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# Measuring Residential Energy Efficiency Improvements with DEA

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Abstract

This paper measures energy efficiency improvements of US single-family homes between 1997 and 2001 using a two-stage procedure. In the first stage, an indicator of energy efficiency is derived by means of Data Envelopment Analysis (DEA), and the analogy between the DEA estimator and traditional measures of energy efficiency is demonstrated. The second stage employs a bootstrapped truncated regression technique to decompose the variation in the obtained efficiency estimates into a climatic component and factors attributed to efficiency improvements. Results indicate a small but significant improvement of energy efficiency over the studied time interval, mainly accounted for by fuel oil and natural gas users.

JEL Classification: C14, C61, D13, Q4

Keywords: Energy efficiency, household production, data envelopment analysis, bootstrap

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# 1 Introduction

Two issues characterize the current debate on energy markets and policy. On the one hand, the large amount of climate gas emissions by both the world's rich and emerging economies threatens serious consequences for the climate (Stern 2007). On the other hand, today's industrialized world depends largely on a limited set of countries for their supply with fossil fuels (Frondel and Schmidt 2008). One possible avenue to reduce both the greenhouse effect and import dependencies on fossil fuels are improvements in the efficiency of the utilization of energy. It is quite reasonable to expect that the residential sector, in particular, can contribute substantially to such efficiency improvements. Not only do residents account for a large share of final energy consumption, but their homes are often equipped with out-of-date and energy-inefficient appliances. The improvement of residential energy efficiency is therefore one major goal of energy policy makers.

A necessary, albeit not completely resolved first step to develop and to monitor a successful policy strategy is the provision of adequate indicators of energy efficiency. Using improper data or even lacking the relevant data may lead to misinformed and poor policy decisions (IEA 2007:136). A number of approaches and concepts to measure energy efficiency have been suggested in the literature; see Ang (2006) for a recent review. The spectrum of candidate indicators ranges from the simple ratio of energy usage per capita to sophisticated composite index approaches. All of these suggestions have their strengths and weaknesses: While the first attempt provides only a rough approximation of efficiency trends, the latter approach measures efficiency on a very disaggregated level. However, such sophisticated indices raise the cost of extensive data requirements, as they require separate figures of energy intensities for each energy end-use. Especially in the residential sector, this prerequisite is rarely fulfilled. Usually, households know their total energy consumption at best, but cannot assess how much energy they have consumed for particular activities, such as preparing hot water.

To circumvent this difficulty, the analyst could either rely on engineering estimates, with the primary disadvantage that these estimates are based upon theoretical considerations rather than observed consumer behavior. Alternatively, the analyst can use exact but expensive metering, with the undesirable feature that due to the great cost the metered data would typically comprise only a limited number of observations. Other approaches combine survey data with regression techniques to extract the required efficiency indicators, but consider only one fuel at a time (Parti and Parti 1980, EIA 1999). Focusing merely on a specific fuel can hardly give a comprehensive picture about residential energy efficiency improvements, since a number of households use several fuels, e.g. natural gas for space heating and electricity for their appliances. The analytical discussion thus would still benefit from the development of a meaningful efficiency index that encompasses all household fuels and energy end-uses while avoiding extensive data requirements.

To offer a practical solution to this problem, this paper measures residential energy efficiency improvements for US single-family homes between 1997 and 2001 in two stages. In the first stage we derive an indicator of individual households' energy efficiency by means of *Data Envelopment Analysis* (DEA), an approach that is firmly anchored in production theory (see e.g. Seiford and Thrall 1990). The second stage decomposes the variation in the obtained efficiency estimates into climatic influences and factors that can be attributed to efficiency improvements.

One of the key advantages of the approach are its light data requirements. In contrast to the usual applied approaches to measure residential energy efficiency, DEA does not require separate energy intensity figures for each end-use. The efficiency indicator can even be calculated from survey data. To illustrate, we use household survey data, publicly available from the US Department of Energy.

Applications of DEA in the context of energy efficiency are sparse. Ferrier and Hirschberg (1992) employ DEA to estimate energy efficiency of US commercial buildings, Phylipsen et al. (1997, 1998) apply a comparable benchmarking procedure for the European cement industry, but neither of theses studies considers efficiency improvements. Just recently, Mukherjee (2008) uses DEA to estimate energy efficiency time trends in the US manufacturing sector. We are not aware of any study which estimates residential energy efficiency improvements with DEA.

The outline of the paper is as follows. In Section 2, we discuss the methodological aspects. Section 3 provides an overview of our data set. In Section 4, we discuss our results, while section 5 concludes.

# 2 Methodology

## 2.1 Measuring Energy Efficiency

Residential energy consumption derives from the demand for energy services, such as the demand for thermal comfort. Households 'produce' those services with their energy commodities (e.g. heating equipment) by using a set of fuel inputs. The standard approach to measure residential energy efficiency draws on the framework of Becker's (1965) home-production function. Along these lines, Wirl (1997) defines residential energy efficiency as the ratio between the amount of a particular produced service $s$ and the amount of energy $e$ consumed for the production:

$$\varphi := \frac{s}{e}. \tag{1}$$

To condense the individual-level information, $\varphi$ is usually computed for an average household, and an improvement of energy efficiency would result in an increase of the (average) $\varphi$.

Frequently, the literature uses the inverse measure $1/\varphi$ (often called energy intensity) to express efficiency tendencies for the particular service. For instance, Haas (1997), Schipper et al. (1985), and Schipper et al. (2001) all combine

$1/\varphi$ with non-efficiency related indices to explain changes in residential energy consumption for that service. The major drawback with such a procedure are its extensive data requirements, because separate figures of energy intensities for each produced service are required. This means that the researcher needs detailed information on how much energy is consumed for a wide range of home activities, e.g. for cooking meals. Such data are rarely available in the residential sector. A more desirable approach to measure efficiency improvements would encompass a sound theoretical justification with less onerous data requirements.

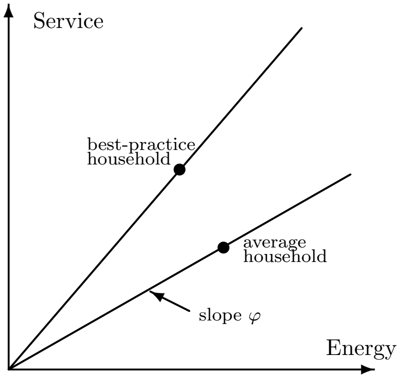
## 2.2 Energy Efficiency and DEA

Put simply, DEA can be considered as a generalization of the energy efficiency definition (1). Figure 1(a) illustrates the similarities between DEA and $\varphi$. Computed for the average household, $\varphi$ is the slope of the ray through the origin and the average household. In contrast, DEA computes a best-practice frontier, which is in the one-input one-output case the steepest ray through the origin that has support from at least one data point. The production plans of all households are bounded by the best-practice frontier, and are benchmarked against this frontier.

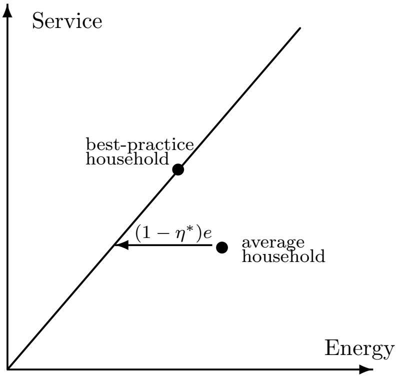
To formalize, let $\boldsymbol{s}_l = (s_{1l}, \ldots, s_{Jl})'$ be a vector of $j = 1, \ldots, J$ produced services $s_{jl}$ from household $l$ ($l = 1, \ldots, L$), and let $e_l$ be $l$'s total energy input.[1] Each household uses a positive amount of energy to produce at least one service. The following optimization problem suggested by Charness et al. (1978) resembles definition (1) of energy efficiency:

[1]For reasons that become clear later, we restrict our analysis to the case of only one input (energy) and multiple outputs (services), although DEA can easily deal with multiple inputs and outputs. See e.g. Seiford and Thrall (1990).

Figure 1: Benchmarking against the best-practice frontier




(a) Best-practice and average practice




(b) Conservation potential

(2a) $$\max_{\boldsymbol{u}_o\, v_o} \eta_o = \frac{\boldsymbol{u}_o'\boldsymbol{s}_o}{v_o e_o} = \frac{\sum_{j=1}^{J} u_{jo}s_{jo}}{v_o e_o} \qquad \text{subject to}$$

(2b) $$\frac{\sum_j u_{jo}s_{jl}}{v_o e_l} \leq 1 \quad l = 1, \ldots, L,$$

with weights, $\boldsymbol{u}_o = (u_{1o}, \ldots, u_{Jo})'$, $u_{jo} \geq 0$, and $v_o \geq 0$, assigned to the outputs and the input, respectively. Problem (2) must be solved for every household, while $o$ denotes the household currently under consideration. It is a ratio of weighted service output to weighted fuel input, subject to the condition that the similar ratio for each of the $L$ households is less than or equal to unity. Due to its weighting scheme, problem (2) can handle several services simultaneously, and a decomposition of total energy demand to derive service-specific energy intensities is not necessary. An important implicit assumption is that the underlying technology exhibits constant returns to scale.

Let $(\eta_o^*, \boldsymbol{u}_o^*, v_o^*)$ describe the optimal solution of problem (2) for household $o$. The product $\eta_o^* e_o$ is a measure of how much energy consumption is justified for the service production of household $o$ such that $o$ will become efficient. Thus,

$\eta_o^* = 1$ indicates a position on the (technically) efficient frontier, as depicted for the best-practice household in Figure 1(b). If $0 < \eta_o^* < 1$, household $o$ can reduce its energy consumption by $(1 - \eta_o^*)$ percent, or by $(1 - \eta_o^*)e_o$ units, without being forced to diminish the service level. The same amount of services may be maintained by improved efficiency. In Figure 1(b) the corresponding conservation potential is illustrated for the average household as the distance to the frontier.

By setting $\tilde{u}_{jo} = u_{jo}/v_o > 0, \tilde{\boldsymbol{u}}_o = (\tilde{u}_{1o}, \ldots, \tilde{u}_{Jo})'$, and $h_o = \eta_o e_o > 0$, we obtain a linear optimization problem in which the assigned weights have a sound interpretation (Dyson and Thanassoulis 1988):

$$\text{(3a)} \qquad \max_{\tilde{\boldsymbol{u}}_o} h_o = \tilde{\boldsymbol{u}}_o' \boldsymbol{s}_o = \sum_j \tilde{u}_{jo} s_{jo} \qquad \text{subject to}$$

$$\text{(3b)} \qquad \sum_j \tilde{u}_{jo} s_{jl} \leq e_l \quad l = 1, \ldots, L.$$

Similar to problem (2), the optimal value $h_o^* = \eta_o^* e_o$ is a measure of how much energy consumption is justified for the service production of household $o$. The weights $\tilde{u}_{jo}$ can be interpreted as the amount of energy consumed by household $o$ in the production of one unit of $s_j$, as it can be seen in (3b). For example, if service 1 stands for space heating (measured in square-meters, $m^2$) and energy consumption $e$ is expressed in kilowatthours (kWh), then $\tilde{u}_{1o}$ is measured in $kWh/m^2$. Loosely speaking, the vector $\tilde{\boldsymbol{u}}_o$ can be thought of as the vector of energy intensities from household $o$.

## 2.3 Decomposing Efficiency Variation

The individual efficiency indicator $\eta_l^* = h_l^*/e_l$ is derived subject to the household's realizations $(e_l, \boldsymbol{s}_l)$, while assuming that the underlying production possibility set is alike for every household. However, the variation in the vector of efficiency estimates $\boldsymbol{\eta}^* = (\eta_1^*, \ldots, \eta_l^*, \ldots, \eta_L^*)'$ might be at least in part due to favorable or unfavorable operating conditions of the individual household. For example, living in a climatic moderate zone lowers the demand for space heating and air-conditioning, and an affected household will typically exhibit a comparably low energy consumption, implying a rather high efficiency. Likewise, by comparing households across several years, those households having access to latest technology operate under a more favorable environment, since the latest technology usually requires less energy per unit service output. Improvements in $\boldsymbol{\eta}^*$ due to climatic reasons cannot be treated as energy efficiency improvements whereas the replacement of out-of-date equipment or enhanced dwelling insulations affects efficiency positively. To summarize, the efficiency estimates in $\boldsymbol{\eta}^*$ might differ systematically, because the individual operating environment constrains the household's choice of fuel inputs and service outputs, and hence its production possibility set.

Regression analysis enables us to decompose the efficiency variation in $\boldsymbol{\eta}^*$, while a set of explanatory variables $\boldsymbol{z}_l$ controls for the individual operating environment including climate. However, such a procedure is (in finite samples) associated with inference problems, basically caused by a complex correlation structure inherent in $\boldsymbol{\eta}^*$ (Simar and Wilson 2007). While $(e_l, \boldsymbol{s}_l, \boldsymbol{z}_l)$ are assumed to be realizations of $L$ independent sample observations, DEA estimates the technical efficient frontier by enveloping the data points $(e_l, \boldsymbol{s}_l)$ of the best-practice households. The efficiency indicators $\boldsymbol{\eta}^*$ are thus subject to the condition that these best-practice households belong to the sample, and therefore exhibits a complex and unknown correlation pattern, with $Cov(\eta_o^*, \eta_l^*) \neq 0$ for some households $o$ and $l$. In a regression equation this dependency in turn implies correlation among the regressions residuals. Fitting a regression model and ignoring this inherent dependency in the residuals gives incorrect standard errors for the coefficient estimates, and the usual test statistics are not applicable. As a consequence, we cannot infer with confidence as to whether $\boldsymbol{z}_l$ affects $\eta_l^*$.

To overcome this inference problem, we extent our regression analysis using a two-stage bootstrap procedure proposed by Simar and Wilson (2007). This procedure simulates the data-generating process yielding $(e_l, \boldsymbol{s}_l, \boldsymbol{z}_l)$, and encompasses the operating environment using truncated maximum likelihood regression. While $\eta_l^*$ is bounded from both sides ($0 < \eta_l^* \leq 1$), the bootstrap procedure is designed for a left-truncated efficiency indicator. We thus use the reciprocal $1/\eta_l^* \geq 1$ as dependent variable in a truncated regression with a truncation point at 1 to explain efficiency variation due to the individual operation environment:

$$1/\eta_l^* = \boldsymbol{z}_l'\boldsymbol{\beta} + \epsilon_l. \tag{4}$$

In its standard form, the truncated regression ignores the (unknown) correlation pattern among the residuals $\boldsymbol{\epsilon}$. We therefore augment our analysis for the proposed bootstrap procedure using 2000 replications. See the appendix for more details.

# 3 The Data

We use data from the US *Residential Energy Consumption Survey*, conducted regularly by the US Energy Information Administration (EIA).[2] For the present purpose, we use the surveys of 1997 and 2001 to check whether energy efficiency improvements have occurred between the years. Each survey contains household micro data of energy consumption, dwelling characteristics and the number of electric appliances. We restrict our attention to households living in single-family homes.

We had to drop a couple of observations from both years because of missing or implausible data. Especially households using coal, wood, district heating, or renewable energies must be removed because of missing consumption figures. The remaining sample comprises 4,212 households in total, from which 2,367 come from the 1997 survey, and 1,845 households from the 2001 survey.

[2]The data are available online at http://www.eia.doe.gov/emeu/recs/contents.html.

Table 1: Data summary

| | | 1997 | | 2001 | |
|---|---|---|---|---|---|
| | | Mean | Median | Mean | Median |
| Total energy | kWh | 35,434 | 32,953 | 32,464 | 30,439 |
| Living space | $m^2$ | 165 | 151 | 218 | 193 |
| Persons | number | 2.63 | 2 | 2.68 | 2 |
| Electric appliances | number | 3.76 | 3 | 4.67 | 4 |
| Fridges, freezers | number | 1.58 | 1 | 1.64 | 2 |
| Heating Degree Days | number | 4,815 | 5,139 | 4,358 | 4,591 |
| Cooling Degree Days | number | 899 | 673 | 1,066 | 905 |

2,367 sampled observations are from 1997, and 1,845 observations from 2001.

In a first step, model (3) is solved for every observation. The households' total energy consumption serves as the only input, measured in kWh. Turning to the outputs (the 'produced' energy services), we approximate the demand for space heating and cooling, and lightning with the size of living space. The number of household members serves as a proxy for the amount of hot water preparation and cooked meals. To account for energy consumption due to the use of electric appliances, we incorporate the joint number of TV-sets, videos, DVDs, and computers. The overall number of refrigerators and freezers in the household are likewise included in our estimation. The upper panel of table 1 summarizes the employed input and output data for the DEA analysis.

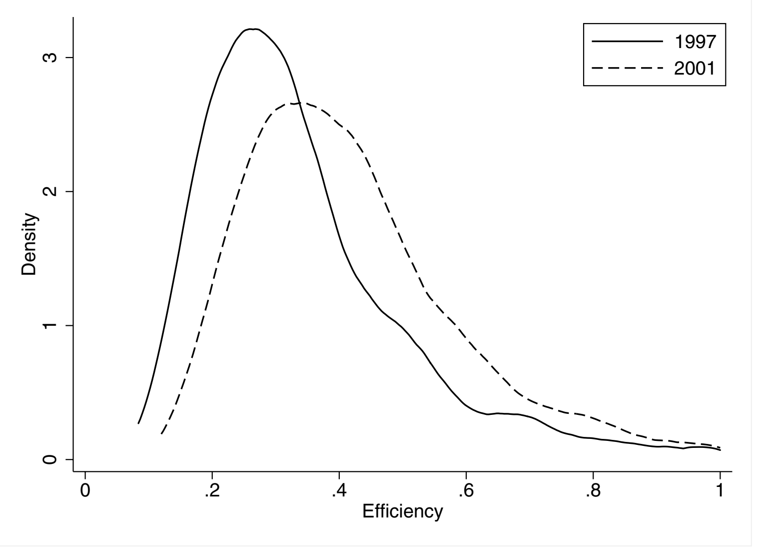
We benchmark all households against an intertemporal best-practice frontier (Tulkens and Vanden Eeckhaut 1995) by pooling both periods to obtain an efficiency indicator $\eta_l^* = h_l^*/e_l$ for every observation. If efficiency improvements have occurred between 1997 and 2001, a general tendency of larger $\eta_l^*$ for the later period should be embodied in the empirical distribution.

The local climate conditions are among the first candidates to be included in the set of covariates $\boldsymbol{z}$ for the second stage regression. We choose the amount of measured Heating Degree Days ($HDD$) and – in case the household has air-conditioning – the Cooling Degree Days ($CDD$) as proxies for climate conditions. $HDD$ are calculated as the difference between 65° F indoor temperature and the daily average outdoor temperature below 65° F, summed over all days of a year. $CDD$ are calculated in a like manner. A large value of $HDD$ indicates a rather large demand for space heating, while a large value for $CDD$ does the same for cooling purposes. To allow for nonlinear effects, we likewise include the respective squared terms $HDD^2$ and $CDD^2$. Summary statistics for the climate variables for both sample years are given in the lower panel of table 1.

The building characteristics may define a favorable or unfavorable operating environment. Because of differences in the heat transmitting surface, we control for whether the respective home has a detached or an attached structure. Dummy variables indicate the construction decade of the home. Starting with homes built before 1940, we expect that newer homes exhibit a higher insulation standard, and choose buildings constructed in 1990 or later as the reference case. Further, different main heating fuels may cause efficiency differences. For instance, fuel oil and natural gas are fuels that are converted into useable energy within the home, and the household must bear the conversion leakage involved with the transformation process. For electricity on the other hand, these leakages arise already at the power plants such that the amount of delivered energy is much smaller. We hence choose households heating with electricity as the reference.

Finally, we interact the variables that capture building characteristics and main heating fuel with a time dummy for 2001 to assess whether efficiency improvements took place. Because efficiency decreases with the dependent variable $1/\eta_l^*$, the overall impact of the estimated coefficients for the interaction terms have to be negative if any efficiency improvement has occurred between 1997 and 2001.

Figure 2: First-stage efficiency estimates $\boldsymbol{\eta}^*$




# 4 Results

The empirical densities of the two distributions for $\boldsymbol{\eta}^*$, obtained by the first-stage computations, are illustrated in Figure 2, one for each year. Because $0 < \eta_l^* \leq 1$, any efficiency shortfall can be interpreted as conservation potential $(1 - \eta_l^*)$, measured in percent of actual energy consumption.

The bulk of observations lie within a range of $0.1 < \eta_l^* < 0.8$, with a tail to the right. There are 121 households with $\eta_l^* \geq 0.8$, of which 16 households serve as best-practice benchmark with $\eta_l^* = 1$. The average $\eta^*$ of 1997 amounts to 0.34, whereas the average $\eta^*$ of 2001 is 0.42. A classical t-test and a nonparametric Kolmogorov-Smirnov test both confirm that the two distributions differ significantly in their means and in their cumulative distribution, respectively.[3]

The regression analysis of the second stage fits equation (4), and thereby

[3]The test statistics for the t-test amounts to $|t| = 14.7$, with $p = 0$, and the Kolmogorov-Smirnov test computes a maximal difference between the two cumulative distributions of $D = 0.23, p = 0$.

decomposes the efficiency variation into components attributed to climatic differences and improvements of energy efficiency. Table 2 reports the estimated parameters and their standard errors for the plain truncated regression, and shows further the mean parameter estimates of the bootstrapped truncated regression procedure along with the 99% and 95% percentile confidence intervals. Both approaches tell a consistent story, as all parameters share the same sign, are of comparable magnitude, and no deviance is apparent between the models with respect to statistical inference.

The coefficients for $HDD$ and $CDD$ suggest that a very cold or, in case the home has air-conditioning, a very warm location yield weaker efficiency, since such an environment usually causes a comparably higher energy consumption. Interestingly enough, the significant parameter for $HDD^2$ denotes a concave relationship between heating demand and the dependent variable $1/\eta_l^*$, which in turn implies a parabolic, u-shaped effect with respect to efficiency. A closer inspection of the bootstrap estimates reveals that $1/\eta_l^*$ increases for $HDD < 7,464$ and decreases beyond that level. This non-linear relationship indicates that investing in a home insulation while having only a low heating demand is in most instances not a profitable option. Below a certain level of $HDD$ people therefore rather spent their money for energy consumption instead for a retrofit if $HDD$ increases, and efficiency thus falls within a specific range of $HDD$. However, beyond the level of 7,464 $HDD$ an investment in dwelling insulation might appear economical, and the estimated effect reverses.[4]

Apart from climatic influences, the building's structure, its age and the respective main heating fuel affects the household's energy efficiency. Surprisingly, homes with an attached structure exhibit an inferior efficiency, although we expected that they benefit from the heat transmission from their neighbors. The

[4]Note that levels of 7,000 $HDD$ and more are usually observed in states like Montana, Wyoming, North- and South Dakota, and Minnesota. See, e.g., the climate zones map at http://www.eia.doe.gov/emeu/recs/climate_zone.html.

Table 2: Regression results

| | Truncated regression | | Bootstrapped truncated regression | | | | |
|---|---|---|---|---|---|---|---|
| | | | lower bound | | | upper bound | |
| | $\hat{\beta}$ | *s.e.* | 1% | 5% | $\hat{\beta}$ | 5% | 1% |
| Constant | **-2.937** | 0.297 | -3.733 | -3.503 | **-2.923** | -2.351 | -2.205 |
| $HDD$ | **1.046** | 0.080 | 0.844 | 0.894 | **1.045** | 1.202 | 1.248 |
| $HDD^2$ | **-0.070** | 0.008 | -0.091 | -0.086 | **-0.070** | -0.056 | -0.052 |
| $CDD$ | *0.217* | 0.090 | -0.011 | 0.045 | *0.220* | 0.393 | 0.444 |
| $CDD^2$ | 0.053 | 0.029 | -0.022 | -0.006 | 0.052 | 0.107 | 0.125 |
| **Main Effects** | | | | | | | |
| Attached structure | *0.233* | 0.106 | -0.046 | 0.016 | *0.231* | 0.439 | 0.496 |
| Construction decade | | | | | | | |
| before 1940 | **1.230** | 0.178 | 0.758 | 0.887 | **1.228** | 1.584 | 1.695 |
| 1940-1949 | **1.204** | 0.192 | 0.718 | 0.834 | **1.202** | 1.585 | 1.712 |
| 1950-1959 | *-0.288* | 0.134 | -0.645 | -0.559 | *-0.291* | -0.045 | 0.040 |
| 1960-1969 | **0.495** | 0.168 | 0.079 | 0.163 | **0.494** | 0.823 | 0.925 |
| 1970-1979 | 0.113 | 0.142 | -0.255 | -0.156 | 0.110 | 0.375 | 0.464 |
| 1980-1989 | 0.099 | 0.200 | -0.413 | -0.285 | 0.096 | 0.495 | 0.592 |
| Main heating fuel is | | | | | | | |
| Fuel oil | **2.298** | 0.178 | 1.830 | 1.940 | **2.292** | 2.633 | 2.755 |
| Natural gas | **2.333** | 0.151 | 1.920 | 2.027 | **2.327** | 2.631 | 2.725 |
| LPG | **1.190** | 0.222 | 0.654 | 0.759 | **1.187** | 1.604 | 1.716 |
| Kerosene | **1.640** | 0.501 | 0.095 | 0.548 | **1.589** | 2.526 | 2.795 |
| **Interaction with dummy for 2001** | | | | | | | |
| Attached structure | *-0.386* | 0.176 | -0.828 | -0.720 | *-0.382* | -0.042 | 0.057 |
| Construction decade | | | | | | | |
| before 1940 | 0.032 | 0.217 | -0.538 | -0.384 | 0.040 | 0.462 | 0.569 |
| 1940-1949 | -0.212 | 0.258 | -0.884 | -0.719 | -0.208 | 0.271 | 0.416 |
| 1950-1959 | -0.051 | 0.235 | -0.641 | -0.506 | -0.042 | 0.399 | 0.550 |
| 1960-1969 | 0.106 | 0.232 | -0.507 | -0.344 | 0.115 | 0.559 | 0.693 |
| 1970-1979 | -0.421 | 0.247 | -1.061 | -0.917 | -0.416 | 0.062 | 0.173 |
| 1980-1989 | -0.060 | 0.260 | -0.729 | -0.554 | -0.053 | 0.432 | 0.597 |
| Main heating fuel is | | | | | | | |
| Fuel oil | **-1.221** | 0.254 | -1.897 | -1.738 | **-1.226** | -0.750 | -0.620 |
| Natural gas | **-1.009** | 0.192 | -1.485 | -1.386 | **-1.014** | -0.634 | -0.490 |
| LPG | -0.558 | 0.323 | -1.381 | -1.213 | -0.577 | 0.026 | 0.221 |
| Kerosene | -1.112 | 0.830 | -3.771 | -2.979 | -1.154 | 0.399 | 0.726 |

**Bold** parameters indicate significance at the 1% level, *italic* figures do so for the 5% level. LPG = Liquified petroleum gas. $HDD$ and $CDD$ are measured in 1000 heating and cooling degree days, respectively.

order of magnitude of the coefficients for the construction decade suggests a pretty clear relation between the building's age and its efficiency. While homes constructed before 1940 exhibit the worst performance, this effect mitigates with declining age, and even vanishes for homes built in 1970 or thereafter. The one exemption from this general trend are homes built between 1950 and 1959, showing even a better performance as the reference case of just recently constructed homes. An explanation for this finding is not immediately forthcoming, other than to speculate that homes of this category have just been recently retrofitted.

Any main heating fuel other than electricity yields an efficiency shortfall. The largest efficiency deduction are exhibited by homes heated either with fuel oil or natural gas. However, this result is unsurprising because households that do not heat with electricity must bear the conversion leakage involved with the transformation process of e.g. oil into heat. The efficiency shortfall of homes heated either with liquified petroleum gas (LPG) or kerosene is less pronounced. These fuels are typically used in homes heated with an oven instead of having a central heating. To the extent that ovens typically heat a small portion of the living space, such homes have a lower energy consumption.

Turning to efficiency improvements between 1997 and 2001, we note that climatic differences can explain a considerable share of the observed change in $1/\eta_l^*$. The mean value of $1/\eta^*$ in 1997 is 3.6 while the mean value in 2001 is 0.8 units less. As the summary statistics in table 1 show, 2001 had on average 457 $HDD$ less but 167 $CDD$ more than 1997. Keeping in mind that the coefficients in table 2 refer to thousands of $HDD$ and $CDD$, respectively, we can explain some 57% of the decrease of the average $1/\eta^*$ by climatic differences.

Efficiency improvements are captured by the the interaction effects in the lower panel of table 2. Users of fuel oil and natural gas sampled in 2001 increased their energy efficiency, as did owners of attached homes. All respective coefficients appear significantly negative. Beyond that, neither the coefficients for other fuels nor for the construction decades appear statistically significant. To conclude, these results suggest that indeed an improvement in energy efficiency had occurred, but basically triggered only by a few factors.

# 5 Summary

This paper measures energy efficiency improvements of US single-family homes between 1997 and 2001 by using a two-stage procedure. The first stage derives a comprehensive energy efficiency indicator by means of DEA, while making use of an intertemporal version of Dyson and Thanassoulis' (1988) model formulation. In the second stage, we decompose the variation in the obtained efficiency indicator estimates into a climatic component, and factors attributed to energy efficiency improvements. Using truncated regression in its standard form as well as in a bootstrap context (Simar and Wilson 2007), we pay attention to the inference problem that arises from the inherent correlation among the DEA estimates in finite samples. Our results are mixed: a substantial part of the variation in efficiency scores is due to climatic influences, but households have nevertheless improved their energy efficiency. In particular, households heating mainly with fuel oil or natural gas show significant improvements.

A key advantage of the applied procedure is its ease in measuring residential energy efficiency improvements. The light data requirements obviate the burdensome demands that accompany traditional measurement approaches. Moreover, while the usual definition of residential energy efficiency draws on the framework of Becker's (1965) home production framework, the derived indicator not only resembles this definition methodologically, but has in addition a strong theoretical background in production theory (Seiford and Thrall 1990). This might suggest the procedure for other applications in energy economics, far beyond the measurement of energy efficiency improvements.

# Appendix: The Bootstrap Procedure

The inherent but unknown correlation among the individual elements of $\boldsymbol{\eta}^*$ makes regressing the inverse efficiency estimate $1/\eta_l^*$ on a set of covariates a critical issue. Obviously, it is possible to induce dependency among observations within a regression context by specifying an error component $\varsigma$ that exhibits a distribution with zero mean and some other distribution parameters:

$$1/\eta_l^* = \boldsymbol{z}_l'\boldsymbol{\beta} + \varsigma + \varepsilon_l, \tag{5}$$

where $\varepsilon_l$ is a standard iid regression residual free from correlation. Because of the unobservability of $\varsigma$, we can only perceive $\epsilon_l = \varsigma + \varepsilon_l$, implying the well-known inference problems because of the invalid estimated standard errors. However, we can simulate the relationship $1/\eta_l^* = \boldsymbol{z}_l'\boldsymbol{\beta} + \varepsilon_l$ by means of the bootstrap, which is the heart of the bootstrap procedure proposed by Simar and Wilson (2007). In particular, we follow their suggested 'Algorithm #1':

{1} Solve the optimization problem (3) for each of the $L$ sample households, and obtain for every household an efficiency estimate $\eta_l^* = h_l^*/e_l$.

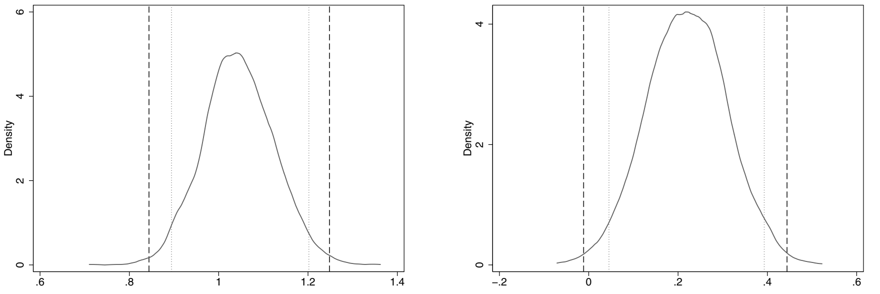
{2} Obtain parameter estimates $(\hat{\boldsymbol{\beta}}, \hat{\sigma}_\epsilon)$ by estimating equation (5) with truncated maximum likelihood regression and truncation point at 1, thereby using the subset of households $\mathcal{F}$ for which $\eta_l^* > 1$.

{3} Looping over the next three steps $B$ times yields a set of bootstrap estimates $\mathcal{A} = \left\{ \left( \hat{\boldsymbol{\beta}}^{bs}, \hat{\boldsymbol{\sigma}}_\varepsilon^{bs} \right)_b \right\}_{b=1}^{B}$:

- {3.1} For each household $l$ in $\mathcal{F}$ draw at random $\varepsilon_l$ from the truncated normal distribution $N(0, \hat{\sigma}_\epsilon)$ with left truncation at $(1 - \boldsymbol{z}_l'\hat{\boldsymbol{\beta}})$, using the estimates from step {2}.

- {3.2} Compute for each household in $\mathcal{F}$: $(1/\eta_l^*)^{bs} = \boldsymbol{z}_l'\hat{\boldsymbol{\beta}} + \varepsilon_l$.

Figure 3: Distributions of parameter bootstrap estimates




(a) $HDD$ (b) $CDD$

{3.3} Regress $(1/\eta_l^*)^{bs}$ on $\boldsymbol{z}_l$ using truncated regression and truncation point at 1 to obtain bootstrap estimates $\left(\hat{\boldsymbol{\beta}}^{bs}, \hat{\boldsymbol{\sigma}}_{\varepsilon}^{bs}\right)_b$.

{4} Construct bootstrap percentile confidence intervals from $\mathcal{A}$.

Percentile intervals to the confidence level $\alpha$ are simply ordered lists of the parameters of interest, excluding the upper and the lower tail (Efron and Tibshirani 1993:170-171). Suppose we have $B$ bootstrap estimates $\left\{\hat{\beta}_1^{bs}\right\}_{b=1}^{B}$. The endpoints for a $(1-\alpha)$ percentile confidence interval for $\beta_1$ are the $\alpha/2 * B$ upper and lower ordered values in this list.

Figure 3 shows the distributions for two estimated coefficients obtained by $B = 2000$ bootstrap loops. The vertical dashed lines illustrate the respective upper and lower endpoints for a 99% percentile confidence interval, the dotted lines illustrate the 95% percentile confidence interval. The coefficient for heating degree days ($HDD$) is significant on both confidence levels. By contrast, the coefficient for cooling degree days ($CDD$) is only significant on the 5% confidence level since its 99% percentile interval incloses zero.

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