CER-ETH – Center of Economic Research at ETH Zurich

Transient and Persistent Energy Efficiency in the US Residential Sector: Evidence from Household-level Data

A. Alberini and M. Filippini

Working Paper 15/220
September 2015

Economics Working Paper Series

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Transient and Persistent Energy Efficiency in the US Residential Sector: Evidence from Household-level Data

Anna **Alberini** and Massimo **Filippini**

Department of Agricultural Economics, University of Maryland,
and
Centre for Energy Policy and Economics (CEPE), ETH Zurich

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

Last revision: 02.09.2015

Abstract

In this paper, we measure the energy efficiency in residential energy consumption using a panel dataset comprised of 40,246 observations from US households observed over 1997-2009. We fit a stochastic frontier model of the minimum input of energy needed to meet the level of energy services demanded by the household. This benchmarking exercise produces a transient and a persistent efficiency index for each household and each time period.

We estimate that the US residential sector could save approximately 10% of its total energy consumption if it reduced persistent inefficiencies and 17% if it was able to eliminate transient inefficiencies. These figures are in line with the assessment by McKinsey (2008, 2009, 2013) and greater than those indicated by the Electric Power Research Institute (2009). They suggest that savings in energy use and associated emissions of greenhouse gases (and other pollutants) may benefit from both policy measures that attain short-run behavioral changes (e.g., nudges, social norms, display of real-time information about usage, and real-time pricing) as well measures aimed at the long run, such as energy-efficiency regulations, incentives on the purchase of high-efficiency equipment and incentives towards a change of habits in the use of the equipment.

JEL Classification: D, D2, Q, Q4, Q5.
Keywords: US residential energy demand; efficiency and frontier analysis; Household data; CO2 emissions reductions.

1. Introduction

Government statistics indicate that in the US a household living in a single-family home uses on average about 90 million Btu each year for space and water heating, air conditioning, refrigerators and other appliances, and other energy services. The average household living in a single-family home generates about 12 tons of carbon dioxide a year (EIA 2012).

This is because more than 80% of the energy end-use consumption comes from fossil fuels. The residential sector is producing more than 20% of the total annual U.S. carbon dioxide emissions. It is widely believed that improving energy efficiency in US homes may yield significant reductions in CO_2 emissions.[1]

One important question is just how large the potential of energy saving in the residential sector is. Electric Power Research Institute (2009) surveys several earlier studies, which indicate that the attainable potential energy savings range between 7 and 21%. McKinsey (2009, 2013) estimates the potential energy savings to be approximately 20-30%. All of these studies use an economic-engineering approach based on bottom-up models.

Such promising energy-saving and emissions-reducing potentials have called attention to the important task of assessing each building or housing unit's *current* energy efficiency level. In the US, for example, the Energy Efficiency Improvement Act of 2015 requires that model leasing provisions be developed and published to encourage building owners and tenants to use greater cost-effective energy efficiency measures in commercial buildings, and spurs the benchmarking of energy usage in commercial buildings.[2] In the residential sector, schemes are available to get new homes EPA Energy-Star certified and to offer low-cost or free energy audits to old and new homes. While these are voluntary undertakings, New York City's Local Law 84 mandates that

[1] See, for example, President Obama's strategy at https://www.whitehouse.gov/the-press-office/2015/08/03/fact-sheet-president-obama-announce-historic-carbon-pollution-standards (last accessed 31 August 2015).
[2] The Act also requires the General Services Administration (GSA, a federal agency) to develop policies and practices to implement the measures for the realty services provided by GSA to other government agencies.

the owners of specific buildings, including large residential buildings, report their annual energy usage figures, which are then posted as weather-normalized BTUs per square foot, along with CO_2 emissions and Energy Star score.[3]

In many European countries, benchmarking is routine even for homes and follows government-prescribed protocols. In the UK government's Standard Assessment Procedure and the Irish Building Energy Rating, typical outputs include estimates of energy and CO_2 emissions per square meter, and fuel-cost based energy ratings. These are subsequently used to assign the appropriate energy label to each home, which is mandatory for real estate transactions. Assessments are based on engineering calculations where the typical inputs are home size, structure, types of fuels, and presence and characteristics of insulation, and standard assumptions are made in terms of appliance usage rates, family size and composition, etc. so that the efficiency ratings are independent of the home's current occupants and their usage patterns.[4]

There are obvious limitations to these assessments. For starters, they do not take behaviors into account. Second, they compute a home's energy *intensity*, and the ranking of units or structures may change considerably when one accounts for the vintage of the structure, the activities that take place in it, the size and composition of the household and the energy-using capital stock in the home.[5]

In this paper we circumvent these limitations by measuring the level of efficiency in the use of energy using an approach based on microeconomic production theory and on estimating an energy demand stochastic frontier

---

[3] See http://www.nyc.gov/html/gbee/html/plan/ll84_scores.shtml (last accessed 27 August 2015).

[4] See https://www.gov.uk/guidance/standard-assessment-procedure and http://www.seai.ie/Your_Building/BER/BER_Assessors/Technical/DEAP/ (last accessed 27 August 2015).

[5] Filippini and Hunt (2012), for example, note that the ranking of countries in terms of energy intensity of GDP changes dramatically once a proper estimate of energy efficiency is obtained that takes into account the composition of economic activities within the country's economy and other factors.

function. This frontier represents the minimum energy input required to meet the desired demand for energy services on the part of households (see Filippini and Hunt, 2015b).

Stochastic frontiers are often used to study the productivity of private firms, utilities and government agencies (Fried et. al., 2008), but have rarely been applied to end users in the residential sector. Some recent studies analyze the level of energy efficiency for the whole economy, while others analyze the energy efficiency for the residential sector.[6] The majority of these studies use aggregate data. Filippini and Hunt (2011) estimate a stochastic energy demand frontier function for the entire country with an unbalanced panel of 29 OECD countries from 1978 to 2006. Zhou et al. (2012) fit a Shephard energy distance function using stochastic frontier analysis and cross-section data for 21 OECD countries for 2001. Lin and Du (2013) employ the Shephard energy distance approach to examine the efficient use of energy across China's 30 administrative regions over 1997-2010.

We are aware of only three studies that measure the energy efficiency in the residential sector using stochastic frontier methods. Two use aggregate data at the state level (Filippini and Hunt, 2012) or by country (Filippini et al., 2014), and one uses data at the household level (Weyman-Jones et al., 2015, which is based on 3500 households in Portugal). The latter is closely related to our paper, but differs from it in that it i) uses a parsimonious model with only two explanatory variables, income and household size; ii) treats electric heating and electric water heating as determinants of the level of electric efficiency, and iii) is based on a cross section, and as such it is unable to

[6] Earlier empirical work has used stochastic frontiers for other sectors and the whole economy. For instance, Buck and Young (2007) use a stochastic frontier model to estimate the level of energy efficiency of a sample of Canadian commercial buildings, whereas Filippini and Hunt (2011) focuse on the economy-wide level of energy efficiency of OECD countries. Zhou et al. (2012) estimate a stochastic frontier model using an energy distance function for 21 OECD countries using 2001 data. Boyd (2008) estimates an energy input distance function using data on the energy consumption of 37 firms fron 1992 to 1997. Zhou and Ang (2008) use DEA, a nonparametric approach to examine the energy efficiency performance of 21 OECD countries over 5 years (1997-2001). Wei et al. (2009) use DEA and panel data to estimate the level of energy efficiency of Chinese provinces.

address unobserved heterogeneity. None of these three studies makes the distinction recently introduced by Tsionas and Kumbhakar (2012) between persistent and transient efficiency.

The main goal of this paper is to advance the state of the art by measuring the level of persistent and transient energy efficiency in US households. We estimate an energy input demand frontier function at the household level to isolate energy efficiency. We use a large panel dataset at the household level, and explicitly control for income and energy price, household size, weather, regional effects, and a common "Underlying Energy Demand Trend" (UEDT), that captures both exogenous technical progress and other exogenous factors. We use the estimation results to compute the potential decrease in CO2 emissions associated with an improvement in the level of energy efficiency in the US residential sector.

This paper contributes to the literature in three ways. First, we present the first empirical analysis of the level of energy efficiency of the US residential sector using household-level data, a large panel dataset, a stochastic frontier model and a rich specification. The stochastic frontier approach allows us to control for dwelling and household characteristics, taking us a step further than the mere energy intensity of a dwelling. The frontier is estimated with actual consumption of electricity and natural gas—not engineering-imputed quantities—and thus reflects the structure as well as the behaviors of the occupants.

Second, we use a novel econometric approach by Filippini and Greene (2015), which decomposes the level of energy efficiency into a transient and a persistent part. Third, we provide an assessment of the potential energy and CO2 savings in the US residential sector attributable to improving energy efficiency using a completely different approach than earlier studies.

Briefly, we find that the energy efficiency of US homes could be improved by up to 17% if it was able to remove transient inefficiencies and 10% if it was able to remove permanent inefficiencies. These findings emphasize the importance and potential of policies aimed at short-run behavioral changes (nudges, social norms, information, real-time pricing, etc.) as well as measures designed for the long-run, such as energy efficiency regulations and incentives towards capital and equipment replacement.

The remainder of the paper is organized as follows. Section 2 presents the residential energy demand model. The data and the different econometric specifications are introduced in Section 3. The econometric results, the estimated level of energy efficiency and the CO2 potential reductions are presented in Section 4. Section 5 concludes.

2. A Model of Energy Demand

People do not demand energy per se: Rather, they demand energy services such as a warm home, cooked food, hot water, lighting, etc., and the demand for energy is simply a derived demand. Within a basic household production model, households purchase inputs on the market such as energy and capital (appliances, electronics, light bulbs, heating and cooling systems) to produce energy services, which appear as arguments in the household's utility function (Flaig, 1990; Filippini and Pachauri, 2004; and Alberini and Filippini, 2011).[7]

Within this theoretical framework, it is possible to derive the optimal input demand functions for energy and capital (Flaig, 1990 and Alberini and Filippini, 2011). Conventional theory assumes perfect knowledge of technical relationships and prices, and results in a situation characterized by overall productive efficiency (Farrell, 1957) in the production of energy services. In practice, however, inefficiencies in the use of the inputs, i.e. combinations of inputs that do not minimize costs, are likely.

Filippini and Hunt (2011) propose a non-radial input specific measure of efficiency in the use of energy based on the difference between the optimal

[7] Approximately 40% of the energy used in a household is for washing, cooking and lighting, whereas space heating, water heating and air conditioning account for 60%.

use of energy (E^*, that which minimizes input costs) and the observed use of energy.[8] In this paper we follow this approach and estimate a measure of efficiency in the use of energy based on the estimation of a single conditional input demand frontier function, i.e., the demand function for energy.[9] This function shows the minimum amount of energy that is necessary to produce a given level of output (energy services), given the technology, input prices and other factors.

In our empirical work, which uses micro-level data from US households, we posit the following household energy demand function:

$$E = \mathrm{f}\,(PE, PC, Y, W, X, T, EF) \qquad (1)$$

where E is household energy consumption, PE is the price of energy (in dollars per thousand BTU), PC is the price of capital (i.e., the price of appliances and/or heating and cooling equipment), Y is income, W is weather, X is a vector of house and household characteristics thought to influence the energy services demanded by a household, and T is a vector of time dummies.

In practice, we are forced to leave PC, the price of energy-using capital, out of equation (1). We assume that the price of equipment is roughly the same across the US, except for the state sales tax, which is captured into the state or city dummies (see below).

Vector X includes the square footage of the dwelling, the number of rooms, household size, and the age of the home. It also includes $GAS\text{-}HEAT_{it}$, a dummy for a natural gas heating system, $GAS\text{-}HEW_{it}$, a dummy for gas water

[8] As discussed in more detail in Filippini and Hunt (2015), there are three approaches that can be used to estimate the level of efficiency in the use of energy, namely the input requirement function, the sub-vector input distance function and the energy demand frontier function. All these approaches are based on a non-radial notion of efficiency measure first devised in Kopp (1981).

[9] In theory, it would be more appropriate to estimate a *system* of input demand functions. In practice, however, we do not have detailed information on the stock of appliances, and heating and cooling systems, or the breakdown of energy use by type of equipment, in our dataset.

heating, and $GAS\text{-}DRY_{it}$, a dummy for gas clothes dryer. Air conditioning is an important driver of electricity demand, and we capture it using two dummies—one for window-unit AC ($AC-ROOM_{it}$), and one for central AC ($AC-CENTRAL_{it}$). Dummy indicators for the number of floors (DFL_1 , DFL_2 , DFL_3), and the metropolitan area ($DCITY_j$) are also included.

Equation (1) indicates that energy use depends on *EF,* the unobserved level of energy efficiency of the household. A low level of energy efficiency implies an inefficient use of energy ("wasted energy," as discussed in Filippini and Hunt, 2015b). EF is not directly observed. It is estimated as a regression residual, and distributional assumptions about the error terms in the stochastic frontier regression model are usually required for EF to be identified from the data.

We estimate EF using the stochastic frontier function approach (SFA) by Aigner et al. (1977). In our application, the energy input demand frontier function reflects the minimum level of input used by a household for any given level of energy services; hence, the difference between the observed energy and the cost-minimizing energy demand represents productive inefficiency, which implies the presence of both technical as well as allocative inefficiency.[10] As discussed by Schmidt and Lovell (1979) and Filippini and Hunt (2011), the sign of the allocative efficiency in an input demand function can be positive or negative. In other words, it is possible to observe the under- or over-use of an input. Which situation dominates in attaining a cost-minimizing input combination (reduction of energy and increase of other inputs, or increase of energy and reduction of other inputs) is an empirical question. However, it is generally assumed that households tend to overuse, rather than underuse, energy.

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

The classical SFA approach proposed by Aigner et al. (1977) is based on the assumption that the level of inefficiency in the use of energy efficiency can be approximated by a one-sided non-negative term. We recast equation (1) using a log-log functional form and panel data:

$$\ln E_{it} = \alpha + \alpha_p \ln PE_{it} + \alpha_C \ln PC_{it} + \alpha_Y \ln Y_{it} + \alpha_W \ln HDDCDD_{it} + \mathbf{x}_{it}\boldsymbol{\beta} + \mathbf{T}_t\boldsymbol{\gamma} + (v_{it} + u_{it}) \qquad (2)$$

where HDDCDD is the sum of the heating and cooling degree days in the 12 months prior to the date of the survey and the other variables are as before.

The error term in Equation (2) is comprised of two independent components. The first component, v_{it}, is a symmetric disturbance capturing "noise" and, as usual, is assumed to be normally distributed. The second part, u_{it}, is interpreted as an indicator of the inefficient use of energy ("waste energy").[11] It is a one-sided non-negative random disturbance term that can vary over time and is assumed to follow a half-normal distribution.[12]

In equation (2) we are assuming that the level of efficiency in the use of energy varies over time and is comprised of just one element. However, with panel data it is possible to think of input-specific efficiency as comprised of two parts—a persistent one and a transient one (Tsionas and Kumbhakar, 2012, and Filippini and Greene, 2015). The persistent part is related to the presence of structural problems in the production of energy services or systematic behavioral failures in minimizing costs for any given level of energy consumption. The transient part may be due to the presence of non-systematic minimization problems that can be solved in the short term.

[11] This indicator provides the level of inefficiency in the use of energy and varies from 0% to infinity. From this indicator it is also possible to compute an indicator of the level of efficiency in the use of energy, the energy efficiency, which varies from 0 to 100%.

[12] It is sometimes argued that imposing a distribution is a strong assumption for *EF*, but it does allow the identification of the efficiency for each household separately. The half-normal distribution is standard in the production frontier literature. Alternative distributions are the truncated normal or the gamma distribution. See Kumbhakar and Lovell (2000, p. 148) for a discussion.

In the next section we explain how we specify and estimate variants of the basic stochastic frontier model by Aigner et al. (1977) using panel data. Some of these models include only a time-varying (transient) part. Others include only a time-invariant (persistent) indicator of energy efficiency, and others yet contain both.

3. Data and the Econometric Specification

A. The Data

Our data come from the American Housing Survey, which has been conducted by the Department of Housing and Urban Development at regular intervals since the 1970s. The American Housing Survey (AHS) is a longitudinal study that follows dwellings (not households). New homes are added to the sample or terminated to mirror new construction and demolitions.

The AHS gathers information about the structural characteristics of the dwelling, the occupants' tenure status, the price paid for the home (or the rent amount), maintenance costs and fees, utility and energy bills, renovations done to the home in the last two years, mortgage and insurance, sociodemographics of the occupants, and subjective perceptions of the quality of the home and the neighborhood. The AHS is comprised of the national survey, which takes place every two years and is a longitudinal study, and the metro surveys, where cross-sectional samples of homes are drawn from selected cities.

The public-use version of the AHS provides city identification only if the home is located in a metropolitan area with population 100,000 or more. As in Alberini et al. (2011), we selected these observations from the 1997, 1999, 2001, 2003, 2005, 2007, and 2009 waves,[13] matched them with electricity and gas prices measured at the city level in each year, and further merged with the heating degree days and the cooling degree days in that metro area in the 12 months prior to the date of the survey. Attention is restricted to homes that i) were present in the AHS for two or more years, and ii) are in buildings with no

[13] These were all national surveys.

more than two dwelling units.[14] Our final sample is comprised of 40,246 observations. Descriptive statistics of the key variables are presented in Table 1.

Table 1. Definition of Variables and Descriptive Statistics. N=40246

Variable	**Label**	**Mean**	**Std. Dev.**
Energy demand, thousand BTU	E	9276127.3	5356257
Price of energy per thousand BTU (2009 dollars)	P	.017527	.007326
Income of the households in (thou. 2009 dollars)	Y	88018.52	93523.38
heating degree days (base: 65° F)	HDD	3461.954	2235.537
Cooling degree days (base: 65° F)	CDD	1603.495	1245.866
Household size	SIZE	1855.	1109.512
Number of rooms	ROOMS	6.386647	1.704164
Number of people	PERS	2.857923	1.553322
Age of the home	AGEH	42.12394	21.789
Floor 1	DFL1	.47324	.49929
Floor 2	DFL2	.308055	.461695
Floor 3	DFL3	.195398	.396512
Gas heat	GAS-HEAT	.749441	.43334
Room air condition	ROOMAC	.194032	.395458
Central air condition	CENTRALAC	.672116	.469448

B. Specification of the Stochastic Frontier Model

In this paper, we employ three alternative stochastic frontier models for panel data. The first is the basic version of the random effects model by Pitt and Lee (1981) (REM hereafter), the second is the so-called true random effects model (TREM hereafter) proposed by Greene (2005a, 2005b) and the third is the generalized true random effects model (GTREM) (Colombi et al., 2014, and

[14] This includes single-family homes, and duplexes/townhomes with at most two dwelling units. As of 2009, these structures accounted for 71.3% of the total dwelling units in the United States (see http://www.census.gov/compendia/statab/2012/tables/12s0989.pdf, last accessed 27August 2015).

Filippini and Greene, 2015). As explained in table 2, these specifications differ from one another for the components subsumed into the error term in (2).

The Pitt and Lee REM interprets the individual random effects as inefficiency rather than unobserved heterogeneity as in the traditional literature on panel data models. This model provides information on the persistent part of the inefficiency in the use of energy. One issue with the REM is that any time-invariant group-specific unobserved heterogeneity is considered inefficiency. As a result, this model tends to underestimate the level of persistent efficiency in the use of energy.

The second model used in this empirical analysis is the TREM by Greene (2005a and 2005b). This model extends the SFA model in its original form (Aigner, et al., 1977) by adding an individual random effect in the model. With the TREM the constant term, α, in equation (2), is replaced with a series of household-specific random effects. This model has the advantage that it controls for unobserved heterogeneity that is constant over time. However, any time-invariant component of inefficiency is completely absorbed in the household-specific constant terms. Therefore, the TREM tends to underestimate the level of inefficiency. Generally, the TREM provide information on the time-varying part of the inefficiency.

The third model, the GTREM, offers the possibility to estimate at the same time the persistent and transient part of inefficiency. Colombi et al. (2014) provide a theoretical construct that distinguishes between persistent and transient inefficiency. Filippini and Greene (2015) develop a straightforward empirical estimation method for the GTREM.

As shown in table 2, the GTREM is obtained by adding to the TRE model a time persistent inefficiency component in the time varying stochastic frontier. Therefore, this model includes a four-part disturbance with two-time varying components and two time-invariant components. One of these components captures the persistent inefficiency in the use of energy that may be due to regulation, investments in inefficient appliances or buildings or habits that tend to waste energy. The other component captures the transientinefficiency that may be due to behavioral aspects or non-optimal use of some electrical appliances or heating systems. In the short run, even in the presence of some inflexibilities, a household may be able to adjust the use of appliances and heating systems.

Table 2: Econometric specifications of the stochastic cost frontier: Effects, Error Term and Inefficiency

	Model I REM	*Model II* TREM	*Model III* GTREM
household effects α_i	α	$N(\alpha, \sigma_w^2)$	$N(\alpha, \sigma_w^2)$
Full random error ε_{it}	$\varepsilon_{it} = u_i + v_{it}$ $u_i \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = w_i + u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_v^2)$ $w_{it} \sim N(0, \sigma_w^2)$	$\varepsilon_{it} = w_i + h_i + u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $h_i \sim N^+(0, \sigma_h^2)$ $v_{it} \sim N(0, \sigma_v^2)$ $w_i \sim N(0, \sigma_w^2)$
Persistent Inefficiency Estimator	$E(u_i \mid \varepsilon_{i1}, \ldots \varepsilon_{iT})$	None	$E(h_i \mid \mid \varepsilon_{it})$
Transient Inefficiency Estimator	None	$E(u_{it} \mid \varepsilon_{it})$	$E(u_{it} \mid \mid \varepsilon_{it})$

After Equation (2) is estimated using one of these three approaches, it is possible to calculate the level of energy efficiency. For the REM and TREM we compute the energy efficiency indicator as shown in Jondrow et al. (1982), whereas for the GTREM we use the approach suggested by Filippini and Greene (2015) and based on Colombi (2010). [15]

The level of energy efficiency is:

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

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

4. Results

Table 3 displays the regression results for the three frontier models. The majority of the estimated coefficients and *lambda*[16] have the expected signs and are statistically significant at the 1% level. Further, the magnitude of the coefficients is remarkably similar across all models.

All models show a similar and relatively high price elasticity, and low income elasticity.[17] Alberini et. al. (2011) found similar results. The low income elasticity of demand is likely due to the fact that in the model we are controlling for several variables related to income such as size of the home, the number of rooms and the presence of specific appliances. All of these coefficients are positive and strongly significant. As to the weather variables, the estimated heating and cooling degree day elasticity has the expected positive sign and is significant at the conventional levels. The coefficients on the presence of gas heating, a water heater or a dryer are likewise positive and significant.

---

[15] All these measures are based on the conditional mean of the efficiency term. See also Greene (2002).

[16] Lambda (λ) is the ratio of the standard deviation of the inefficiency term to the standard deviation of the stochastic term and gives information on the relative contribution of u_{it} and v_{it} on the decomposed error term ε_{it}. In this case, it shows that the one-sided error component is relatively large.

[17] Given the use of a log-log functional form, most of the coefficients are elasticities.

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

	REM	TREM	GTREM
Constant	9.921*** (67.84)	10.054 *** (82.19)	9.365 *** (64.48)
LNPEN	-.587*** (-70.24)	-.582 *** (-78.19)	-.553 *** (-60.70)
LNY	.018*** (9.70)	.018 *** (11.42)	.042 *** (22.55)
LNHDDCDD	.152*** (8.65)	.165 *** (11.25)	.212 *** (12.21)
LNSIZE	.020*** (9.86)	.019 *** (14.53)	.019 *** (12.58)
LNROOMS	.440 *** (51.87)	.435 *** (63.74)	.533 *** (67.07)
LNPERS	.146 *** (39.69)	.140 *** (47.48)	.085 *** (24.40)
LHOUSEAGE	.040 *** (11.20)	.004 *** (15.87)	.052 *** (17.68)
GAS_HEAT	.122 *** (14.98)	.113 *** (17.68)	.111 *** (14.74)
ROOMAC	.040 *** (6.93)	.041 *** (8.42)	.041 *** (6.94)
CENTRALA	.084 *** (13.43)	.083 *** (16.91)	.098 *** (17.04)
GAS_HW1	.0821 *** (9.76)	.077 *** (12.08)	.065 *** (8.53)
GAS_DRYE	.029 *** (5.57)	.024 *** (5.93)	.013 *** (2.62)
DFL1	-.028 * (-1.78)	-.0458 *** (-3.95)	-.043 (-3.14)
DFL2	-.024 * (-1.60)	-.032 *** (-2.83)	-.005 (-0.42)
DFL3	.008 (.52)	.002 (.17)	.021 (1.56)
Time dummies	YES	YES	YES
City fixed effects	YES	YES	YES
Lambda	1.142 (0.017)	.768 (0.038)	.811 (0.046)
σ (variance of $u_{it}+v_{it}$)	0.377 *** (0.005)	0.374 *** (0.004)	0.435 *** (0.005)
σ_w		0.229 *** (0.001)	0.193 *** (0.002)
σ_h	-	-	0.163 *** (0.007)
Log Likelihood	- 17616.8	-17523.9	-18225.5

The time dummies are jointly significant and suggestive of an overall declining trend. The coefficients on the year dummies are not monotonic, implying that the combined impact of technical progress and other exogenous variables is non-linear. Moreover, the coefficients on the last two years of data are positive and offset the negative coefficients of the previous years.

Table 4 provides descriptive statistics for the energy efficiency levels for the 40426 households in our sample based on equation (3). It shows that with the REM model the estimated mean and median energy efficiency are 75% and 77%, respectively, whereas in the TREM these values are around 84%. We remind the reader that the REM provides information on the persistent level of inefficiency, whereas the TREM provides information on the transient part of efficiency.[18]

Table 4: Energy efficiency scores

	REM	**TREM**	**GTREM Persistent**	**GTREM Transient**
Min	.29	.447	.801	.433
Max	.977	.945	.942	.931
Mean	.750	.837	.897	.824
Median	.77	.841	.898	.829

Our preferred model is the GTREM because it estimates persistent as well as transient energy efficiency. The estimated mean and median values of persistent energy efficiency from this model are approximately 90%, whereas the estimated mean and median values of the transient part are around 83%. These values are higher than their counterparts from the REM and the TREM models, and highly correlated with them. The coefficient of correlation between the individual household GTREM persistent components and the individual REM efficiencies is 0.93; that between the individual household GTREM

[18] The REM does not prevent households from using less energy by adopting new technologies over time. This possibility is captured by the UEDT in the form of year dummies. Most of these year dummies have negative coefficients.

transient portions and the individual TREM efficiency is 0.98. Despite the different approaches and nature of the data, the average GTREM components are remarkably close to those in Filippini and Hunt (2015a), who estimate a residential energy demand stochastic frontier using state-level data from the US and report median values of the persistent level of energy efficiency between 0.85 and 0.90.

This and the other results reported in table 4 indicate that the US residential sector could save roughly 10% of its energy usage by correcting systematic inefficiencies and 17% if it was able to eliminate transient inefficiencies. It is interesting to note that these values in line with the assessment by McKinsey (2008), although they were derived in a completely different fashion, and that households appear to be attaining lower levels of efficiency in their day-to-day, short-run unsystematic behaviors, rather than in their systematic use of equipment.

Table 5. CO2 emissions reductions associated with energy efficiency improvements.

	avg CO2 emissions reductions per household (kg/year)	avg CO2-equivalent emissions reductions per household (kg/year)	avg non-baseload CO2 emissions reductions per household (kg/year)
Pitt Lee REM			
5% improvement	398.33	400.16	583.8
10% improvement	739.89	743.26	1000.47
15% improvement	1018.92	1023.56	1377.84
TREM			
5% improvement	346.12	347.7	466.92
10% improvement	653.93	656.91	881.97
15% improvement	899.53	903.64	1212.91
GTREM (persistent component)			
5% improvement	319.65	321.11	430.73
10% improvement	595.61	598.33	802.75
15% improvement	637.7	640.61	861.88
GTREM (transient component)			
5% improvement	350.95	352.55	473.28
10% improvement	663.17	666.2	894.26
15% improvement	929.63	933.88	1253.05

Table 5 summarizes our calculations of the CO2 emissions reductions that would be realized assuming improvements in energy efficiency of 5, 10, and 15 percentage points, respectively, and using the different measures of efficiency.[19] We use state-specific greenhouse-gas emissions rates associated with electricity generation from the US EPA's eGRID, focusing on average CO2 emissions rates, average CO2-equivalent emissions rates, and CO2 emissions rates for non-baseload generation, which at most (but not all) locales are higher than the average CO2 emissions rates because the fuel of choice of peakload generation is usually natural gas (which has higher emissions rates than nuclear, hydro, and renewables).[20] All figures can be scaled up the US economy through multiplying them by 129,950,000, the number of dwelling units in building with no more than 2 dwelling units in 2009.

5. Conclusions

We estimate the residential energy efficiency for a sample of US households using an energy demand frontier function. We apply three alternate specifications that differ in the components the error term is broken into, and hence in whether they allow for transient and permanent parts of the (in)efficiency. All models control for income, price, heating degree days, cooling degree days and other socioeconomic variables.

The three approaches—namely REM, TREM and GTREM—yield similar assessments of the current level of residential energy consumption in the sample. The mean and median values of the individual estimates of the energy

[19] For example, an improvement of 5 percentage points would bring a household from, say, 0.75 to 0.80. When the energy efficiency improvement being considered would bring a household over 100% efficiency, we set it to 100%. We ignore any rebound effect associated with energy efficiency improvements. Our calculation assume that the energy efficiency improvements are attained only in the use of electricity.

[20] The eGRID documentation recommends using non-baseload emissions rates for calculations related to energy efficiency improvements. See http://www.epa.gov/cleanenergy/energy-resources/egrid/ (last accessed 27 August 2015).

efficiency are similar, and suggest that there is considerable potential for saving energy and thus the associated CO2 emissions. The broadest of the three models we use (GTREM) actually suggests that the permanent component of the efficiency—which we may think of as associated with systematic equipment use and behaviors—is higher than the transient component. The former averages 90% in our sample, while the latter averages about 83%. Our calculations based on the CO2 and other greenhouse-gas emissions rates from electricity generation reported in the EPA's eGRID show that even modest improvements in energy efficiency with respect to the 2009 baseline can significantly reduce energy use and CO2 emissions. This is especially true for the transient part of inefficiency.

These findings have important implications in terms of policy. Policy measures based on nudges, social norms (Allcott, 2011; Allcott and Rogers, 2014), new information devices (Gans et al., 2013; Jessoe and Rapson, 2014) or information campaigns may attain improvements in the level of transient efficiency in the use of energy. By contrast, improvements in the levels of persistent efficiency would be typically sought through energy efficiency regulations on homes and equipment, incentives promoting a change of habits in the use of equipment, and/or by offering incentives on the purchase of new, high-efficiency equipment (Alberini et al., 2015; Alberini and Towe, 2015) and structures, and/or by introducing. Our results underscore the promise of well-conceived policies aimed at behaviors.

References

Aigner, D. L., Lovell, C. K., and Schmidt, P. (1977) 'Formulation and estimation of stochastic frontier production function models', ***Journal of Econometrics***, 6, 21–37.

Alberini, A., Gans W. , and Velez-Lopez D. (2011), 'Residential Consumption of Gas and Electricity in the U.S.: The Role of Prices and Income', *Energy Economics*, 33, 870-881.

Alberini, A. Towe C. and Gans W. (2014), "Energy Efficiency Incentives: Do They Work for Heating and Cooling Equipment? Evidence from Maryland Homeowners," ***The Energy Journal***, (forthcoming).

Alberini, A. and Towe C. (2015), "Information v. Energy Efficiency Incentives: Evidence from Residential Electricity Consumption in Maryland," ***Energy Economics,*** (forthcoming).

Allcott, H. (2011). 'Social Norms and Energy Conservation**.'** ***Journal of Public Economics***, 95, 1082-1095.

Allcott, H., and Rogers T. (2014). **'**The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation**.'** ***American Economic Review***, 104, 3003-3037.

Buck, J. and D. Young (2007) 'The Potential for Energy Efficiency Gains in the Canadian Commercial Building Sector: A Stochastic Frontier Study,' ***Energy - The International Journal***, **32**, 1769–1780.

Deaton, A. and Muellbauer, J. (1980), *Economics and consumer behavior* (Cambridge University Press).

Evans J. Filippini M. and Hunt L., The Contribution of Energy Efficiency towards meeting CO2 targets. In Fouquet, R. (2013) Handbook on Energy and Climate Change, Edward Elgar Publications. Cheltenham, UK, and Northampton, MA.

EPRI (Electric Power Research Institute, 2009), 'Assessment of Achievable Potential from Energy Efficiency and Demand Response Programs in the U.S. (2010-2030)'.

Farrell, M. J. (1957) 'The measurement of productive efficiency', ***Journal of the Royal Statistical Society***, 120, 253–281.

Flaig, G. (1990) 'Household Production and the Short-Run and Long-Run Demand for Electricity', ***Energy Economics*** 12, 116-121.

Filippini, M. (1999) 'Swiss residential demand for electricity', ***Applied Economic Letters,* 8**, 533–538

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

Filippini M. and L. C. Hunt (2012) 'US Residential Energy Demand and Energy Efficiency: A Stochastic Demand Frontier Approach', ***Energy Economics,* 34**, 1484–1491.

Filippini M. and L. C. Hunt (2015a) 'Measuring persistent and transient energy efficiency in the US**, Energy Efficiency,** (forthcoming).

Filippini M. and Hunt, L. C. (2015b) 'Measurement of Energy Efficiency Based on Economic Foundations', ***Energy Economics***, (forthcoming).

Filippini, M. and Greene, W. (2015) 'Persistent and Transient Productive Inefficiency: A Maximum Simulated Likelihood Approach', *Journal of Productivity Analysis (Forthcoming).*

Fried, H. O., C. A. K. Lovell, and S.S. Schmidt, eds., (2008), *The Measurement of Productive Efficiency. (*New York: Oxford University Press.

Gans W., Alberini A., and Alberto Longo (2013), "Smart Meter Devices and The Effect of Feedback on Residential Electricity Consumption: Evidence from a Natural Experiment in Northern Ireland," ***Energy Economics***, 36, 729-743

Greene, W. H. ,1990, *Econometric Analysis* (MacMillan Publishing Company).

Huntington, H G (1994) 'Been top down so long it looks like bottom up to me' ***Energy Policy*****,** **22**, 833–838.

Jessoe K. and Rapson D., 2014. 'Knowledge Is (Less) Power: Experimental Evidence from Residential Energy Use' ***American Economic Review***, 104, 1417-38.

Jondrow, J., Lovell, C. A. K., Materov, I. S., and Schmidt, P. (1982),'On the estimation of technical inefficiency in the stochastic frontier production function model' ***Journal of Econometrics***, 19, 233-238.

Kumbhakar S. C. and C. A. K. Lovell (2000) *Stochastic frontier analysis*, Cambridge: Cambridge University Press.

McKinsey & Company (2009), 'Unlocking Energy Efficiency in the U.S. Economy.'

McKinsey & Company (2013), 'Sizing the potential of behavioral energy-efficiency initiatives in the US residential market.'

Pitt, M. and L. Lee (1981) 'The measurement and sources of technical inefficiency in the Indonesian weaving industry', ***Journal of Development Economics***, **9**, 43–64.

Weyman-Jones T., Boucinha J.M. and Feteira Inácio C., "Measuring electric energy efficiency in Portuguese households: A tool for energy policy, ***Management of Environmental Quality: An International Journal***, 26, 407-422.

Wei, C., Ni, J., and Shen, M. (2009) 'Empirical analysis of provincial energy efficiency in China', ***China & World Economy***, 17, 88-103.

Zhou, P., B. W. Ang (2008) 'Linear programming models for measuring economy-wide energy efficiency Performance', ***Energy Policy,*** **36**, 2911– 2916.

Working Papers of the Center of Economic Research at ETH Zurich

(PDF-files of the Working Papers can be downloaded at www.cer.ethz.ch/research).

15/220 A. Alberini and M. Filippini
Transient and Persistent Energy Efficiency in the US Residential Sector: Evidence from Household-level Data

15/219 F. Noack, M.-C. Riekhof, and M. Quaas
Use Rights for Common Pool Resources and Economic Development

15/218 A. Vinogradova
Illegal Immigration, Deportation Policy, and the Optimal Timing of Return

15/217 L. Bretschger and A. Vinogradova
Equitable and effective climate policy: Integrating less developed countries into a global climate agreement

15/216 M. Filippini and L. C. Hunt
Measurement of Energy Efficiency Based on Economic Foundations

15/215 M. Alvarez-Mozos, R. van den Brink, G. van der Laan and O. Tejada
From Hierarchies to Levels: New Solutions for Games with Hierarchical Structure

15/214 H. Gersbach
Assessment Voting

15/213 V. Larocca
Financial Intermediation and Deposit Contracts: A Strategic View

15/212 H. Gersbach and H. Haller
Formal and Real Power in General Equilibrium

15/211 L. Bretschger and J. C. Mollet
Prices vs. equity in international climate policy: A broad perspective

15/210 M. Filippini and F. Heimsch
The regional impact of a CO2 tax on gasoline demand: a spatial econometric approach

15/209 H. Gersbach and K. Wickramage
Balanced Voting

15/208 A. Alberini and C. Towe
Information v. Energy Efficiency Incentives: Evidence from Residential Electricity Consumption in Maryland

14/207 A. Bommier
A Dual Approach to Ambiguity Aversion

14/206 H. Gersbach, U. Schetter and M. T. Schneider
Taxation, Innovation, and Entrepreneurship

14/205 A. Alberini and A. Bigano
How Effective Are Energy-Efficiency Incentive Programs? Evidence from Italian Homeowners

14/204 D. Harenberg and A. Ludwig
Social Security in an Analytically Tractable Overlapping Generations Model with Aggregate and Idiosyncratic Risk

14/203 A. Bommier, L. Bretschger and F. Le Grand
Existence of Equilibria in Exhaustible Resource Markets with Economies of Scale and Inventories

14/202 L. Bretschger and A. Vinogradova
Growth and Mitigation Policies with Uncertain Climate Damage

14/201 L. Bretschger and L. Zhang
Carbon policy in a high-growth economy: The case of China

14/200 N. Boogen, S. Datta and M. Filippini
Going beyond tradition: Estimating residential electricity demand using an appliance index and energy services

14/199 V. Britz and H. Gersbach
Experimentation in Democratic Mechanisms

14/198 M. Filippini and E. Tosetti
Stochastic Frontier Models for Long Panel Data Sets: Measurement of the Underlying Energy Efficiency for the OECD Countries

14/197 M. Filippini and W. Greene
Persistent and Transient Productive Inefficiency: A Maximum Simulated Likelihood Approach

14/196 V. Britz, P. J.-J. Herings and A. Predtetchinski
Equilibrium Delay and Non-existence of Equilibrium in Unanimity Bargaining Games

14/195 H. Gersbach, M. T. Schneider and O. Tejada
Coalition-Preclusion Contracts and Moderate Policies

14/194 A. Bommier
Mortality Decline, Impatience and Aggregate Wealth Accumulation with Risk-Sensitive Preferences

14/193 D. Harenberg and A. Ludwig
Social Security and the Interactions Between Aggregate and Idiosyncratic Risk

14/192 W. Mimra, A. Rasch and C. Waibel
Second Opinions in Markets for Expert Services: Experimental Evidence

14/191 G. Meunier and J-P. Nicolai
Higher Costs for Higher Profits: A General Assessment and an Application to Environmental Regulations

14/190 A. Alberini, M. Bareit and M. Filippini
Does the Swiss Car Market Reward Fuel Efficient Cars? Evidence from Hedonic Pricing Regressions, Matching and a Regression Discontinuity Design

14/189 J-P. Nicolai and J. Zamorano
"Windfall profits 2.0" during the third phase of the EU-ETS

13/188 S. Hector
Accounting for Different Uncertainties: Implications for Climate Investments

13/187 J-P. Nicolai
Delaying the pollution cap determination when firms invest?

13/186 C. Christin, J-P. Nicolai and J. Pouyet
Pollution Permits, Imperfect Competition and Abatement Technologies

13/185 L. Bretschger and S. Valente
International Resource Tax Policies Beyond Rent Extraction

13/184 L. Bretschger and C. Karydas
Optimum Growth and Carbon Policies with Lags in the Climate System

13/183 M. Filippini and L. Zhang
Measurement of the "Underlying energy efficiency" in Chinese provinces

13/182 J. G. Becker and H. Gersbach
A Theory of Threshold Contracts

13/181 M. Filippini and L. C. Hunt
'Underlying Energy Efficiency' in the US

13/180 O. Tejada
Complements and Substitutes in Generalized Multisided Assignment Economies

13/179 A. Rasch and C. Waibel
What drives fraud in a credence goods market? Evidence from a field study