in other factors such as climate and structure of the economy and relative prices.

The two situations of waste energy in the production of energy services, discussed above, are presented in more detail below within the framework of the microeconomic theory of production (Huntington, 1994). This is based on the definition of technical, allocative and cost efficiency or overall productive efficiency introduced by Farrell (1957). Within this theoretical framework, the expression 'energy efficiency' is imprecise. In fact, in order to reduce energy consumption for the production of a given output with a given technology, the level of technical and/or allocative efficiency generally has to improve, which implies a change in the combination of the inputs it is possible to consume.[9] Figure 1 presents the

[8] This situation is related to the 'energy efficiency gap' concept often discussed in the energy economics literature (see, for example, Jaffe and Stavins, 1994). The energy efficiency gap is a situation where households or firms do not perform an investment in a new energy saving technology, although from an economic point of view the investment is profitable and sustainable.

[9] Although, it should also be noted that an improvement in the level of technical and/or allocative efficiency could actually result under certain circumstances in an increase in energy consumption; such as changes in prices or type of technical progress (neutral, energy saving, capital saving and labour saving).

situation of an economic agent that is using capital (K) and energy (E) in order to produce an energy service or an output (y).[10] The situation is illustrated using an isoquant (IS_0) and some isocost (IC) lines. A technically efficient economic agent uses combinations of E and K that lie on the Isoquant IS_0.

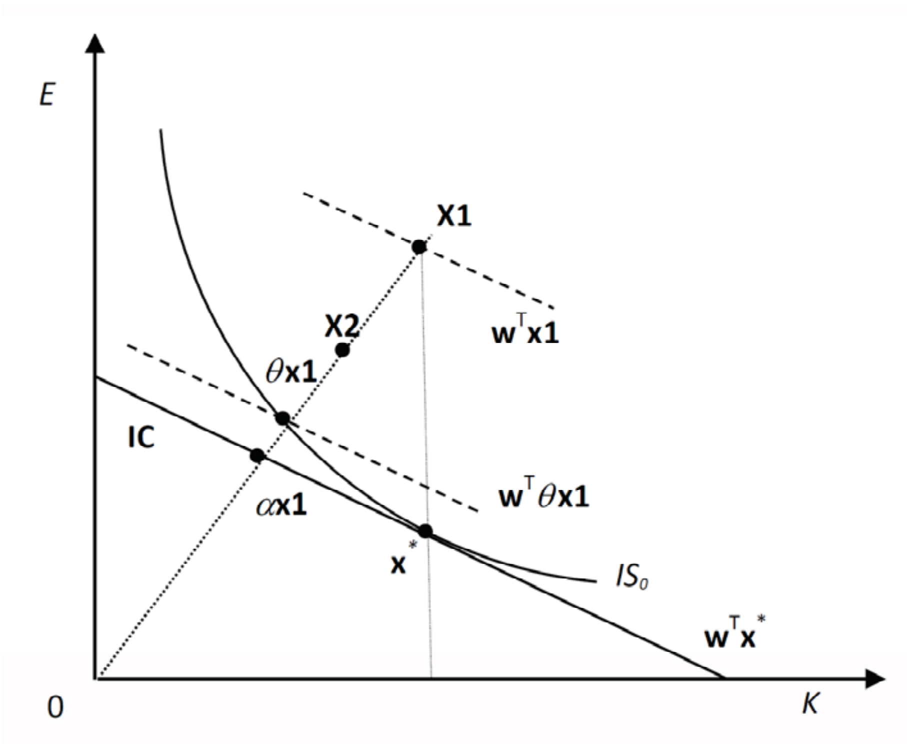


Figure 1: Productive efficiency

If an economic agent uses quantities of inputs defined by point **x1** in Figure 1, it is technically inefficient as the point lies above IS_0. The level of technical inefficiency of the economic agent is represented by the distance between points **x1** and θ**x1**, which is the amount by which all inputs could be proportionally reduced without a decrease in the level of production. Technical efficiency θ can be expressed as the ratio between the distance

[10] An economic agent could be a firm or a household. Moreover, Figure 1 could also represent the economy wide aggregate production function for a state.

from the origin to technically efficient input vector $\theta\mathbf{x1}$ and the distance from the origin to input vector $\mathbf{x1}$.

If the input price ratio, represented by the slope of isocost line $\mathbf{w}^T\mathbf{x1}$, is known, then a cost efficient input combination can be identified. An economic agent that uses a cost-minimising input vector is presented by point $\mathbf{x}^*$, where isocost line $\mathbf{w}^T\mathbf{x}^*$ is a tangent to input isoquant IS_0. Thus, the minimum costs that can be achieved for the production of a given output y are $\mathbf{w}^T\mathbf{x}^*$. From Figure 1 the economic agent operating at $\theta\mathbf{x1}$ is technically efficient but allocatively inefficient since it operates with higher costs (isocost line $\mathbf{w}^T\theta\mathbf{x1}$ lies above the line $\mathbf{w}^T\mathbf{x}^*$). The distance between $\alpha\mathbf{x1}$ and $\theta\mathbf{x1}$ measures the allocative inefficiency of the economic agent. The allocative efficiency is defined as the ratio between the distance from the origin to $\alpha\mathbf{x1}$ and the distance from the origin to $\theta\mathbf{x1}$, whereas the total cost efficiency α can be calculated as the ratio between the distance from the origin to $\alpha\mathbf{x1}$ and the distance from the origin to $\mathbf{x1}$. To reach the optimal input combination and thus become cost efficient, the economic agent would have to change its relative input use in the direction of increasing the use of input K and decreasing the use of input E.

It is now possible to identify several cases that can improve the level of productive efficiency and, therefore, reduce the energy consumption by keeping the level of production of energy services or output constant:

- *Case A:* The economic agent is producing the level of energy service y that corresponds to the isoquant IS_0 using the input combination $\theta\mathbf{x1}$. In this case, the economic agent could improve the level of allocative efficiency by moving to the optimal inputs combination $\mathbf{x*}$. In this case, energy consumption will decrease, that is energy is substituted with capital allowing the economic agent to consume less energy. In order for the economic agent to reach **x*** it improves the use of capital stock, for example installing a device on a cooling system to improve the function of the system.

- *Case B:* the economic agent is producing the level of energy service *y* using the input combination **x1**. In this case, the economic agent could improve the level of overall productive efficiency by moving to the optimal inputs combination **x***. In this case, energy consumption will decrease and there is no substitution with capital. So for example, a household optimises the amount of time that the windows in the house are opened during the day to reach **x***or a firm optimises the use of a cooling system. This is a special case and reflects the concept of input specific technical efficiency introduced by Kopp (1981) which is defined as the ratio of minimum feasible to observed use of energy, conditional on the production technology and the observed levels of outputs and other inputs.[11]

- *Case C:* the economic agent is producing the level of energy service *y* using the input combination **x2**. In this case, the economic agent could improve the level of overall productive efficiency by moving to the optimal input combination **x***. In this case, energy consumption will decrease, as energy is substituted with capital allowing the economic agent to consume less energy. This occurs when a household or a firm improve the insulation of the building in order to reach **x***.

It is important to note, that an improvement of the level of the productive efficiency can also result in an increase in energy consumption. This situation is depicted in Figure 2, which shows that this situation could come about when the energy price is relatively low compared to the capital price. In this case, the economic agent is producing the level of energy service *y* using the input combination θ**x1**. The economic agent could improve the level of allocative efficiency by moving to the optimal inputs combination **x***. In this case

[11] Note, that by estimating a production or distance frontier function it is possible, using the empirical approach suggested by Reinhard et al. (1999), to estimate an input specific technical efficiency indicator. For instance, Reinhard et al. (1999) estimate the level of water efficiency for a sample of farmers.

the energy consumption will increase, that is capital is substituted with energy allowing the economic agent to consume less capital. One situation where this might apply is a new technology based on renewable energy source, for instance solar, which produces energy at relatively low cost. In this case, building highly insulated houses would not necessarily be the most efficient solution. Hence, when thinking about 'true' efficiency, although generally it is expected this would reduce energy consumption this might not always be the case since as Figure 3 illustrates, an increase in the level of productive efficiency could bring about an increase in energy consumption.

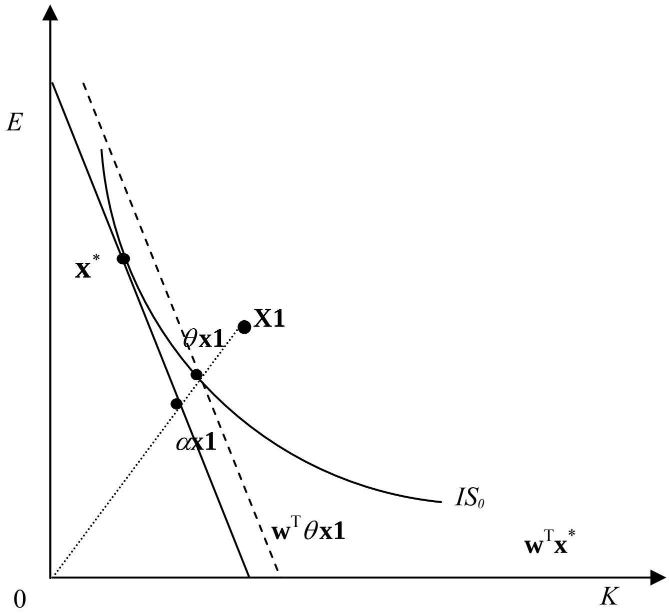


Figure 2: Efficiency and change of the energy price

The discussion above shows that generally behind any increase in the level of productive efficiency, there is an underlying increase in the efficiency of the use of the input energy. Therefore, the term 'underline energy efficiency' is felt to be a more appropriate given the rather nebulous term of 'energy efficiency' is not based on production theory.

When technological change allows the economic agent to produce the same level of the energy service *y*, with less energy and capital, such technical progress shifts the isoquant. For instance, this occurs when the temperature of rooms in a house is maintained at say 20° Celsius, with less energy and capital maybe due to new insulation technology or a new heating system. In this case, the technological progress will move the isoquant, IS_0, to the left as depicted in Figure 3.[12] In this case, the amount of energy and capital used to produce the energy service has decreased and the economic agent reaches point **xt1***.[13]

From this discussion, it is clear, that the level of energy consumption for the production of a predefined level of output can change over time because of an increase of the level of the productive efficiency and/or technical progress.[14] Therefore, an empirical analysis of the improvement of the level of energy productivity should measure, beside other factors such as weather and population, the impact of the increase in the level of productive efficiency on the use of energy as well as the impact of the introduction of new technologies on the use of energy. However, as Kumbhakar and Lovell (2000) note, when using parametric

[12] See also Gillingham et al. (2009) for a discussion of this effect.

[13] In this figure, we are assuming a homothetic production function. This implies a parallel shift of the isoquant.

[14] It should be noted that, the so- called 'rebound effect' is often discussed in terms of such technical improvements. This is where consumers do not reduce the amount of energy by the amount predicted by the engineering technological improvement given they adjust their behaviour according to the new implicit price of the energy service (see, for example, Greening et al., 2000; Sorrell, 2009). However, this is not what is considered here, because, as explained in more detail in Section 2 the analysis here is based on the theory of productive efficiency. This paper attempts to unpick exactly what is meant by the term 'energy efficiency' and redefine it in terms of productive economic efficiency and inefficiency. However, it is worth noting that if consumers of energy and energy services were to reduce this inefficiency and become more efficient, then a rebound effect could also result given that the implicit price of the energy service would fall. Nevertheless, it is important to be clear that the cause of this is an improvement in the economically efficient use of energy and not an engineering improvement in technology; hence, it is rather different from the rebound effect normally discussed in the literature.

methods to estimate production frontier functions the distinction between the impact of the increase in the level of productive efficiency and the impact of the introduction of new technologies on output can be difficult.

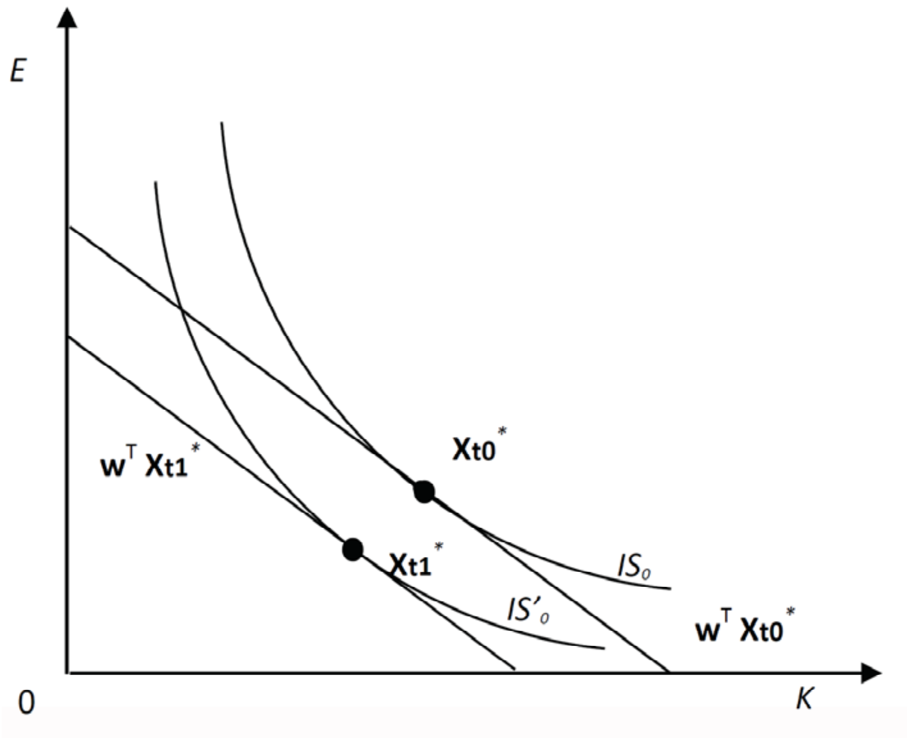


Figure 3: Technical progress

In order to estimate the level of overall productive efficiency and the level of technical progress it is possible to use the frontier analysis approach based on the estimation of production, distance, cost and input demand frontier functions using both parametric and non-parametric approaches using panel data. The non-parametric approaches include DEA and the Free Disposal Hull (FDH). In these approaches, the frontier function is considered as a deterministic function of the observed variables. These methods are non-parametric in that they do not impose any specific functional form or distribution assumption. Apart from a few exceptions, all parametric methods have a stochastic element in their frontier function. Thus, this group of methods is also labelled SFA. The main exception to a deterministic frontier is the Corrected Ordinary Least Squares (COLS) method.

From a theoretical point of view, the estimation of a production frontier function or a frontier distance function allows the estimation of the level of technical efficiency, while the estimation of a cost frontier function allows the estimation of the level of cost efficiency or overall productive efficiency. It is also possible to estimate simultaneous-equation cost frontier models, that is, to estimate the cost frontier function together with input demand frontier functions. In this case, as illustrated by Schmidt and Lovell (1979) the self-duality of the Cobb-Douglas production function is used to derive a system of log-log stochastic cost-minimizing input demand equations which are also known as input frontier equations. In this context, actual input demands differ from the input frontier demands due to the presence of both allocative and technical inefficiency.[15]

Estimation of production and distance functions for energy services requires information on outputs, labour, capital and energy, whereas for the estimation of the cost and input demand functions, information on outputs and input prices are required. Sometimes, when there is a lack of data mainly on some inputs or input prices, it is also possible to estimate just one input frontier demand function; for instance, an energy demand frontier function as in this study. This approach, which can be considered as an ad-hoc approach, does not completely consider the theoretical restriction imposed by the production theory; however, it does allow, in an approximate way, the estimation of the difference between the actual input demand and the input frontier demand. In order to consider the effect of technological

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

change on production, cost or input demands, all frontier models can be estimated by introducing a time trend or a set of time dummy variables. Generally, it is assumed that these variables capture the shift in the frontier functions due to change in the technology.[16] Given this theoretical background, the next section introduces and discusses the aggregate frontier energy demand model that the estimation is based upon.

3 An aggregate frontier energy demand model

As discussed above 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 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:

$$E_{it} = E(P_{it,}, Y_{it}, POP_{it}, HDD_{it}, CDD_{it}, HS_{it}, SHI_{it}, SHE_{t}, A_i, UEDT_{t,} EF_{it}) \qquad (1)$$

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 SHE_{it} is the share of value added for the service sector; 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 (as in Filippini & Hunt, 2011).

[16] However, in line with the econometric estimation of energy demand literature, it is assumed below that such shifts might also come about by changes in a range of exogenous impacts that cannot usually be measured explicitly, consistent with the idea of the UEDT.

and EF_{it} is the unobserved level of 'underlying energy efficiency' of an economy for state *i* in year *t*. This could incorporate a number of factors that will differ across countries, including different state 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. Of course, as discussed in the previous section, 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 'underlying energy efficiency' is not observed directly, but instead this indicator has to be estimated. Consequently, in order to estimate this economy-wide level of 'underlying energy efficiency' and identify the best practice economy in term of energy utilization, the stochastic frontier function approach introduced by Aigner et al. (1977) is used.

An aggregate input demand frontier function, as discussed in the previous section, 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.[17] In the case of an aggregate total energy demand function, used here, the frontier gives the minimum level of energy consumption necessary for the 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

[17] 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 'underlying energy efficiency' directly measures the energy saving due to an improvement of the level of the productive efficiency.

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.[18]

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:

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

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 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 D_t is a series of time dummy variables to capture the UEDT.[19] SHI_{it}, and SHS_{it} are as defined above. Furthermore, the error term in Equation (2) is composed of two

[18] As discussed in the context of 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 of the efficiency in the use of energy.

[19] As pointed out by Kumbhakar and Lovell (2000), the inclusion of a time trend or a series of time dummies as regressors 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. Given this, in order to reduce the number of parameters to be estimated, each time dummy variable consist of two years rather than one.

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 'underlying energy 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.[20] An improvement in the 'underlying 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 state. 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 and through the price effect.

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

4. 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.

[20] 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.

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 1982$, P_{it} is each state's real energy price for each year in per million BTUs 1982$. Total energy consumption figures and prices are provided by 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.[21] The data on area size (A_i) and number of houses (HS_{it}) is collected from the U.S. Census Bureau. Descriptive statistics of the key variables are presented in Table 1.

Table 1: Descriptive statistics

Variable Description	Variable Name	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Energy consumption *(Trillion Btu)*	***E***	227.63	209.64	19.80	915.6
GDP *(Million 1982US$)*	***Y***	155731	173787	10000	1025710
Real Price of energy *(per million Btu)*	***P***	8.40	1.41	4.97	13.10
Number of houses *(1000)*	***HS***	2430	2435	207	13312
Population *(1000)*	***POP***	5863	6275	485	36378
Heating degree days *(base: 65F)*	***HDD***	5087	1998	555	10745
Cooling degree days *(base: 65F)*	***CDD***	1142	796	128	3870
Share of industrial sector	***SHI***	20.74	6.04	2.19	36.66
Share of service sector	***SSI***	75.49	7.17	52.90	97.76
Area *(square miles)*	***A***	63717	47641	61	268820

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

There are a number of different SFA model specifications using panel data that could be considered suitable for the task at hand.[22] These include the following basic models for panel data: the pooled model (PM hereafter); the random effects model (REM hereafter); the true fixed effects model (TFEM hereafter); and true random effects model (TREM hereafter). Moreover, as shown by Farsi et al. (2005) and by Filippini and Hunt (2012) it is also possible to estimate some of these models using an adjustment introduced by Mundlak (1978) in order to take account of the econometric problem of unobserved heterogeneity bias. As discussed below, 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 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 present 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.[23] 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. In order to solve this problem using panel data, Greene (2005a and 2005b) proposed the TFEM and the TREM

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

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

whereby the PM is extended by adding fixed and random individual effects respectively.[24] The TFEM can be estimated in two ways: *either* by using a simulated maximum likelihood procedure (proposed by Greene, 2005a) *or*, if the number of units of observation is not large, by introducing state specific dummy variables into the function, which is equivalent to the Dummy Variable Pooled Model (DVPM). However, because of the use of different estimation procedures, the two models do not produce the same results, but the DVPM approach is arguably a better method given it does not require the use of simulated maximum likelihood estimators where there are sometimes problems with convergence. Therefore, the DVPM is the version used for the TFEM in this paper.

In general terms, for the TFEM and the TREM, the constant term, α, in Equation (2), is substituted with a series of state-specific fixed or random effects that take into account all unobserved socioeconomic and environmental characteristics that are time-invariant. The TFEM and the TREM are able to distinguish time invariant unobserved heterogeneity from the time varying level of efficiency component. These models therefore arguably overcome some of the limitations of conventional SFA panel data models (see Greene, 2005a and 2005b). 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 'underlying energy efficiency'. Finally, the PM, the REM and the TREM could all be affected by the so-called unobserved heterogeneity bias, e.g. a situation where correlation between

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

observables and unobservables could bias some coefficients of the explanatory variables.[25] In order to address this econometric problem in the REM, this study follows the approach taken by Farsi et al. (2005) and Filippini and Hunt (2012) by using a Mundlak version of the REM. The Mundlak version of the REM (MREM hereafter) is based upon Mundlak's (1978) modification of the REM for the general specification; whereby the correlation of the individual specific effects (u_i) and the explanatory variables are considered in an auxiliary equation given by:

$$u_i = AX_i \pi + \gamma_i \qquad AX_i = \frac{1}{T}\sum_{t=1}^{T} X_{it} \text{ , } \gamma_i \sim iid(0, \sigma_\delta^2) \tag{3}$$

where X_{it} is the vector of all explanatory variables, AX_i is the vector of the averages of all the explanatory variables and π is the corresponding vector of coefficients.[26] Equation (3) is readily incorporated in the main frontier Equation (2) and estimated using the REM. Nevertheless, in a frontier model the error term is a composite asymmetric term, consequently, the estimated coefficients are not the within estimators as in Mundlak's classical formulation. However, since the correlation between the individual effects and the explanatory variables is at least partially captured in the model, the heterogeneity bias is expected to be relatively low.

[25] Nevertheless, this heterogeneity bias can be reduced to some extent by introducing several explanatory variables and by considering a relatively long period. Filippini and Hunt (2011) adopted this approach in estimating an energy demand frontier model for OECD countries using a PM and in that case, the coefficients obtained using different models were relatively similar.

[26] Note that the Mundlak's formulation (i.e. with the introduction of this auxiliary equation in a REM) produces the 'Within Estimator'. In its original form, the Mundlak (1978) general panel data regression model is $Q_{it} = X_{it}\beta + AX_i \pi + \gamma_i + v_{it}$; however, Mundlak (1978) showed that the estimation of this model using GLS yields: $\hat{\beta}_{GLS} = \hat{\beta}_{within}$ *and* $\hat{\pi}_{GLS} = \hat{\beta}_{Between} - \hat{\beta}_{within}$. The direct interpretation of the coefficients $\hat{\pi}_{GLS}$ is therefore not straightforward. Usually, the discussion on the results concentrate on $\hat{\beta}_{within}$.

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.[27] The Mundlak adjustment can also be applied to the PM to obtain the Mundlak version of the PM (MPM hereafter). In this paper, it is argued that the Mundlak adjustment applied to the PM and the REM are the appropriate approaches to take when attempting to measure the level of 'underlying energy efficiency' for the 49 states in the US given the way the unobserved heterogeneity bias is taken into consideration.[28]

It is worth noting that the MPM has the advantage that it considers the unobserved heterogeneity problem and produces an estimate of the level of 'underlying energy efficiency' that varies over time. However, this model could suffer from a positive autocorrelation problem, due to the presence of time invariant inefficiency part in the inefficiency term. In fact, the term γ_i of the Mundlak adjustment Equation (4) should represent the time persistent inefficiency and should be absorbed in the inefficiency term; nonetheless, the possibility that this term is absorbed by the error term cannot be ruled out. In this case, the inefficiency term would only partially include the time persistent inefficiency. However, the MREM is not affected by this problem, but does have the limitation that it produces indicators of the level of energy efficiency that remain constant over time. Yet, with the inclusion of the Mundlak adjustment, the MREM gains in attractiveness because the unobserved heterogeneity bias problem is solved and the time-invariant unobserved factors are captured by terms of the Mundlak adjustment and not by

[27] In this specification, it is assumed that the effect of unobserved state characteristics is captured by the coefficients of the group mean of the explanatory variables of Equation (3).

[28] The Mundlak adjustment could be also applied to the TREM; however, given it is argued here that the TREM is not the favoured model it was decided not to apply this approach.

the inefficiency term. For this reason, it is expected that the level of 'underlying energy efficiency' obtained with MREM to be higher than the one obtained with REM.

Given the discussion above, six models are estimated in this paper: Model I, the PM; Model II, the MPM; Model III, the REM; Model IV, the MREM; Model V, the TFEM; and Model VI, the TREM. Furthermore, it is believed that the MPM and the MREM should be preferred given that the disadvantages of these techniques are arguably less acute than the disadvantages of the other models; however, the PM, the REM, the TFEM and the TREM are still estimated for comparison purposes. Table 2 summarizes the six models.

Table 2: Econometric specifications of the stochastic cost frontier

	Model I **PM**	*Model II* **MPM**	*Model III* **REM**	*Model IV* **MREM**	*Model V* **TFEM**	*Model VI* **TREM**
State effects α_i	none	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$	*iid* $(0, \sigma_\alpha^2)$	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$	Fixed (group dummies α_i)	*iid* $(0, \sigma_\alpha^2)$
Random error ε_{it}	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = a_i + v_{it}$ α_i $\sim N^+(0, \sigma_a^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = \delta_i + v_{it}$ $\delta_i \sim N^+(0, \sigma_\delta^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$
Inefficiency	$E(u_{it}\ I\ v_{it})$	$E(u_{it}\ I\ v_{it})$	$E(\alpha_i\ I\ v_{it})$	$E(\delta_i\ I\ v_{it})$	$E(u_{it}\ I\ v_{it})$	$E(u_{it}\ I\ v_{it})$

After Equation (2) is estimated, it is possible to calculate the level of 'underlying energy efficiency'. A 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) and the level of 'underlying energy efficiency can be expressed in the following way:

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

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 'underlying 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 energy efficiency lower than 100%, receive scores below one. This therefore gives the measure of 'underlying energy efficiency' estimated below.[29] 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.

5. Estimation results

The estimation results of the frontier energy demand models using the six models discussed above are given in Table 3. Most of the estimated coefficients and *lambda*[30] have the expected signs and are statistically significant at the 10% level; the only exceptions being in some models some variables such as, the weather variables and the shares of the industrial and service sectors.[31] Generally, the value of several coefficients of the PM are different from that in the MPM, the REM, the MREM, the TFEM and the TREM; the difference being probably due to the problem of unobserved heterogeneity mentioned above. For instance, the price coefficient in the PM is much higher than in the other models and suggests that US total energy demand is price-elastic, with and estimated elasticity of about -1.2. In addition, the value of the income elasticity obtained with this model is low relative to that obtained by the other models that explicitly take into account unobserved time-

[29] 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%.

[30] 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.

[31] 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).

invariant factors. However, overall, the results obtained in the other models are relatively similar.

Table 3: Estimated coefficients (*standard errors* in parentheses)

	PM	MPM	REM	MREM	TFEM	TREM
Constant	19.495*** (0.515)	20.481*** (0.415)	16.387*** (0.983)	20.430*** (3.292)	19.115*** (1.027)	11.037*** (0.215)
α^{y}	0.309*** (0.033)	0.267*** (0.101)	0.357*** (0.039)	0.374*** (0.060)	0.377*** (0.049)	0.529*** (0.016)
α^{p}	-1.226*** (0.045)	-0.114* (0.066)	-0.213*** (0.029)	-0.188*** (0.046)	-0.164*** (0.027)	-0.200*** (0.020)
α^{pop}	0.598*** (0.037)	0.631*** (0.150)	0.553*** (0.039)	0.422*** (0.055)	0.409*** (0.063)	0.544*** (0.017)
α^{hdd}	0.006 (0.019)	0.089 (0.063)	0.142** (0.058)	0.170*** (0.075)	0.154*** (0.033)	0.066*** (0.007)
α^{cdd}	0.053*** (0.011)	0.002 (0.023)	0.013 (0.022)	0.010 (0.025)	0.005 (0.010)	0.003 (0.004)
α^{hs}	-0.526*** (0.090)	-1.097*** (0.369)	-0.921*** (0.106)	-0.877*** (0.152)	-0.752** (0.134)	-1.014** (0.031)
α^{SHI}	1.207*** (0.370)	-0.696 (0.704)	-0.703** (0.353)	0.579 (0.550)	-0.159 (0.294)	-0.364** (0.132)
α^{SHS}	-0.325 (0.372)	-1.107 (0.686)	-1.034*** (0.396)	-0.814 (0.608)	-0.322 (0.292)	-0.472*** (0.131)
α^{a}	0.035*** (0.007)	0.012* (0.006)	0.126*** (0.035)	0.016 (0.042)		0.292*** (0.004)
Av-α^{y}		0.005 (0.106)		0.097 (0.279)		
Av-α^{p}		-1.570*** (0.078)		-1.559*** (0.296)		
Av-α^{pop}		0.026 (0.155)		0.220 (0.280)		
Av-α^{hdd}		-0.095 (0.064)		0.180 (0.158)		
Av-α^{cdd}		0.068*** (0.024)		0.054 (0.122)		
Av-α^{hs}		0.370 (0.372)		0.039 (0.450)		
Av-α^{SHI}		1.898** (0.808)		2.035 (2.055)		
Av-α^{SHS}		1.349** (0.789)		1.440 (2.148)		
Lamda (λ)	2.441*** (0.226)	7.498*** (1.105)	9.630* (5.703)	4.268** (1.793)	1.413*** (0.295)	1.868*** (0.213)

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

For most models that take into account time-invariant unobserved heterogeneity factors the results suggest that US total energy demand is price-inelastic, with estimated elasticities varying between -0.1 and -0.2. The results also suggest that US total energy demand is income-inelastic, with an estimated elasticity that varies between 0.3 and 0.4.[32] For the weather variables, the estimated heating and cooling degree day elasticities have the expected signs but are not very significant in all models. The estimated household size energy demand elasticities are significant and, as expected, are negative, suggesting that an increase of 10% in household size will decrease energy consumption that varies between 5% and 11% depending on the model. 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, at least in some models, a marginal negative impact of these two variables on US total energy demand (noting that the reference sector is agricultural and mining). Finally, although not all of the individual time dummy coefficients are significant in the models that consider unobserved heterogeneity, collectively, as a group, they are found to be significantly different from zero.[33]

[32] Although rarely considered in the econometric energy demand literature, it could be argued that y_{it} is endogenous; therefore, the Wu-Hausman test was conducted using lagged variables as instruments. However, the test could not reject the Null Hypothesis that the variables are exogenous (p = 0.1648); an unsurprising result given the weight of energy to total GDP is relatively small.

[33] For both the MPM and the MREM the likelihood ratio tests reject the null hypothesis that jointly the time dummies coefficients are equal to zero, with probability values less than 0.001.

Table 4 provides descriptive statistics for the overall US 'underlying energy efficiency' estimates for the 49 states obtained from the econometric estimation, showing that the estimated mean average efficiency is about 89% to 98% (median 90% to 98%).

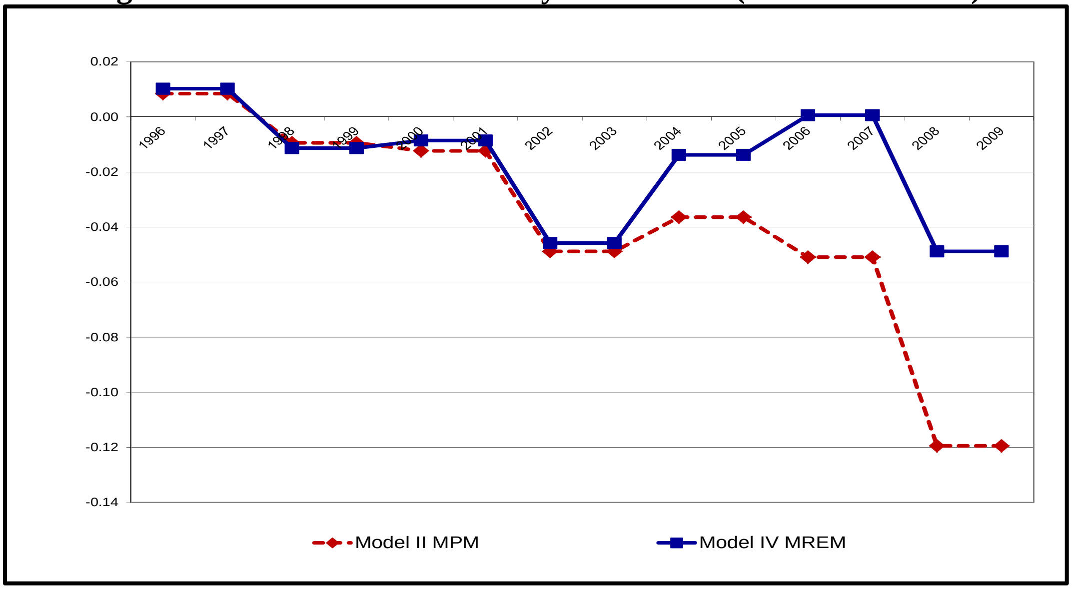
Table 4: Energy efficiency scores

	PM	MPM	REM	MREM	TFEM	TREM
min	0.63	0.85	0.24	0.64	0.87	0.79
max	0.98	0.99	0.99	0.99	0.99	0.99
mean	0.86	0.89	0.73	0.87	0.97	0.96
median	0.88	0.87	0.75	0.90	0.96	0.96

As discussed above, the TFEM and the TREM generally produce higher average values for the level of efficiency than the other models, probably due to the time-invariant state-specific underlying energy inefficiency being captured by the individual effects. Therefore, to the extent that there are certain sources of underlying energy inefficiency that result in time-invariant excess energy consumption, the estimates from the TFEM and the TREM arguably provide imprecise estimates resulting in overestimated levels of 'underlying energy efficiency'. On the other hand, the estimated coefficients of the PM could be affected by the so-called unobserved heterogeneity bias and the REM model tends to underestimate the level of efficiency because all time invariant unobserved factors are captured by the individual effects that are the base for the computation of the level of efficiency. The MPM and the MREM are therefore seen as the most appropriate alternatives to the PM and the REM given the Mundlak adjustment appears to solve, at least partially, the unobserved heterogeneity bias. Furthermore, the estimated coefficients for the MREM are similar to the classical TFEM that explicitly considers the time-invariant unobserved factors in the individual effects – which does *not* suffer from the unobserved heterogeneity bias. In summary, the chosen 'preferred models' are the MPM and the MREM. The advantage of the MPM, as discussed above, is that it produces an estimated level of efficiency that varies over time, whereas the MREM does not. On the other hand, the coefficients obtained from the MREM are closer to those obtained from the TFEM, and therefore, not affected by heterogeneity bias. Nevertheless, the correlation coefficient between the estimated 'underlying energy efficiency' obtained from the MPM and the MREM is relatively high at 0.67.[34] Given this discussion, further analysis of the empirical results focusses on the MPM and the MREM.

Figure 4 illustrates the estimated time dummy coefficients for the MPM and MREM. This shows that generally the trend of the time dummy coefficients is negative although more so for the MREM than the MPM;[35] however, they do not fall continually over the estimation period, reflecting the 'non- linear' impact of technical progress and other exogenous variables.

Figure 4: Estimated Time Dummy Coefficients (relative to 19995)



[34] It is also worth noting that, as expected, the correlation between the estimated levels of 'underlying energy efficiency' obtained from the MPM and the MREM with those obtained from the TFEM and the TREM is relatively low (the correlation coefficients all being about 0.3). This is due to the fact, that these latter models do not consider the level of efficiency that remain constant over time, but because the analysis is conducted at the state level, it is expected that part of the inefficiency remains constant over time.

[35] The trend of the estimated time coefficients is about -0.3% per annum and -0.09% per annum for the MPM and the MREM respectively.

As discussed in Filippini and Hunt (2011 and 2012) 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 estimated level of 'underlying energy efficiency'. However, as Filippini and Hunt (2011) argue, if this technique were to be a useful tool for teasing out the 'true' 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 with the overall correlation coefficients between the estimated 'underlying energy efficiency' measure from the MPM and the MREM and the simple energy intensity ratio (energy consumption to GDP ratio) being -0.2 and -0.3 respectively.[36]

Furthermore, US policy makers need to know the relative energy efficiency position of the individual states and for energy intensity to be a good proxy for the 'true' energy efficiency there would need to be a high (positive) correlation between the rankings of the energy intensity measures and the estimated 'underlying energy efficiency'. However, this is not the case with the results presented here, the Spearman's rank correlation coefficient between the estimated 'underlying energy efficiency' from the MPM and the MREM and

[36] Further work could further investigate the relationship between the estimated 'underlying energy efficiency' and energy intensity over time by attempting to decomposing the change in energy intensity resulting from the estimated equation, for example:

$$\widehat{\Delta ei_{it}} = (\widehat{\alpha^{y}}-1)\Delta y_{it} + \widehat{\alpha^{p}}\Delta p_{it} + \widehat{\alpha^{pop}}\Delta pop_{it} + \widehat{\alpha^{hdd}}\Delta hdd_{it} + \widehat{\alpha^{cdd}}\Delta cdd_{it} + \widehat{\alpha^{h}}\Delta h_{it} + \widehat{\alpha^{SHI}}\Delta SHI_{it} + \widehat{\alpha^{SHS}}\Delta SHS_{it} + \widehat{\alpha^{t}}\Delta D_{t} + \widehat{\Delta u_{it}}$$

So that: $(\widehat{\alpha^{y}}-1)\Delta y_{it}$represents the contribution from a change in GDP; $\widehat{\alpha^{p}}\Delta p_{it}$the contribution from a change in the real energy price; $\widehat{\alpha^{pop}}\Delta pop_{it}$ the contribution from a change in population; $\widehat{\alpha^{hdd}}\Delta hdd_{it}$ the contribution from a change in heating degree days; $\widehat{\alpha^{cdd}}\Delta cdd_{it}$ the contribution from a change in cooling degree days; $\widehat{\alpha^{h}}\Delta h_{it}$ the contribution from a change in the number of houses; $\widehat{\alpha^{SHI}}\Delta SHI_{it}$ the contribution from a change in the share of the industrial sector; $\widehat{\alpha^{SHS}}\Delta SHS_{it}$ the contribution from a change in the share of the service sector; $\widehat{\alpha^{t}}\Delta D_{t}$ the contribution from a change in the UEDT; and $\widehat{\Delta u_{it}}$ the contribution from a change in the underlying energy inefficiency.

‘energy intensity’ (measured as the energy GDP ratio) across the 49 states is only 0.06 and 0.09 respectively.

This is further highlighted in Table 5 and Table 6 that classify the states’ estimated ‘underlying energy efficiency’ into three groups: relatively efficient states; relatively inefficient states; and relatively moderately efficient states. These show that in general the classifications are similar for both the MPM and the MREM. These can be compared with Table 7 that presents a similar classification based on energy intensity (the simple energy to GDP ratio) which show that energy intensity would appear to be a good predictor of a state’s relative ‘underlying energy efficiency’ for some states but a very poor indicator for others.

Table 5: Classification of member states based on the MPM model.

Estimated ‘Underlying Energy Efficiency’	**Group**	**Member states**
Below 87%	Inefficient states	California, Connecticut, Delaware, Illinois, Kansas, Louisiana, Maine, Maryland, Massachusetts, Minnesota, Mississippi, Montana, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, Texas, Vermont, & Wyoming
From 86% to 94%	Moderately efficient states	Alabama, Arkansas, Colorado, Georgia, Iowa, Kentucky, Nebraska, Rhode Island. South Dakota, Tennessee, Virginia, Washington, & West Virginia
Above 94%	Efficient states	Arizona, District of Columbia, Florida, Idaho, Indiana, Michigan, Missouri, North Carolina, Oregon, South Carolina, Utah, & Wisconsin

NB: The classifications in the table are based on the following:

- *Inefficient states*: where a state‘s average value of estimated ‘underlying energy efficiency’ is lower than the median estimated ‘underlying energy efficiency’.
- *Moderately efficient states*: where a state‘s average value of estimated ‘underlying energy efficiency’ is between the median and upper quartile estimated ‘underlying energy efficiency’.
- *Efficient states*: where a state‘s average value of estimated ‘underlying energy efficiency’ is higher than the upper quartile estimated ‘underlying energy efficiency’.

Table 6: Classification of member states based on the MREM model.

Estimated 'Underlying Energy Efficiency'	Group	Member states
Below 90%	Inefficient states	California, Connecticut, Delaware. Illinois, Iowa, Kansas, Louisiana, Maine, Maryland, Massachusetts, Mississippi, Montana, New Hampshire, New Jersey, New Mexico, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, South Dakota, Texas, Vermont, & Wyoming
From 90% to 97%	Moderately efficient states	Alabama, Arkansas, Georgia, Kentucky, Minnesota, Missouri, Nebraska, Nevada, Rhode Island, Tennessee, Virginia, Washington, & Wisconsin
Above 97%	Efficient states	Arizona, Colorado, District of Columbia, Florida, Idaho, Indiana, Michigan, North Carolina, Oregon, South Carolina, Utah, & West Virginia

NB: See notes to Table 5.

Table 7: Classification of member states based on Energy Intensity.

Energy Intensity	Group	Member states
Above 12523 Btu per 1982US$	States with relatively high levels of energy intensity	Alabama, Arizona, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Massachusetts, Missouri, Montana, Nevada, New Hampshire, New York, Ohio, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, West Virginia, Wisconsin, & Wyoming
From 9540 to 12523 Btu per 1982US$	States with moderate levels of energy intensity	Colorado, Georgia, Indiana, Michigan, Minnesota, Mississippi, Nebraska, New Mexico, Oregon, Pennsylvania, Vermont, Virginia, & Washington
Below 9540 Btu per 1982US$	States with relatively low levels of energy intensity	Arkansas, California, Connecticut, Delaware, District of Columbia, Florida, Maine, Maryland, New Jersey, North Carolina, North Dakota, & Rhode Island

NB: The classifications in the table are based on the following:

- *Relatively high levels of energy intensity*: where a state's average level of energy intensity is higher than the median level of energy intensity.
- *Moderate levels of energy intensity efficient states*: where a state's average level of energy intensity is between the lower quartile and median level of energy intensity.
- *Relatively low levels of energy intensity*: where a state's average level of energy intensity is lower than the lower quartile of energy intensity.

For example, Kansas, Louisiana, Massachusetts, Montana, New Hampshire, Ohio, Oklahoma, Texas, and Wyoming are classified as being relatively inefficient states according to the estimated 'underlying energy efficiency' and are states with relatively high levels of energy intensity. An at the other end of the spectrum, the District of Columbia, Florida and North Carolina are classified as being relatively efficient states according to the estimated 'underlying energy efficiency' and are states with relatively low levels of energy intensity measure.

However, California, Connecticut, Delaware, Maine, New Jersey and North Dakota are classified as being relatively inefficient states according to the estimated 'underlying energy efficiency' and are states but are states with relatively low high levels of energy intensity. And Arizona, Idaho, South Carolina, and Utah are classified as being relatively efficient states according to the estimated 'underlying energy efficiency' and are states but are states with relatively low levels of energy intensity.

5. Summary and Conclusion

Building on Filippini and Hunt (2011 and 2012) this research attempts to define and estimate the 'underlying energy efficiency' for 49 US states by combining energy demand modelling and frontier analysis. The energy demand specification controls for income, price, population, the number of houses, heating degree days, cooling degree days, the area, the share of the industrial sector, the share of the service sector and an underlying energy demand trend and is estimated using the MPM and the MREM. These two models are seen as the most appropriate techniques for attempting to uncover the 'true' energy efficiency of the 49 states. Despite some limitations, the MPM and the MREM are seen as superior to the range of other techniques available, and moreover they avoid the problem of unobserved heterogeneity – thus arguably giving robust estimates of each state's 'underlying energy efficiency'.

The estimates show that for some states the simple measure of energy intensity might give a reasonable indication of a state's relative energy efficiency (such as Florida, Kansas Louisiana, and North Carolina) but this is not so for others states (such as Arizona California, Connecticut, and South Carolina). 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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