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Understanding the spectrum of residential energy consumption: A quantile regression approach

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A B S T R A C T

Residential energy consumption accounts for 22% of the total energy consumption in the US. However, the impacts of local planning policies, such as increasing density and changing the housing type mix, on residential energy consumption are not well understood. Using Residential Energy Consumption Survey Data from the Energy Information Administration, quantile regression analysis was used to tease out the effects of various factors on entire distribution on the energy consumption spectrum instead of focusing on the conditional average. Results show that while housing size matters for space conditioning, housing type has a more nuanced impact. Self-reported neighborhood density does not seem to have any impact on energy use. Furthermore, the effects of these factors at the tails of the energy use distribution are substantially different than the average, in some cases differing by a factor of six. Some, not all, types of multifamily housing offer almost as much savings as reduction in housing area by 100 m^2, compared to single family houses.

1. Introduction

Increasing interest in the relationships between energy consumption, climate, land use and transportation is evidenced by recent work (e.g. Ewing and Rong 2008; Amato et al., 2005; Barnes et al., 2005). While the transportation sector accounts for 28%, the residential sector accounts for 22% of the annual US energy consumption (Energy Information Administration, 2008). In particular, linkages between energy consumption and greenhouse gas emissions have refocused the attention of urban planners on this issue (Andrews, 2008). Housing characteristics such as size, type, density and envelope affect energy consumption. It has been posited that low density development, along with associated increase in housing area, decrease in household size and increasing number of energy consuming appliances have contributed to rapid increase in energy consumption, even while efficiency standards have been tightening. Through careful analysis of impacts of these variables, over which planners have at least some influence on, state and local public policies and programs that promote energy conservation can be fashioned. Most of the research in this area has been focused on the effect of particular policies, such as weatherization programs and energy standards, on average effects (see e.g. Berry, 2003).

While smaller houses would consume less energy than larger ones, temperaments of households, incentives for maintenance, etc., also contribute immensely to the variation in energy use by households (Lindén et al., 2006). This paper investigates if residential energy consumption, in particular, space conditioning, can be explained by the housing characteristics, such as density, type and its location when controlling for household characteristics. It also investigates, if the conditional distribution of energy use is different than the average and if so, public policies can be targeted to reduce energy consumption at the higher end of the spectrum. It introduces quantile regression approaches, which help us get a sense of the marginal impacts across the distribution. One obvious advantage of this approach is to understand how changes in the tiered price structure affect energy consumption at the tails of the distribution.

This research finds that household size matters for cooling energy uses, housing size matters for all energy uses, and neighborhood density does not affect the energy use directly. Not surprisingly, climate variables are crucial components of energy consumption. Owners, compared to renters, use less cooling energy but use more other energy. In general, the marginal effect of the other housing types is not significantly different from single family detached (SFD) houses except for multifamily units in large apartment buildings. These results suggest that, contrary to some claims, the local governments' focus should be on increasing efficiency standards of construction and appliances, changing the housing type mix to include more large multi-family houses and reducing the overall housing size. Furthermore, these marginal impacts are significantly different across the spectrum of energy consumption and, relying on averages undercuts the savings that can be gained from tailoring policies to suit large energy consuming households.

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In the next section, we discuss the existing literature, motivation and the expected contributions of the work. We then suggest methods that can effectively target conservation policies at the right tail of the consumption distribution. We then present the results of the analyses as tradeoffs between various policy options and how they affect different energy consumers. The paper then concludes with the policy implications of this work and suggests directions for further research.

2. Motivation

Single family detached housing is the predominant housing type in the US and accounts for over 64% of the housing stock (US Department of Housing and US Census Bureau, 2008). Preference for such housing type, accompanied by low density-large lot development, is one of the main causes for variety of ills such as rapid destruction of natural habitats, congestion and others, commonly lumped under 'sprawl' (Peiser, 2001). In contrast to this traditional development, Ewing and Rong (2008) argued that compact urban forms have substantial energy savings. Using a variety of data sources and methods, they suggest that most of the energy savings are realized because of increase in density and changes in housing type mix. However, Holden and Norland (2005) argue that in Oslo, Norway, controlling for the age of the house, the effect of housing type on energy conservation is largely negligible after 1980. Nevertheless, the prevailing wisdom is that non-SFD housing types have energy savings because of shared walls and floors. On the other hand, Staley (2008) argues that multifamily residences have a 'U' shaped relationship to the greenhouse gas emission and presumably through similar shaped relationship to energy consumption. That is, when common spaces such as corridors and parking garages in multi-family units are accounted for, lower density multifamily units have higher energy savings than high density multifamily units or low density single family detached units, (Myors et al., 2005). In his critique of Ewing and Rong (2008), Randolph (2008) argues that substantial reduction in energy consumption is possible due to energy efficiency improvements rather than due to changing density or housing type. Furthermore, much of energy savings in compact developments are realized due to changes in travel patterns rather than changing building energy consumption patterns (see e.g. Boarnet and Crane, 2001). This current study contributes to this debate about the role of housing type on energy consumption pattern.

Climate is important in accounting for space conditioning energy use and, to some extent, of other uses due to water heating component. Cooling degree days (CDD) and heating degree days (HDD) are climate variables that account for the number of days the average temperature is above or below a certain threshold (65 °F or 18 °C in this case) and the actual deviation. From a national policy perspective, large energy savings can be realized by encouraging growth in temperate climates, rather than in the extreme climes. In the US, HDD are larger than CDD, and unsurprisingly heating is the largest consumption category, followed by water heating in residences. However, for locations such as Texas and Florida have more than 2000 CDD and less than 4000 HDD, where proportion of energy used in air conditioning use is higher than the rest of the country. This study tries to analyze the effects of different variables on different types of energy use.

Another persistent debate in energy planning literature is about the role of density in household energy consumption. Using Life Cycle Approach, Norman et al. (2006) report that in low-density suburban house consumes 2–2.5 times more energy than a high density urban living in Toronto, Canada. Most of this difference is primarily due to differences in transportation and building construction practices. Discounting those, annual energy consumption of an SFD is 1.8 times more than a high density urban dwelling. On the other hand, Perkins, (2002) found that, in Adelaide, Australia, the residents of high density inner ring suburbs used only 22% less energy than their low density outer ring suburban counterparts. These differences suggest that the relationship between density and energy consumption is not straightforward and the differences in results are perhaps

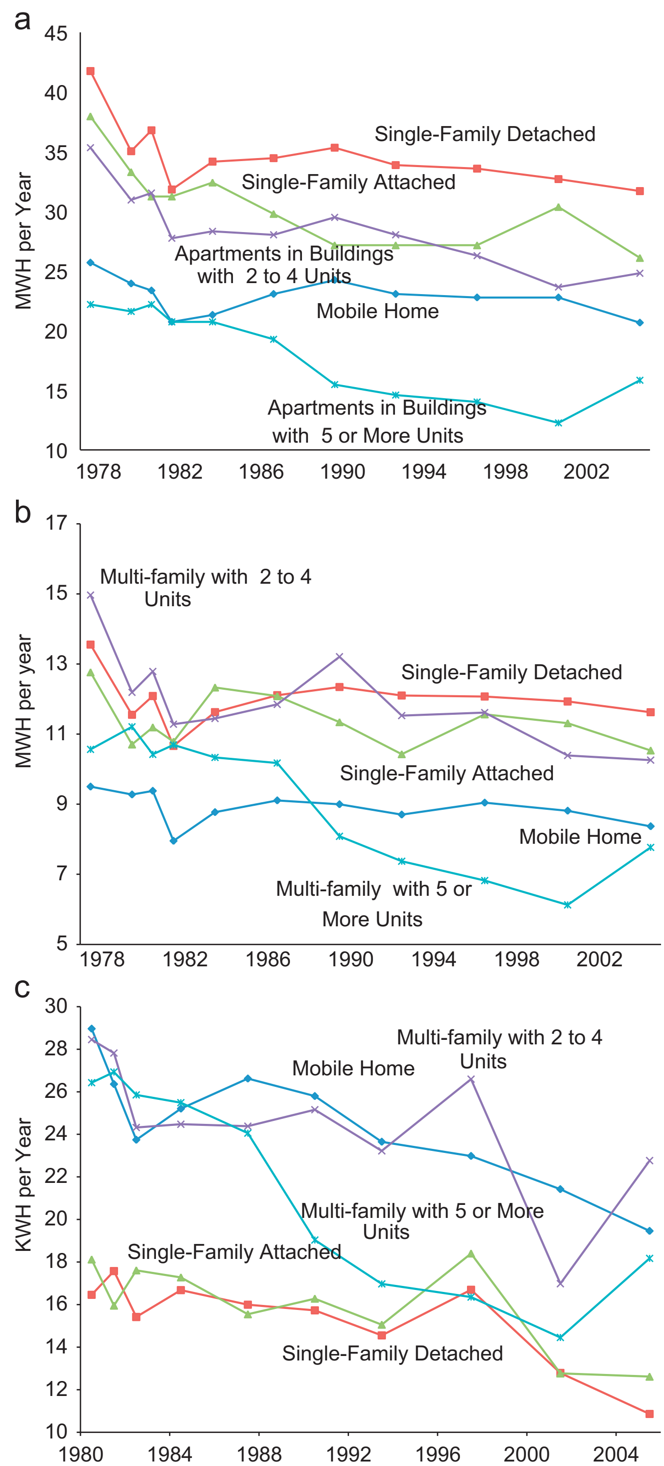

Fig. 1. Trends in household energy consumption for US (weather adjusted): source Energy Information Administration. (a) Per household, (b) per person and (c) per square meter.

suggestive of correlated variables such as income and ownership. In this study, we try to tease out these relationships.

To illustrate the above points, it is instructive to look at the patterns of average energy consumption by various housing types in the United States. As seen in Fig. 1(a), in general, there has been a decline in the energy consumption by all categories of households from 1978 to 2005. Overall, 20–30% less energy is consumed today than in the 1980s. In general, single family detached houses have consistently consumed more energy than other types of housing, suggesting that the prevailing wisdom is indeed correct. Multifamily units in large apartment blocks have consumed between 50 and 60% less, whereas units in smaller blocks consumed only 10–20% less than single family homes.

Norman et al. (2006) claim that building operational energy consumption per unit area, is same for both high density urban and low density suburban homes. While the average housing size increased by 39% to 270 m^2 between 1980 and 2005 for SFD, it essentially remained the same in multi-family units. Energy consumption per area of SFD is consistently lower than other housing types (Fig. 1(b)). While SFDs are more efficient than multi-family units, they tend be larger and, thus, the total energy consumption is higher (Fig. 1(a)). This is similar to the 'rebound effect' documented by Haas et al. (1998), where efficiency gains are offset by increases in consumption. While efficiency and consumption are positively correlated, Geller and Attali (2005) argue that increasing energy efficiency is not usually completely offset by the increase in consumption.

Adjusting for the numbers of persons in the household, household size, the trends paint a different picture (Fig. 1(c)). Household size has been consistently decreasing in the US as the trend towards nuclear and non-traditional families continues. However, the largest decreases are seen in SFD; Average household size decreased by 12% compared to 2% in large multi-family housing in the last three decades. In these apartments, except for a brief period in the late '80s and the early '90s, per person consumption has been less than SFD. However, apartments in larger blocks consumed, per person, much less than the single family units. This difference widened since the '80s until 2000 after which the gap has narrowed considerably. Furthermore, per person consumption in SFD has stayed essentially the same since late '80s whereas most of the other housing types register reduction in per capita consumption over time. This suggests that technology efficiency gains are offset by decreases in household size (Fig. 1(a)).

If we posit that appliances are getting more efficient over time, changes in housing construction are resulting in better insulation practices as evidenced by Fig. 1(c), then Figs. 1(a) and 1(b) suggest that such efficiencies are offset by other factors such as increase in the house area, and decrease in the household size itself. Furthermore, large differences in the trends in the average consumption, suggest that different housing types have different implications for energy conservation. The key question then for local policy makers, is to understand how land use policies can be leveraged for energy conservation goals.

These figures represent only the averages for the whole of the US. Focusing on the averages obscures the opportunities to target policies at the upper tail of the distribution of energy consumption. Randolph (2008) argues that due to high variability in the energy consumption dataset, the conclusions drawn are suspect. When the variability is quite high in a sample, ordinary least squares (OLS) regression does a poor job of estimating the marginal impacts. In particular, it is very sensitive to outliers. Fortunately, there are other methods available to estimate the marginal impacts that are not as sensitive to outliers but use the variability in the sample to their advantage. Clark and Berry (1995) in their study of energy efficiency measures in Phoenix, AZ suggest that "[T]o maximize savings, planners should concentrate on the less energy-efficient houses. The lesson from our study is that unless houses are carefully targeted, residential retrofit conservation measures may produce only modest energy and power savings. (p. 394)".

3. Methodology

Such careful targeting of public policy towards energy conservation is not possible if only effects on the averages are considered. Policy analyses using standard OLS techniques are not particularly suitable to target conservation policies towards high energy consumers. Quantile regression, on the other hand, estimates the effects of individual independent variables on specific quantiles of the dependent variable and therefore offers a simple method to estimate how different tiers of energy consumers respond to changes in the dependent variables. (Koenker and Hallock, 2001; Hao and Naiman, 2007). Readers are referred to the brief appendix and above exhaustive texts for further details. It may be tempting to pick a subsample of high energy users and analyze the effects of various variables (such as price), to target policies that promote conservation in that group. However, such analyses are clouded by sampling bias (Heckman, 1979). Quantile regression approach uses the entire sample to estimate the effect on the distribution, not merely the data in the neighborhood of the quantile of interest of the dependent variable.

One of the advantages of quantile regression approach is to understand the differential effect of variables on the entire distribution of consumption. For example, in a simple case of one independent variable, $\beta_{0.1} > 0$ implies that the 10th percentile of the dependent variable is positively influenced by increase in the independent variable. At the same time, $\beta_{0.9} < 0$ implying that the 90th percentile of the dependent variable is negatively influenced by the same increase, all this while the OLS coefficient may be close to 0. If the dependent variable is energy use, as is of interest here, and say the independent variable is income, this would suggest that increases in income changes the lower end of the energy consumption spectrum to increase their energy consumption, while the high energy consumers would lower their consumption. Therefore, looking only at the average effect of the independent variable masks the impact and the explanatory power of the dependent variable. Other advantages are that assumption about the Gaussian nature of the errors is unnecessary and the coefficients are robust with respect to outliers[1]. The analysis in this paper uses R, (R Development Core Team, 2009) and builds upon 'Quantreg' package (Koenker, 2009).

A concrete example on the usefulness of quantile regression can be demonstrated by the effect of energy prices on consumption. Since most of the household energy is delivered by publicly regulated entities, using a tiered price structure, we can begin to analyze the impact of prices on different tiers of energy consumers. The coefficients of price at $\tau = 0.1$ and 0.9 (10th percentile and 90th percentile) tell us how the tails of consumption react differently to increase in energy prices and therefore how much the prices have to change at different levels to get at the requisite conservation goals. While price of energy should have negative effect on

[1] Quantiles have other useful properties as well. Many empirical analyses are done using log transformations of the dependent variable. Because $E[\ln(x)] \neq \ln(E[x])$, when β's are estimated using log transformation of the dependent variable, it is not easy to predict the effect of the independent variable on the original dependent variable. For example, if $E[\ln(y)] = c + \beta x$, then $E[y] \neq \exp(c + \beta x)$, though this is common practice. Unlike the expectation, both sample and regression quantiles do not suffer from this problem, making the interpretation of the transformed regressions much easier.

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consumption, low energy users should not be as sensitive to small deviations in prices, when controlling for income.

In general, it is expected that housing area, household size, climate and income variables are expected to have positive impact on energy consumption (Table 1). Increase in HDD or CDD is expected to increase the right tail by a larger amount than at the left tail, because high energy consumers are likely to be very sensitive to climate variables. On the other hand, increase in house area should also increase the space conditioning at the right tail. However, such effect may be mitigated by lower surface to volume ratios. On the other hand, house area is positively correlated with the number of energy-consuming appliances and therefore would likely to increase other energy consumption at the right tail significantly than at the left. While some claim that neighborhood density in itself reduces energy consumption, as has been argued before, the observation is likely to do with correlated variable since causal mechanism is unclear. Such correlated variables include household income and housing type mix. Increasing income, may lead to increase in consumption, which could also be negated by increase in newer and more efficient appliances.

It is also expected, that because of shared walls, apartments and attached units should have lower energy consumption with the effect being larger at the right tail. The effect of urban and rural designation on energy consumption is more mixed. If heat island effect holds, then more urban places should have less heating consumption and higher air conditioning consumption. Age of housing should have positive impact on the energy consumption, i.e., while older houses should consume more energy, age should not affect the low energy consumers. In sum, the effect of each of these variables should be markedly different at different points in the consumption distribution.

4. Data description

The Residential Energy Consumption Survey (RECS) public use microdataset has been published by the Energy Information Administration (EIA), an agency part of Department of Energy (DOE), is a nationwide cross-sectional survey that is available for six years between 1987 and 2005. It should be noted that this is a repeated cross-sectional sample, not a panel data and therefore tracking trends in the marginal impacts or behavioral changes are not robust. In this paper, we mainly focus on the 2005 dataset to analyze the determinants of energy consumption patterns. Nevertheless, the same procedure is repeated for each dataset from 1993, 1997 and 2001 in addition to 2005 and the trends in the marginal effects of various variables are briefly alluded to.

RECS data is derived from three sources: an interview with the householders; mailed questionnaires in rental units when some or all of energy costs are included in the rent and energy bills and consumption data from energy providers. In 2005, the data of about 4382 households representing 111 million households were collected. However, the publicly released microdata is shorn of detailed location attribute of the household, saving for the climate variables. Furthermore, the energy in the dataset refers to site energy, not primary energy.

In 2005, space conditioning accounted for roughly half of the residential energy consumption, whereas water heating and other appliance use accounted for the other half, in the US. This dataset, however, suggests that on average 37% of the energy use is consumed by space conditioning (Table 2). The apparent discrepancy is due to the use of sampling weights by the EIA to construct total energy consumption estimates, whereas the summary statistics of the dataset does not account for the stratified sampling procedure. The sample was stratified based on census divisions to represent all of the population in US. The methodology in this paper does not use sampling weights in the analysis, mainly because the weights are not completely reflective of the variation in the covariates of interest. For technical and more complete explanation refer to Winship and Radbill (1994).

Other characteristics of the dataset are briefly worth mentioning. As expected, the climate variables are heavily inversely correlated ($\rho = -0.72$). Housing type and ownership likewise are correlated: SFDs are more likely to be owned and multi-family apartments are likely to be rented (Cramer's $V = 0.66$). However, very little correlation exists between neighborhood density and ownership status (Cramer's $V = 0.2$). Likewise, there is a little correlation between annual income and ownership or household size and housing size. An average house in the suburb is 270 m^2, while the average house in the city is 180 m^2. A city household spends about $1600 annually on energy, whereas a suburban household spends $2000 and consumes 26 and 32 MW h, respectively. On the other hand, the difference in spending by households in SFD and multi-family apartments is even starker ($2000 vs. $1100).

5. Results

While, most of the discussion that follows is based on the 2005 data, where appropriate trends in the marginal impacts of

Table 1
Hypotheses about residential energy consumption.

Covariates	Lower tail	Upper tail	Explanation
Climate	+	++	Higher heating and cooling degree days result in larger energy use. Large energy users are more heavily dependent on the climate than smaller ones.
Housing size	+	+/++	Larger houses require higher energy use, but reductions due to economies of scale and volume to surface ratio may offset the increase.
Household size	+/0	+/0	While appliance use may be positively conditioned on household size, the space conditioning use is likely to be same irrespective of number of people.
Age of house	0	+	Energy conscious households obviate the effect of the age of the house on energy use.
Neighborhood density	0	−/0	Some literature suggests that increasing neighborhood density reduces household consumption. However, controlling for correlated variables density should not matter because the causal mechanism is unclear.
Income	0	+	The higher the income the more energy use. However, because energy use is small portion of the household budget, energy conscious households at the lower tail should not be influenced by income.
Price	–	–	Increases in price should decrease energy consumption but more so at the upper tails.
Ownership status	0	+	Owners should be willing to invest in more efficient space conditioning systems, but are also likely to own more energy consuming appliances. At the lower end of consumption spectrum, ownership status should not matter.
Housing type	–	–	Multi-family and attached houses should consume less energy because of shared surfaces. Most of the literature suggests that energy savings can be achieved via compact and higher density living which includes higher portion of non single family residences

Table 2
Descriptive statistics for RECS 2005 dataset.

Variable	Mean	St. dev.	1st quartile	Median	3rd quartile
Heating energy[a]	12,192	11,929	2575	9088	19,130
Cooling energy[a]	2113	2559	288	1262	3029
Other energy[a]	23,658	15,861	12,241	19,893	23,658
Cooling degree days	1486	966	835	1282	1857
Heating degree days	4311	2181	2383	4639	5926
Total cooling area (m^2)	124	142	21	77	180
Total heating area (m^2)	149	108	77	122	193
Total area (m^2)	212	151	98	172	283
Household Size	2.7	1.48	2	2	4
Avg. price (per MW h)	70.48	24.14	53.53	66.68	82.12
Housing type	**Count**	**Percentage**			
Multi-family 2–4 units	309	7			
Multi-family 5+units	655	15			
Mobile homes	280	6			
Single family attached	338	8			
Single family detached*	2800	64			
Neighborhood density					
City	1882	43			
Rural*	874	20			
Suburbs	826	19			
Town	800	18			
Ownership					
Own	2993	68			
Rent*	1347	31			
No pay	42	1			
Year built					
Before 1939*	640	15			
1940–59	795	18			
1960–79	1240	28			
1980–99	1377	31			
2000+	330	8			
Annual income					
< 20 K*	1143	26			
20–40 K	1133	26			
40–75 K	1169	27			
75 K+	937	21			
Total observations	4382				

[a] Energy use is measured in kW h.
* is used as contrasting variable in the category.

particular variables are discussed using additional analyses from 1993, 1997 and 2001. Care should be taken to interpret the results presented in this paper. In the interests of parsimony, the research primarily focused on variables that are of interest to the planners. Neither omitted variable bias, nor violation of linearity assumption is addressed by quantile regression. However, this method provides a substantial benefit over OLS because of the absence of requirement of Gaussian error structure and the relative independence of the bootstrapped standard errors to the heteroskedastic errors.

Fig. 2 represents the conditional quantile estimates of the dependent variable. The conditional effect of a particular variable is plotted on the *Y*-axis against the quantile of interest on the *X*-axis. Therefore, 1 degree day increase in the HDD increases the 40th percentile of heating use by 1.8 kW h the 90th percentile by 3.5 kW h. The average estimate, provided by the OLS, suggests that 1 degree day increase results in excess consumption of 1.5 kW h. Since this estimate does not change across the quantiles, they are shown using the horizontal lines. An upward sloping line in these graphs in the positive quadrant suggests that the effect of the particular variable is higher in the upper quantiles than the lower ones. A U-shaped graph in the negative quadrants suggests that the effect is greatest in the middle. A horizontal line would suggest that OLS estimates are sufficient.

Tukey's concept of the 'centercept' instead of the intercept[2] is used, to make the interpretation easier (Wainer, 2000). For example for 2005 data, the centercept refers to the annual consumption by an average household that lives in a 212 m^2, SFD unit in a rural area, built prior to 1939, having an annual household income less than 20,000 USD, in a climate zone with about 4300 HDD, 2100 CDD and paying about \$70.2 per MW h. About 16, 2 and 23 MW h are annually consumed, on average, for heating, cooling and other uses (see OLS estimates in Tables 3–5). In the extreme ends of the energy consumption spectrum, (e.g. τ=0.1, 0.9), the heating energy consumption of an 'average' household is 4 (seven-fold lower than average) and 30 MW h (two-fold higher than average). Analysis of other datasets from different years[3] shows that the heating energy consumption of an average household is on decline for most of the last decade whereas air conditioning energy consumption has been on the rise (Fig. 3). This trend could be explained by the rapid increase in the central air conditioning in residences, thereby increasing both the cooled area and total air conditioning usage. The reduction in annual heating energy consumption can be partially explained by the increase in the annual fuel utilization efficiency (AFUE). Furthermore, widespread adoption of technological innovation in new construction explains these reductions (Geroski, 2000; Andrews and Krogmann, 2009).

Tables 3–5 compare coefficients of the OLS regression with that of the τ quantile. The signs of the OLS estimates generally follow the hypotheses. However, it is instructive to see the effect of each covariate on the conditional quantile, across a range of distribution. While a change in 1 HDD, holding other variables constant, changes the 10th percentile heating energy consumption by about 0.9 kW h, it changes the 90 percentile by about 3.5 kW h, about 4 times larger effect in the right tail than the left one. Similar pattern is observed in the effect of CDD on air conditioning use (0.3–2.3 kW h, an 8.5 times larger effect). Since cooling is a much small proportion of the household energy consumption, weatherization programs that obviate the effect of climate are much more effective in the colder climes than in hotter climes; three times as effective in the lower tail and twice as effective in the upper tail. However, the marginal effect of climate on heating is almost the same as the effect of the housing area in the lower quantiles, but twice as much in the upper quantiles. For cooling, the marginal effect of climate is twice as much as that of housing area in the lower quantiles and thrice as much in the upper tail.

Both ownership and household size do not affect heating, but affect both cooling and other energy use. Increasing the number of households, which is a direct result of decrease in household size, thus substantially increase the total energy consumption.

Rural households[4], consume less heating than urban and suburban households (Fig. 3). However, the effect is not statistically significant for air conditioning use (Table 3). Furthermore,

[2] An intercept, would be the value of dependent variable when all covariates are 0, clearly not a useful concept for much of social sciences.

[3] The average household is different for different years because means of the continuous variables in different datasets are different. However, the contrasting variables are consistently maintained across the years.

[4] Urban and rural distinction in the RECS survey is a self-reported variable rather than measured and classified according to density. So caution is required in interpreting these results, as respondents have varying opinions about what constitutes a town, suburb and a city.

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even for heating use, the differences are greatest in the middle quantiles suggesting that densification effect is negligible at the upper end of heating consumption. Furthermore, it is instructive to note that if urban heat island effect holds, then the air conditioning consumption should be significantly affected by the changes in neighborhood density. The lack of detailed location data hampers the ability to draw conclusions about the micro-climate that could explain these anomalous findings.

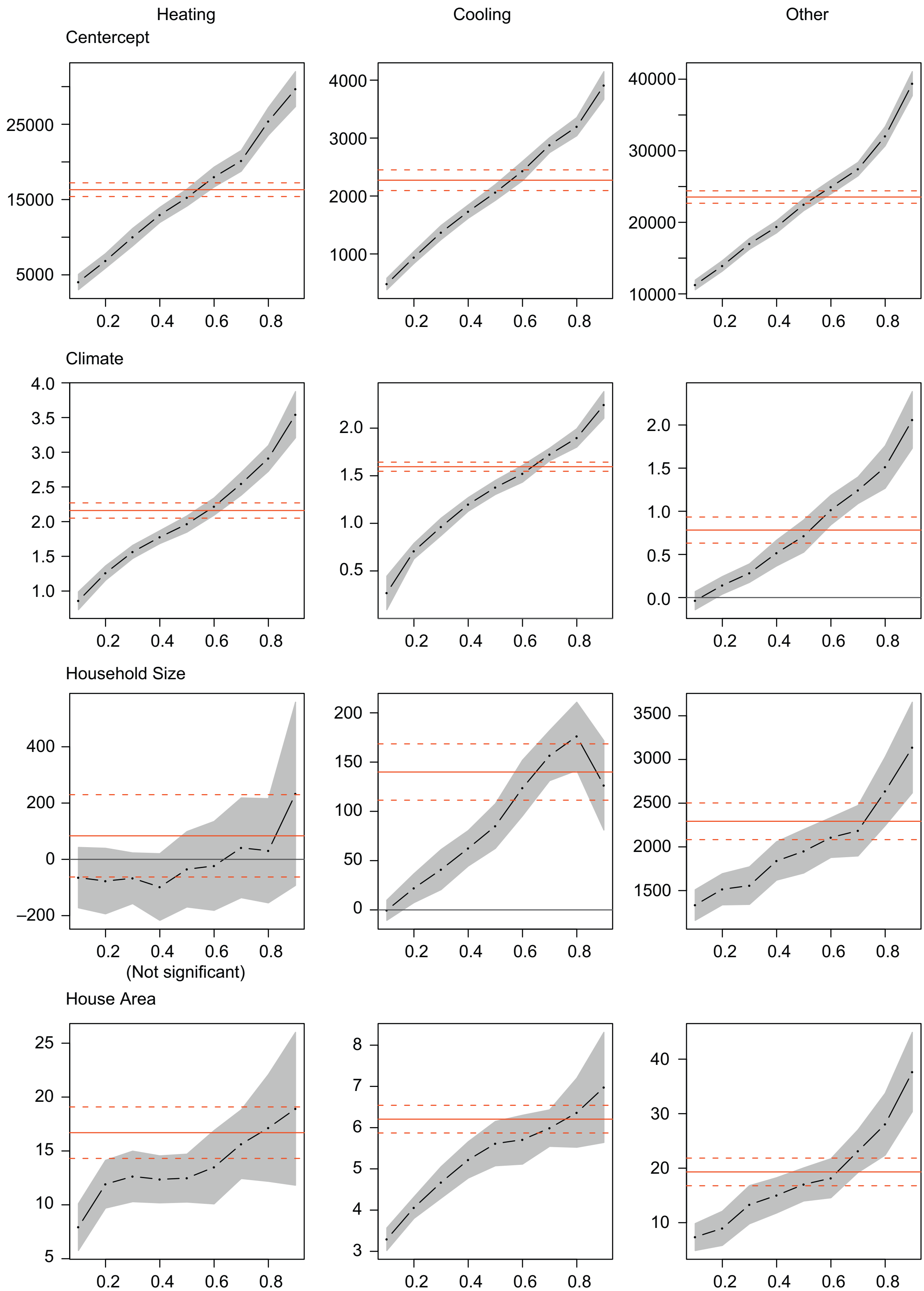

Fig. 2. Marginal effects of various variables on different household energy consumption uses quantiles are on *X*-axis and the coefficient is on *Y*-axis. 90% confidence interval is shown. The horizontal lines are the OLS estimates are shown for reference.

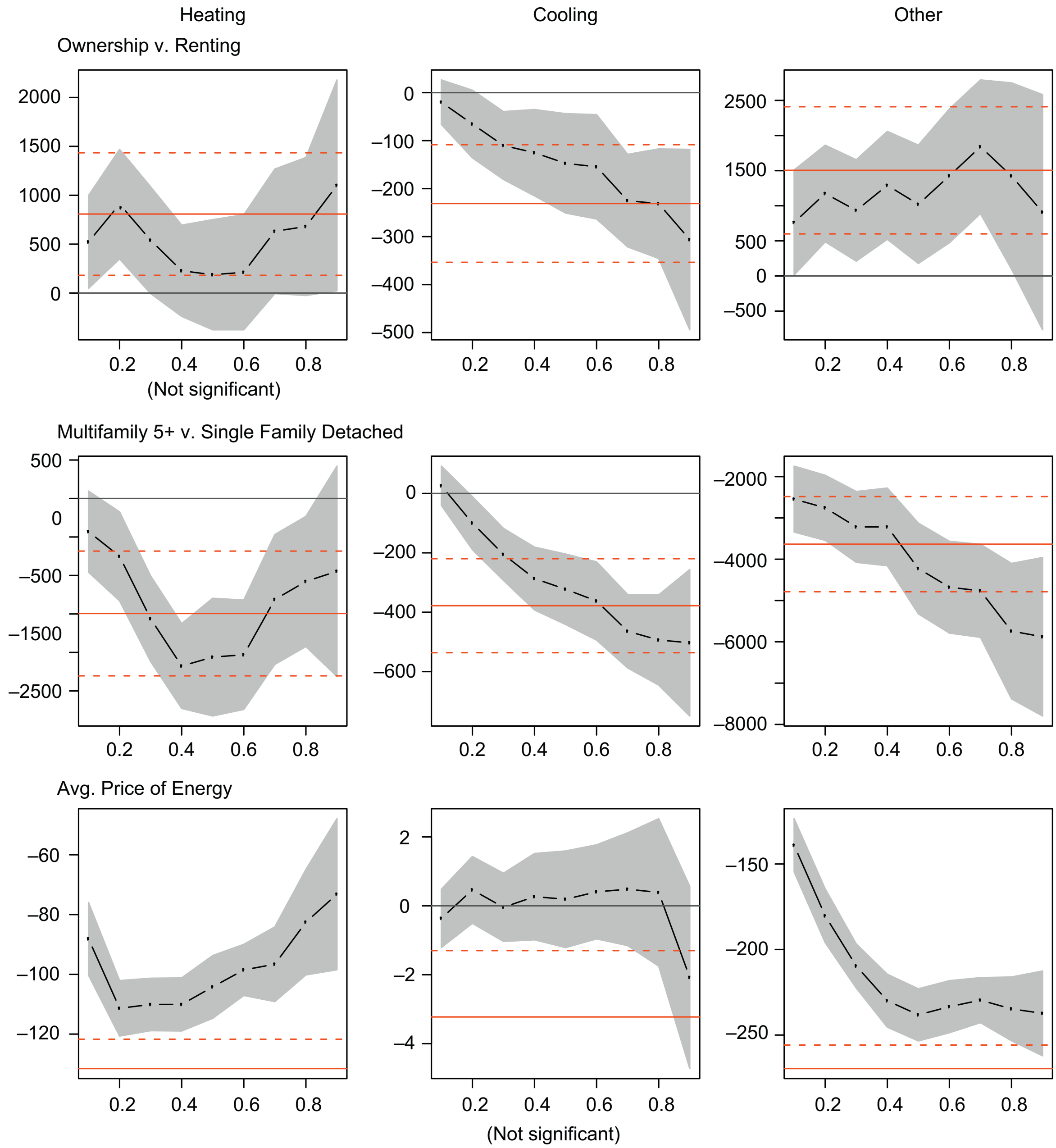

Fig. 2. (*Continued*)

The age of the house matters for heating rather than cooling. Newer houses are much more efficient for high energy users but the distinction does not matter much at the left tail. This provides evidence to the hypothesis that energy conscious households obviate the effect of age of the house, thus, public programs should target high energy users in their weatherization programs.

An increase in the heated area of the residence by 100 m^2 changes the 10 percentile by 0.8 MW h and the 90 percentile by 1.9 MW h. The conditional mean (the OLS estimate) changes by 1.7 MW h, a figure much closer to the higher tail of the distribution (see Fig. 2). This suggests that the OLS estimates are heavily influenced by the outliers on the right. At the upper tail of the cooling consumption, the marginal effect of the cooled area is 2.2 times than at the lower quantiles. As a proxy for number of appliances, total area has a significant effect on the other energy use in a household. Predictably the marginal effect of this variable at the right tail is different by over 5 times than the left tail (see Table 5). The effect of reducing the housing size by 100 m^2 is equivalent to increasing the price only by 9–25 USD per MW h. Since dramatic action is needed for reduction of housing size, it pays to concentrate on price instruments that bring about reduction in energy use. While the marginal effect of the heated area is decreasing since 1997, such decrease is observed only since 2001 in the cooling (Fig. 4). If these trends hold, then public policy targeting size of the housing is unlikely to produce significant savings in energy consumption across the spectrum. Housing size has other implications for environment that are not limited to energy, therefore, regulations and incentives that seek to minimize the number of large homes should not be easily dismissed.

Except, for an unusual case, generally the effect of moving from a single family home to a clustered living in apartments and single family attached homes reduces the energy consumption. However, none of these effects are significantly different from single family detached house, apart from large apartment blocks,

Table 3
Quantile and linear regression estimates for heating consumption (2005 RECS data).

Covariates	Quantiles					OLS
	0.1	0.3	0.5	0.7	0.9	
(Centercept)	4040.7 (624.7)***	10,004.7 (714.1)***	15,256.0 (689.0)***	20,144.9 (843.3)***	29,679.4 (1414.0)***	16,313.8 (553.2)***
Heating degree days	0.9 (0.1)***	1.6 (0.1)***	2.0 (0.1)***	2.5 (0.1)***	3.5 (0.2)***	2.2 (0.1)***
Household size	−64.9 (65.3)	−67.2 (54.8)	−35.3 (81.5)	41.0(107.8)	233.0 (198.0)	83.5(88.9)
Heating Area	7.9 (1.3)***	12.6 (1.4)***	12.5 (1.4)***	15.6 (1.9)***	18.9 (4.3)***	16.7 (1.5)***
Average energy price	−88.1 (7.4)***	−110.1 (5.3)***	−104.2 (6.4)***	−96.6 (7.6)***	−73.2 (15.4)***	−131.5 (6.0)***
The following annual income categories are contrasted with the category 'less than 20 K'						
20–45 K	1034.5 (249.0)***	997.3 (246.0)***	1039.9 (288.8)***	980.7 (359.4)**	1420.4 (685.7)*	1466.4 (301.3)***
45–75 K	32.4 (183.8)	45.4 (201.4)	287.5 (215.4)	785.4 (285.2)**	1508.4 (536.7)*	699.7 (255.5)**
75 K+	−79.7 (175.2)	281.3 (172.7)	413.9 (209.6)*	139.4 (266.7)	674.7 (460.8)	19.0(247.7)
The following ownership categories are contrasted with the category 'Rent'						
Own	522.6$^{\cdot}$ (288.7)	540.5 (332.0)	187.3 (342.5)	631.2 (387.3)	1101.0$^{\cdot}$ (655.6)	807.8 (380.8)*
Occupied without rent	3097.4 (1572.1)*	2247.0 (976.7)*	1477.2 (1263.6)	3641.7 (1672.9)*	3457.0 (2549.4)	3110.6 (1324.6)*
The following urbanization categories are contrasted with the category 'Rural'						
City	1551.2 (371.5)***	1667.0 (341.3)***	922.0 (348.7)*	108.3 (419.8)	200.2 (791.3)	1036.9 (383.1)**
Town	1431.1*** (430.1)	1783.0*** (420.1)	1085.4** (418.3)	779.3 (560.3)	526.5 (949.3)	1337.8** (427.2)
Suburbs	1671.4*** (380.6)	1733.7*** (341.5)	898.0* (389.9)	254.3 (477.6)	341.9 (908.7)	994.9* (426.2)
The following year built categories are contrasted with 'built before 1939'						
1940–59	−1091.2 (542.3)*	−2703.9*** (575.0)	−3643.7*** (632.3)	−4599.3*** (759.3)	−5393.5*** (1545.8)	−3450.6*** (451.6)
1960–79	−2023.5 (489.1)***	−3944.2 (526.8)***	−5180.1 (625.9)***	−6082.5 (747.0)***	−9392.7 (1240.4)***	−5447.5 (422.6)***
1980–99	−2510.6 (517.0)***	−5412.0 (538.2)***	−6969.0 (595.4)***	−8705.2 (761.2)***	−12,336.7 (1346.6)***	−7906.4 (426.7)***
2000+	−2307.6 (586.5)***	−5431.3 (578.1)***	−7273.4 (621.7)***	−9356.2 (824.0)***	−13,715.9 (1449.0)***	−8827.8 (586.6)***
The following housing type categories are contrasted with 'single family detached'						
Mobile	395.4 (613.3)	156.0 (437.3)	−89.2 (385.5)	14.4 (618.6)	−408.5 (976.6)	−253.4 (562.6)
Single family attached	−335.0 (394.9)	−431.9 (380.6)	−570.9 (499.3)	−41.9 (536.2)	−834.8 (925.1)	−653.2 (511.6)
Multifamily 2–4 units	−94.2 (440.3)	−162.1 (585.5)	−47.7 (601.2)	1170.3 (581.7)*	1432.9 (1388.2)	1114.0$^{\cdot}$ (575.6)
Multifamily 5+units	−430.2 (320.5)	−1561.9 (338.1)***	−2061.0 (465.0)***	−1312.0 (512.9)*	−945.6 (830.5)	−1493.7 (492.7)**

Dependent variable is heating use in kW h.

$^{\cdot}$ ($0.05 < p \leq 0.1$).
* ($0.01 < p \leq 0.05$).
** ($0.001 < p \leq 0.01$).
*** ($p \leq 0.001$).

which offer substantial savings in heating (from 1.3 to 2 MW h) and less so in cooling (0.2–0.5 MW h). This contradicts Staley (2008) argument that smaller apartment blocks have higher savings in energy than larger ones. It is interesting to note the pattern of the effect of these multi-family units. While larger amounts of energy is saved in cooling as we move from the left to the right in the distribution, highest savings in heating energy use are realized in the middle of the distribution (τ=0.3–0.7). The effect of moving a household from a single family detached house to a multifamily apartment is reducing the heated area of the house by more than 100 m^2, except for the 10th and 90th percentile, whereas the savings in cooling energy is equivalent to a reduction of 40–70 m^2 in the cooled area.

The price of energy has an expected effect on energy consumption. Increases in price, by and large, bring about decreases in heating and other energy consumption. Cooling use is not affected by the price of energy and since cooling is a minor portion of household energy costs and is mostly significant only in Southern US, this result is expected. While effective in reducing heating consumption, price is particularly effective in reducing energy consumption in the lower and middle of the distribution than at the tails. On the other hand, other discretionary energy consumption is most affected in the mid to the upper tail of the distribution. Analysis of the other years shows that the effect of price especially is decreasing over time (Fig. 5). This suggests that while small increases in energy price may bring about significant decreases, households in US are becoming more energy dependent and therefore energy is becoming more price inelastic. As a way to counteract the trend, local planners, while not discounting the market mechanisms to save energy, should also focus on non-market regulatory mechanisms by increasing the efficiency of housing and appliances.

6. Implications for conservation

Electricity is 40% of the total energy used by in residences. Since electricity production is highly inefficient, opportunities to conserve electricity at residences triple the conservation of primary fuel sources (Randolph and Masters 2008). Nearly 50% of household energy use and 45% of energy expenditure is for space conditioning, followed by water heating and appliance use. Planners have substantial influence on these uses through various regulations such as zoning and building codes, and incentives such as weatherization programs, and efficiency standards, and therefore have an important role to play in energy conservation. Furthermore, different locations have different climate factors, housing mix and sizes and income characteristics, etc., that condition energy use. Setting greenhouse gas targets by local and state governments is focusing the attention of planners on which land use and energy conservation programs and policies should be used.

It is well understood that space conditioning is dependent on the size of the house, and therefore, smaller houses consume less energy. However, the effect of reducing area is small compared to other options. Marginal changes in energy prices bring about reductions in heating energy use that is more reducing the house

Table 4
Quantile and linear regression estimates for AC energy use (2005 RECS data).

Covariates	Quantiles					OLS
	0.1	0.3	0.5	0.7	0.9	
(Centercept)	481.6 (61.2)***	1369.1 (74.7)***	2061.3 (83.8)***	2878.5 (78.9)***	3909.3 (145.3)***	2272.4 (108.5)***
Cooling degree days	0.3 (0.1)*	1.0 (0.1)***	1.4 (0.0)***	1.7 (0.0)***	2.2 (0.1)***	1.6 (0.0)***
Household size	−0.4 (6.2)	40.9*** (12.4)	85.0*** (13.8)	156.6*** (15.5)	126.4*** (27.6)	139.9*** (17.4)
Cooling area	3.3 (0.2)***	4.7 (0.2)***	5.6 (0.3)***	6.0 (0.3)***	7.0 (0.8)***	6.2 (0.2)***
Average energy price	−0.4 (0.5)	0.0 (0.6)	0.2 (0.9)	0.5 (1.0)	−2.1 (1.6)	−3.2 (1.2)**
The following annual income categories are contrasted with the category ‘less than 20 K’						
25 K–45 K	64.4$^{\cdot}$ (35.4)	125.1 (31.0)***	165.7 (44.4)***	255.7 (45.1)***	337.4 (87.2)***	256.5 (58.7)***
45 K–75 K	−24.2 (23.3)	−13.1 (29.1)	−1.5 (37.7)	−12.4 (43.6)	81.9 (74.8)	−9.8 (50.0)
75 K+	27.4 (18.9)	31.7 (26.6)	71.9$^{\cdot}$ (38.5)	25.7 (41.0)	8.3 (67.9)	32.9 (48.6)
The following ownership categories are contrasted with the category ‘Rent’						
Own	−19.9 (28.2)	−110.2 (43.0)*	−147.4 (63.0)*	−225.0 (58.6)***	−306.2 (114.3)**	−231.0 (74.5)**
Occupied without rent	−69.3 (136.8)	−250.0 (181.0)	−430.2 (162.9)**	−564.1 (286.4)*	40.4 (1007.6)	−267.8 (259.9)
The following urbanization categories are contrasted with the category ‘Rural’						
City	2.2 (37.2)	−55.1 (41.4)	−82.7 (57.2)	−176.5 (57.2)**	−68.5 (86.2)	−58.0 (74.2)
Town	78.2 (35.5)*	56.0(44.0)	14.4 (65.3)	−125.1 (57.6)*	41.3 (104.4)	2.5 (83.8)
Suburbs	11.4 (39.4)	−32.0 (55.3)	6.5(69.6)	−75.0 (67.5)	−3.0 (127.7)	87.7 (83.5)
The following year built categories are contrasted with ‘built before 1939’						
1940−59	32.1 (26.1)	−9.7 (43.2)	−71.7 (53.1)	−97.1 (70.5)	83.6 (121.6)	−50.1 (88.3)
1960−79	40.9 (27.3)	79.6 (51.8)	67.9 (55.6)	123.1 (53.2)*	253.4 (100.5)*	47.7 (82.6)
1980−99	65.4 (32.9)*	210.3 (46.4)***	232.9 (56.6)***	298.6 (60.9)***	490.2 (91.0)***	288.3 (83.8)***
2000+	88.7 (59.9)	197.0 (76.5)*	293.4 (94.5)**	339.4 (107.9)**	372.3(182.1)*	388.5 (116.5)***
The following housing type categories are contrasted with ‘single family detached’						
Mobile	46.2 (45.4)	37.6 (61.7)	64.5 (83.0)	105.4 (78.6)	247.4 (187.7)	93.9 (110.0)
Single family attached	−86.6 (52.8)	−251.9 (54.5)***	−311.7(81.3)***	−353.6(74.3)***	−283.0$^{\cdot}$ (145.3)	−343.5(100.4)***
Multifamily 2–4 units	−7.3 (31.8)	−131.3 (56.7)*	−214.2 (90.1)*	−235.9 (83.2)**	−420.3 (126.1)***	−321.9 (112.5)**
Multifamily 5+ units	25.9 (40.2)	−205.2 (53.3)***	−322.6 (72.1)***	−464.1 (75.1)***	−503.0 (149.9)***	−378.1 (96.2)***

Dependent variable is air conditioning use in kW h.

$^{\cdot}$ $(0.05 < p \leq 0.1)$.
* $(0.01 < p \leq 0.05)$.
** $(0.001 < p \leq 0.01)$.
*** $(p \leq 0.001)$.

area by half. Therefore, while zoning could be used to regulate the size of the houses, similar effects are achievable by taxation or altering the pricing in the tiered structure for high energy users so that weatherization programs can be funded. Also, the price effect is largest for the middle of the heating consumption spectrum while the size effect is largest at the right tail, suggesting that large price increases are necessary at the right tail to offset the increases in area. Increasing neighborhood density does not reduce space conditioning use. If at all, heating energy consumption in non-rural households are higher than rural households in the lower tail. Therefore, the focus of the densification of households should be on reductions in the transportation sector rather than the household sector.

The age of the house has a substantial effect on heating energy consumption, but not others. At the upper tail, the heating energy consumption is reduced almost by 5–14 MW h as the age of the house drops every 20 years, compared to 0.9–2 MW h at the lower tail. Part of this can be explained due to the efficiency of the heating system, and part of it can be explained by the tightness of the skin of the envelope. While, this seems to suggest that reducing the age of the housing stock is important for reducing energy consumption, it also suggests that energy conscious households obviate the effect of age. While in some cases replacing old stock of housing to replenish it with new stock of housing is viable, in most cases weatherization programs that effectively reduce the age of the house should be seen as a less wasteful way of achieving energy conservation. Furthermore, education and outreach programs that promote conservation of energy could also be effectively pursued and should be targeted towards high energy users and these programs are helpful in reducing the effects of older housing stock. Stern et al. (1986) argued that outreach and program implementation is much more important for participation in energy conservation programs than the incentive size itself.

Changing housing type mix makes a difference only when replacing single family residences with multi-family units in large apartment blocks. For the most part, other types of housing types do not promote savings in energy use across the consumption spectrum for all uses. This suggests that bold and dramatic changes in the type of housing mix are necessary for energy conservation. Furthermore, owners do not consume less energy than renters. While the owners' air-conditioning use is less than that of renters, they are dramatically dwarfed by larger other uses. Thus, promotion of ownership society programs may negatively affect conservation goals. It should be noted that ownership and housing type mix variables are heavily correlated; while large portion of SFDs are owned, MF5+ units are rented. However, the inclusion of interaction variables does not affect the general thrust of the analysis and therefore the conclusions are robust.

7. Further research and conclusions

This paper uses a national level dataset to understand the implications of various variables on energy use. While this dataset is exceedingly rich at the national level, drawing conclusions that

Table 5
Quantile and linear regression estimates for other energy use (2005 RECS data).

Covariates	Quantiles					OLS
	0.1	0.3	0.5	0.7	0.9	
(Centercept)	11,254.6 (415.6)***	16,991.5 (470.1)***	22,479.9 (519.2)***	27,434.2 (577.5)***	39,381.6 (1024.4)***	23,532.4 (527.5)***
Heating degree days	0.0 (0.1)	0.3 (0.1)***	0.7 (0.1)***	1.2 (0.1)***	2.1 (0.2)***	0.8 (0.1)***
Household size	1334.4*** (106.7)	1556.9 (130.8)***	1950.0 (151.8)***	2185.0 (175.7)***	3136.8 (315.7)***	2292.7 (127.5)***
Area	7.4 (1.5)***	13.3 (2.1)***	17.0 (1.9)***	23.1 (2.4)***	37.6 (4.4)***	19.3 (1.5)***
Average energy price	−139.1 (9.5)***	−209.6 (7.8)***	−238.2 (9.3)***	−229.6 (8.0)***	−237.3 (15.1)***	−269.6 (8.4)***
The following annual income categories are contrasted with the category 'less than 20 K'						
20–45 K	2334.4 (375.4)***	3669.5 (497.0)***	3675.4 (484.7)***	3679.1 (418.8)***	4089.0 (1152.8)***	4088.3 (426.7)***
45–75 K	305.4(289.6)	993.9 (370.1)**	1611.6 (389.1)***	1932.0 (408.1)***	2263.9 (775.3)**	1713.5 (368.4)***
75 K+	165.5(278.9)	383.1 (307.4)	476.5 (339.9)	530.5 (404.9)	146.9 (705.7)	341.1 (357.3)
The following ownership categories are contrasted with the category 'Rent'						
Own	762.3$^{\cdot}$ (454.3)	933.1 (438.8)*	1021.0 (512.3)*	1839.6 (578.5)**	908.3 (1018.0)	1504.6(550.2)**
Occupied without rent	2590.1 (1179.0)*	1834.4 (1171.9)	1334.2 (2045.8)	1660.8 (2923.2)	6102.7 (4747.1)	3007.3 (1908.6)
The following housing type categories are contrasted with single 'family detached'						
Mobile	−597.5 (544.7)	−231.3 (549.8)	−2362.6 (553.1)***	−3552.0 (671.8)***	−5846.0 (1302.0)***	−2461.1 (801.9)**
Single family attached	651.3 (646.6)	328.7 (572.5)	−591.2 (792.5)	−917.4 (956.1)	−2725.2. (1391.7)	−350.9 (725.2)
Multifamily 2–4 units	−1945.4 (707.4)**	−1488.1$^{\cdot}$ (826.4)	−1404.3 (884.6)	783.2 (1101.3)	3671.5 (2698.3)	715.7 (821.7)
Multifamily 5+units	−2545.3 (485.5)***	−3218.4 (521.3)***	−4224.8 (667.6)***	−4766.0 (684.3)***	−5877.4 (1166.3)***	−3636.0 (700.3)***

Dependent variable is other energy use in kW h.

$^{\cdot}$ $(0.05<p\leq 0.1)$.
* $(0.01<p\leq 0.05)$.
** $(0.001<p\leq 0.01)$.
*** $(p\leq 0.001)$.

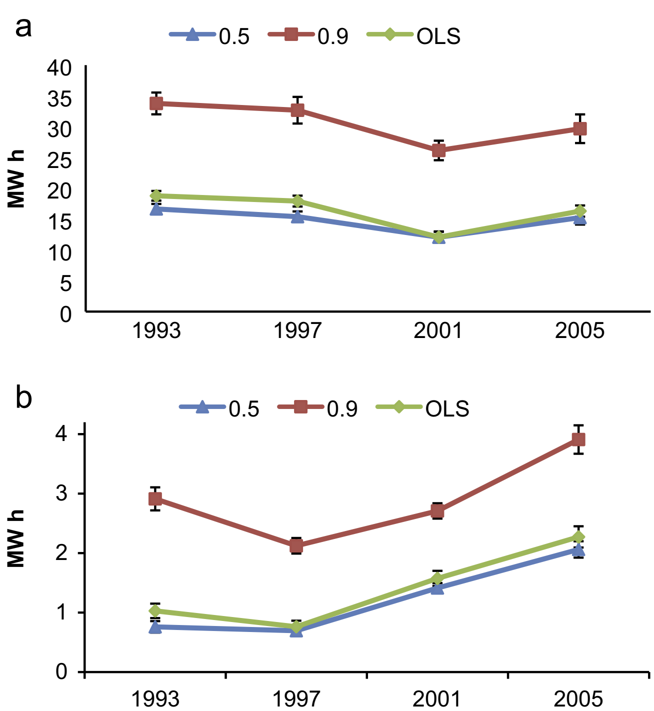

Fig. 3. Trends in Centercepts. a) Heating Energy Model b) Cooling Energy Model.

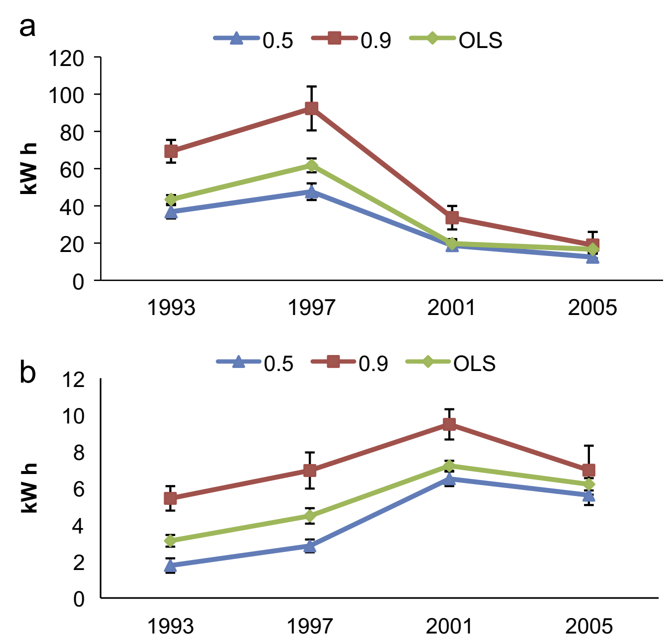

Fig. 4. Trends in the marginal impacts of house area. a) Heating Energy Model b) Cooling Energy Model.

are effective at the local level requires caution. Only four large states – Texas, California, New York and Florida – are explicitly coded into the dataset. This requires that spatial level data to be inferred from the weather data. In the absence of a reliable training dataset, making this connection to test the impacts of specific policies and conditions at local level is hard. For example, it is well known that while climate plays an important part in the residential energy consumption, microclimate plays an even greater role. The impacts of vegetation cover, wind patterns and albedo cannot be inferred from this data. Specific local and detailed data collection is necessary to understand the heterogeneous implications of the policies that are discussed in this paper. Furthermore, different fuel sources have different efficiencies and since the availability of the fuel is location specific, the effect of this variable should be studied before tailoring local policies.

This paper does not evaluate particular energy conservation programs or policies, but suggests ways in which we can begin to think about how they have differential impacts on residential

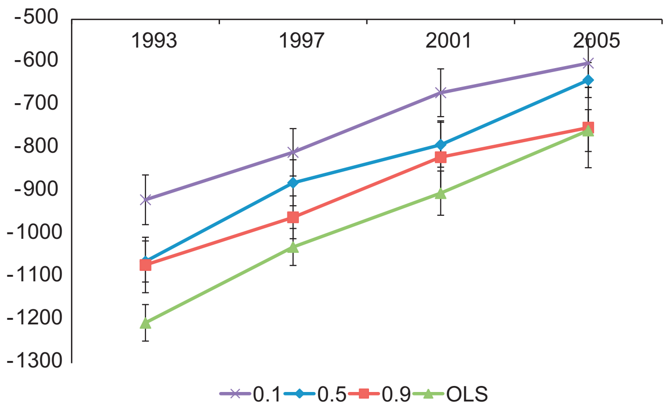

Fig. 5. Trends in the effect of price on total energy use.

energy consumption. For example, increase in the energy prices decreases the energy consumption, but the effect is most noticeable in discretionary use. Graduated increases in the prices in the tier structure would have more noticeable effect than uniform increases. A dollar increase would result in savings of about 3 MW h more at the upper end of the spectrum than at the lower end. The decrease in the air conditioning energy use is offset by more than 8 times, across most of the energy spectrum, by increases in other energy use, when the tenure of a house changes from renting to owning. While owners may have strong incentive to use more energy efficient cooling systems, they have higher tendency to own larger number of energy consuming appliances. While heating consumption of an average household has been on the decline, the air conditioning consumption has been on the rise in the last decade. Self reported neighborhood density reflected in the urban rural classification, does not reduce energy use. Only apartment in large blocks are substantially different in their energy consumption profiles than SFD. These results point to tailoring of targeted policies should focus on costs, benefits and ease of implementation. As the world becomes more conscious of its impact on climate through energy use, planners have a significant role to play in coming years.

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Appendix. Quantile regression

An average μ of a variable y could be understood as a minimizing solution to the problem

$$\sum_i (y_i - \mu)^2 \tag{1}$$

Analogously, a median m (0.5 quantile) is a minimizing solution to

$$\sum_i |y_i - m|$$

The key insight of Koenker and Bassett (1978) is that while minimizing equally weighted sum of the left and right deviations produces a median, minimizing appropriately weighted left and right deviations, generate quantiles. The τ quantile of a variable y (e.g. 10 percentile), denoted by q, is the value of y over which $(1-\tau)$% (e.g. 90%) of the values of y lie. It can be found as a minimizing solution to

$$\sum_i \rho_\tau (y_i - q)$$

where

$$\rho_\tau(x) = \begin{Bmatrix} -x.(1-\tau) & x<0 \\ x.\tau & x \geq 0 \end{Bmatrix} \tag{2}$$

When $\tau = 0.5$ this weighted minimization is a method of finding the minimum absolute deviation (MAD), or the median.

A standard linear regression is the prediction of conditional average of the dependent variable y_i. If X is a set of covariates and β is a vector of coefficients, we understand that the predicted value, $\hat{y}_i$, is what *on average* y_i would be, given x_i.

$$\hat{y}_i = E[y_i | X]$$

and β's are a solution to the optimization problem

$$\min \sum_i (y_i - x'_i \beta)^2 \tag{3}$$

Notice the similarity of the Eqs. 1 and 3. Similarly extending the definition to conditional quantiles, $^{Q\tau}(y|X)$ could be found by estimating β_τ. These β_τ can be found as a solution to the problem

$$\min \sum_i \rho_\tau (y_i - x'_i \beta_\tau) \tag{4}$$

where ρ_τ is a function as defined in Eq. 2. While an analytical solution, such as one to coefficients of an OLS regression is not possible, suffice it to say, many numerical methods exist to solve this linear optimization problem. Even without an analytical solution, this method offers important interpretational as well as statistical advantages.

References

Amato, A., Ruth, M., Kirshen, P., Horwitz, J., 2005. Regional energy demand responses to climate change: methodology and application to the commonwealth of Massachusetts. Climatic Change 71 (1), 175–201.
Andrews, C., 2008. Greenhouse gas emissions along the rural–urban gradient. Journal of Environmental Planning and Management 51 (6), 847–870.
Andrews, C.J., Krogmann, U., 2009. Explaining the adoption of energy-efficient technologies in US commercial buildings. Energy and Buildings 41 (3), 287–294.
Barnes, D., Krutilla, K., Hyde, W., 2005. The urban household energy transition, social and environmental impacts in the developing world. Washington, DC: Resources For Future.
Berry, L., 2003. Metaevaluation of national weatherization assistance program based on state studies, 1993–2002. Technical Report, ORNL/CON-488, ORNL.
Boarnet, M., Crane, R., 2001. The influence of land use on travel behavior, specification and estimation strategies. Transportation Research Part A 35 (9), 823–845.
Clark, K.E., Berry, D., 1995. House characteristics and the effectiveness of energy conservation measures. Journal of the American Planning Association 61 (3), 386–395.
Energy Information Administration, 2008. Annual energy review 2008. Technical Report, US Department of Energy.
Ewing, R., Rong, F., 2008. The impact of urban form on US residential energy use. Housing Policy Debate 19 (1), 1–30.
Geller, H., Attali, S., 2005. The Experience with Energy Efficiency Policies and Programmes in IEA Countries, Learning from the Critics. IEA information paper, International Energy Association, Paris.
Geroski, P.A., 2000. Models of technology diffusion. Research Policy 29 (4–5), 603–625.
Haas, R., Auer, H., Biermayr, P., 1998. The impact of consumer behavior on residential energy demand for space heating. Energy and Buildings 27 (2), 195–205.
Hao, L., Naiman, D., 2007. Quantile Regression. Sage, London, UK.
Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161.
Holden, E., Norland, I., 2005. Three challenges for the compact city as a sustainable urban form, household consumption of energy and transport in eight residential areas in the greater oslo region. Urban Studies 42 (12), 2145–2166.
Koenker, R., 2009. Quantreg, quantile regression. Retrieved from http.//CRAN.R-project.org/package=quantreg.
Koenker, R., Bassett Jr, G., 1978. Regression quantiles. Econometrica 46 (1), 33–50.
Koenker, R., Hallock, K., 2001. Quantile regression. Journal of Economic Perspectives 15 (4), 143–156.

Lindén, A., Carlsson-Kanyama, A., Eriksson, B., 2006. Efficient and inefficient aspects of residential energy behavior: what are the policy instruments for change? Energy Policy 34 (14), 1918–1927.

Myors, P., O'Leary, R., Helstroom, R., 2005. Multi unit residential buildings energy and peak demand study. Energy News 23 (4), 113–116.

Norman, J., MacLean, H.L., Kennedy, C.A., 2006. Comparing high and low residential density, life-cycle analysis of energy use and greenhouse gas emissions. Journal of Urban Planning and Development 13 (1), 10–21.

Peiser, R., 2001. Decomposing urban sprawl. The Town Planning Review 72 (3), 275–298.

Perkins, A., 2002. The influence of urban form on life cycle transport and housing energy and greenhouse gas emissions. Ph.D. thesis, Adelaide, School of Natural and Built Environments, University of South Australia.

Randolph, J., 2008. Comment on Reid Ewing and Fang Rong's the impact of urban form on US residential energy use. Housing Policy Debate 19 (1), 45–51.

Randolph, J., Masters, G.M., 2008. Energy for Sustainability. Island Press, Washington, DC.

R Development Core Team, 2009. R, A language and environment for statistical computing. Vienna, Austria, retrieved from http.//www.R-project.org.

Staley, S., 2008. Missing the forest through the trees? Comment on Reid Ewing and Fang Rong's the impact of urban form on us residential energy use. Housing Policy Debate 19 (1), 31–43.

Stern, P.C., Aronson, E., Darley, J.M., Hill, D.H., Hirst, E., Kempton, W., Wilbanks, T.J., 1986. The effectiveness of incentives for residential energy conservation. Evaluation Review 10 (2), 147–176.

US Department of Housing and US Census Bureau, 2008. American housing survey 2007. Current Housing Reports H 150/07, US Census Bureau.

Wainer, H., 2000. The centercept, an estimable and meaningful regression parameter. Psychological Science 11 (5), 434–436.

Winship, C., Radbill, L., 1994. Sampling weights and regression analysis. Sociological Methods and Research 23 (2), 230–257.

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