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Efficiency in Domestic Space Heating: An Estimation of the Direct Rebound Effect for Domestic Heating in the U.S.

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Efficiency in domestic space heating: An estimation of the direct rebound effect for domestic heating in the U.S.*

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Abstract

Improvements in energy efficiency are increasingly seen as a key strategy to reduce energy consumption in the domestic sector. Yet, concerns are mounting that households rebound, meaning that they adapt to efficiency gains by increasing their demand, as efficiency improvements reduce relative costs of energy. This study investigates the elasticity of household energy consumption for space heating with respect to changes in household heating efficiency. We account for the simultaneity of energy efficiency and energy consumption by applying an instrumental variable approach. Using data from the 2009 Residential Energy Consumption Survey, we document that while there is substantial 'takeback' among US households, rebound rates are far too small to dominate energy savings from these improvements. Estimates of the direct rebound effect in domestic heating are about 30%. Moreover, we find no evidence for a substantial indirect rebound at the household level. However, we document that the degree of 'takeback' increases in energy prices, suggesting that price-based and efficiency-based policy instruments may counteract each other.

Keywords: Energy efficiency, rebound effect, space heating.
Journal of Economic Literature Classification: D12, Q51, Q41, R22

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1 Introduction

Improvements in energy efficiency have been argued to be a double-edged sword with respect to energy savings and reductions in greenhouse gas emissions. On the one hand, they enable households to attain the same level of services using less energy and thus provide substantial scope for energy savings (Dietz et al., 2009; Stern, 2014). At the same time, however, they decrease these services' relative costs stimulating households to increase their demand. As a result potential energy savings are partially or completely offset. For instance, households obtaining a more efficient heating system may react by increasing thermostat settings or heating larger parts of their dwelling, thereby using up (some of) the energy savings gained by installing the more efficient heating system. This phenomenon, known as the 'rebound' or 'take-back' effect (Khazzoom, 1980; Brookes, 1990; Berkhout et al., 2000; Greening et al., 2000), has direct implications for policy making as it determines whether policies aiming to decrease energy use by targeting energy efficiency are likely to meet their objectives. The higher the degree of 'take-back', the less effective energy efficiency policies are in curbing energy use and combatting climate change (Brookes, 1990). For this reason, the rebound effect has sparked widespread interest and considerable concern in academia and politics (Turner, 2013).

While the behavioral mechanisms underlying the rebound effect are well-established in economics (Borenstein, 2014), such that there is little dispute on its existence, its extent remains a question of debate. In particular, estimates from the domestic heating sector are scant in the literature, with a vast majority of studies being several decades old. The empirical estimates of the direct rebound effect in space heating found in these studies vary substantially, ranging from a reassuring 0.6% to a worrying 60% (Sorrell et al., 2009). Hence, substantial confusion exists about the extend of the problem in the domain of domestic heating. Moreover, recent publications have suggested that a number of methodological and theoretical problems like limited sample sizes, focusing on a single heating fuel or unwarranted assumptions on the exogeneity of energy efficiency may seriously undermine the validity of these early results (Sorrell et al., 2009; Turner, 2013; Gillingham et al., 2013, 2014). On top of that, the widespread assumption that efficiency elasticities (i.e., rebound effects) can be equated with and thus estimated from own-price elasticties of demand has been qualified in a number of recent theoretical contributions (Sorrell and Dimitropoulos, 2008; Hunt and Ryan, 2014; Chan and Gillingham, 2015). These studies have called for a more thorough assessment of the magnitude of the rebound effect in the domestic sector, and have argued that further empirical studies are needed in order to understand the extent of bias arising from using own-price elasticities as a measure for the direct rebound effect (Hunt and Ryan, 2014; Gillingham et al., 2014).

In this contribution, we therefore study the direct rebound effect in space heating based on the elasticity with respect to the energy efficiency of the dwelling. To this end, we use data from the latest wave of the Residential Energy Consumption Survey (RECS) containing detailed information on energy expenditures, consumption and usage patterns of more than 11'000 households in the United States. Using this data set we are able to address many of the critical issues outlined above. In particular, we are able to compute measures of energy efficiency at the household level and therefore do not need to rely on the problematic assumption that the rebound effect can be derived from the price elasticity of demand.

Using ordinary least squares and instrumental variable methods, and controlling for a wide range of household and dwelling characteristics, we find that the rebound effect in space heating is, on average, about 30%. We believe that these results are encouraging from a policy perspective. While they clearly demonstrate that there is efficiency-induced rebound in domestic heating, they also suggest that that these take-back effects are modest. Moreover, we find no evidence for an association between efficiency in space heating and energy use for purposes other than space heating. In other words, we find no evidence for an indirect rebound effect. Our estimates, thus, suggest that efficiency policies are not ineffective in curbing energy use for domestic space heating.

2 Direct rebound in space heating

In the economic literature, the direct rebound effect is defined as the elasticity of energy service demand with respect to energy intensity (Berkhout et al., 2000; Greening et al., 2000; Sorrell and Dimitropoulos, 2008; Galvin, 2015):

$$\eta_{\varepsilon}(S) = \frac{\partial S}{\partial \varepsilon} \times \frac{\varepsilon}{S} \tag{1}$$

where S is energy service demand and ε is energy efficiency. A major challenge for studies on domestic heating is to find suitable proxies for both S and ε. While it is commonly argued that thermal comfort, in the sense of satisfactorily warm and sufficiently aired living quarters, is the main service obtained from space heating, an encompassing operationalization of this construct has proven to be elusive. Thermal comfort is a multidimensional construct, depending on a number of different household behaviors like indoor temperature settings, frequency and style of ventilation, duration of heating period and the proportion of living space that is actually heated (Galvin, 2015). This has made it extremely difficult to obtain a single summarizing measure. For the same reason, studies focusing on a single dimension of thermal comfort like thermostat settings are prone to capture behavioral responses to increases in energy efficiency only partially. It is therefore little surprising that such studies have usually found comparatively small rebound effects commonly well below 10% (Dinan and Trumble, 1989; Schwarz and Taylor, 1995; Fowlie et al., 2015).

The more common approach is therefore not to estimate $\eta_{\varepsilon}(S)$ directly, but to define the direct rebound effect with respect to energy consumption. As the energy service derived from space heating can be conceptualized as the product of energy consumption for this purpose q and energy efficiency of the dwelling ε, such that $S = \varepsilon \times q$, equation (1) can be reformulated to:

$$\eta_{\varepsilon}(S) = \frac{\partial q}{\partial \varepsilon} \times \frac{\varepsilon}{q} + 1 \tag{2}$$

which relates the direct rebound effect to the energy efficiency elasticity of energy demand (Sorrell and Dimitropoulos, 2008; Galvin, 2015). It is this definition of the direct rebound effect that informs this analysis. Its intuition is simply that if energy demand is perfectly elastic with respect to changes in efficiency (i.e. $\frac{\partial q}{\partial \varepsilon} \times \frac{\varepsilon}{q} = -1$), actual energy savings will equate expected savings and there will be no rebound. Deviations of the efficiency elasticity from -1 thus imply a departure of observed from expected energy savings. Efficiency elasticities smaller than negative unity are tantamount to negative rebound effects, also known as superconservation. Positive rebound effects are entailed by efficiency elasticities larger than negative unity ($\frac{\partial q}{\partial \varepsilon} \times \frac{\varepsilon}{q} > -1$), with the special case of $\frac{\partial q}{\partial \varepsilon} \times \frac{\varepsilon}{q} > 0$ where the rebound effect becomes larger than 1 thus implying a 'backfire' effect in the sense that improvements in energy efficiency actually increase energy (service) demand beyond levels prior to efficiency improvements.

Many empirical studies on the rebound effect in domestic heating face the additional difficulty that measures of energy efficiency are limited in conventionally used household survey data. A common approach to estimating the size of the rebound effect is therefore to relate it to the size of the price elasticity of demand. The basic intuition behind this approach is that, if individuals are indifferent to the source of a relative price change, an increase in efficiency should have the same effect on the demand of an energy service as a decrease in price. The two effects should thus be symmetrical and the rebound effect can be defined as:

$$\eta_{\varepsilon}(S) = -\eta_{p_q}(q), \tag{3}$$

where $\eta_{p_q}(q) = \frac{\partial q}{\partial p_q} \times \frac{p_q}{q}$ gives the elasticity of energy demand with respect to its price p_q (Sorrell and Dimitropoulos, 2008). However, numerous scholars have pointed out that this definition requires a number of very restrictive assumptions that are rarely met in empirical research (Sorrell and Dimitropoulos, 2008; Binswanger, 2001; Hunt and Ryan, 2014; Chan and Gillingham, 2015). In particular, it has been shown that if a single fuel can be used to deliver multiple energy services, fuel price elasticities may overestimate efficiency elasticities. Since the use of most heat fuels is not limited to space heating but encompasses other services like water heating or - in the case of electricity - the use of electronic equipment, it is likely that own-price elasticities draw an exaggerated picture of the extent of the rebound effect in space heating.

Henly et al. (1988) and Hunt and Ryan (2014) argue that own-price elasticities of energy demand should provide valid measures of the direct rebound effect in specifications controlling for changes in efficiency.

Some studies have used this principle. For instance, Hsueh and Gerner (1993) use data from the 1980-1981 round of the RECS to estimate the rebound effect in space heating based own-price elasticities of demand. Controlling for a comprehensive set of housing characteristics like wall or floor material, they report rebound effects of 35% for households heating with electricity and 58% for households heating with natural gas. In a sample of 440 Canadian households, Guertin et al. (2003) use household characteristics to determine energy service demand and space heating efficiency. Using this information they then estimate rebound effects from the own-price elasticity of energy service demand, yielding an average rebound effect of 38%. They also find that responsiveness to energy service prices varies substantially with income. While the rebound of high-income households is about 29%, low-income households take back 47% of the price-induced energy savings. Similarly, Haas and Biermayr (2000) estimate the rebound effect based on prices and energy intensity for 500 Austrian households. They find that these effects are not identical. Rebound effect based on own-price elasticity is about 20%, while the rebound effect based on intensity and efficiency measures is 32%.

Other studies have relied on comparing predicted energy use based on engineering estimates with observed energy use. Dubin et al. (1986), for example, compare actual to predicted electricity savings from insulation upgrades in 256 single-family dwellings in Florida. They find that engineering predictions significantly overstate actual electricity savings, and report rebound effects for space heating in the range between 8% and 12%. Similarly, Aydin et al. (2014), using an extensive Panel data set of almost 500'000 gas-heating households in the Netherlands, compare expectations based on the energy label of dwellings with the actual energy consumed by households. They address self-selection and the endogeneity of energy efficiency by instrumenting efficiency using the dwelling's year of construction and find average rebound effects of 42% among renters and 28% among owners. Moreover, they also show that there is substantial heterogeneity in the extent of the rebound effect in heating, with poorer households and extensive users exhibiting higher rates.

While the techniques used to generate such predictions are widely used and well-established in structural engineering, several recent studies have shown that they tend to over-estimate both energy use prior to the installation of energy-efficient improvements as well as the potential energy savings of these improvements (Fowlie et al., 2015). For example, a report for three Californian utility companies found that predictions of pre-retrofitted energy use based on such models exceeded actual energy use on average by about 40% (SBW Consulting, 2012, p. 55). What is more, Aydin et al. (2014) report that deviations between predicted and realized energy use depend on the energy efficiency of the dwelling, with low-efficiency households using substantially less energy than predicted by engineering models. This is problematic for econometric models which rely on these differences to identify the rebound effect. In fact, systematic prediction errors of this sort will to lead to an underestimation of the coefficient of predicted energy consumption and thus an over-estimation of the rebound effect.

The present paper therefore takes a different approach, and estimates rebound effects in space heating using variation in energy intensity of space heating based on observed energy use. Moreover, our data allow for the calculation of household level fuel prices. We are thus able to compare efficiency and price elasticities across different specifications. One cause of concern when identifying rebound effects in cross-sectional data is that energy efficiency is not exogenous to energy use, but rather that both are determined simultaneously as households with high energy requirements opt for living in energy-efficient dwellings. Following Aydin et al. (2014), we address this empirical difficulty by using an instrumental variable approach.

3 Data and descriptives

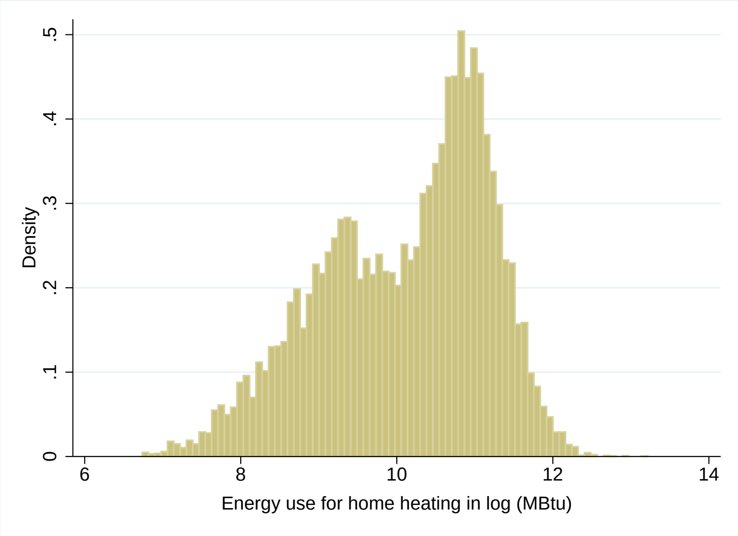
This study uses data from the Residential Energy Consumption Survey (RECS). The RECS is a nationally representative sample of households in the United States which is carried out every four years by the U.S. Energy Information Administration (EIA). We restrict the analysis to data from the latest available wave administered in 2009. Aside from detailed information on household demographics and housing characteristics, the RECS collects comprehensive data on energy expenditures, consumption and usage patterns. A unique feature of the RECS is that it disaggregates energy expenditures and consumption by use, thus allowing for a very detailed analysis of household reactions to changes in energy efficiency in a particular use like space heating. Moreover, energy consumption data of households are checked against supplier information, thus providing more reliable measures of energy use than commonly available in survey data.

The data set contains a total of 12’083 households of whom 11’534 (95.5%) report positive energy use for space heating and were therefore retained for further analysis. A further 138 households (1.1%) were removed because they were identified as outliers based on the fact that values of heating energy use, energy efficiency or energy price were outside an interval of three standard deviations around the sample mean. Thus, estimations are based on 11’304 households.

The dependent variable in this analysis is household energy use for space heating. Households use a variety of different fuels for space heating. Figure 1 plots the share of households in our sample according to the main space heating fuel. It shows that over half of the households rely on natural gas as their main heating fuel, while a further 35% of households use electricity for this purpose. Other fuels, including oil, propane, wood or kerosene are used only by a small fraction of households.

The variety of heating fuels used by households suggests that focusing on a single fuel like electricity or gas is likely to provide only a partial picture of the direct rebound effect in space heating, particularly if the rebound effect differs across heating fuels (Hsueh and Gerner, 1993). A related problem is that almost 40% of the households rely on more than one technology in order to heat their living space and that for a majority of these households the fuel used for the additional system(s) differs from the one used for the primary heating system. In order to obtain a comprehensive picture on energy demand for heating, estimations presented here rely on energy use from all sources converted to British thermal units (Btu). Figure 2 plots a histogram of household energy use for space heating in 1’000 Btus (= 1 MBtu).

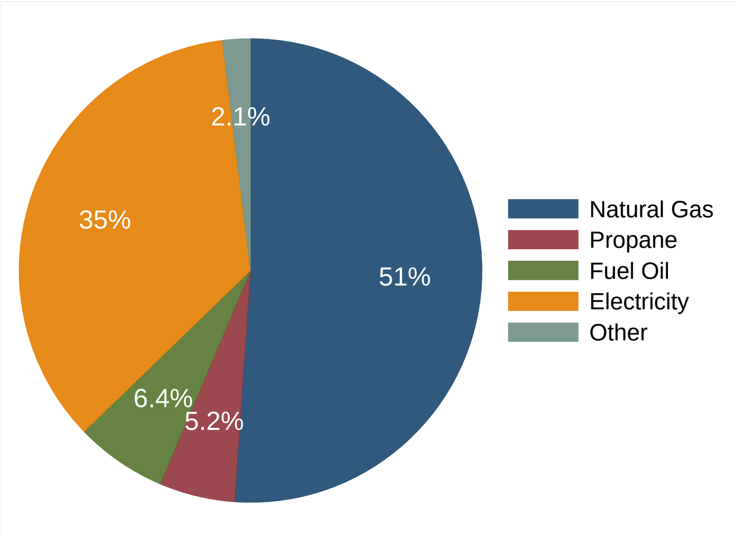
Figure 1: Main space heating fuel



The two main variables of interest in this study are heating efficiency and energy price. Energy prices for space heating faced by individual households depend on a number of factors like the geographical location of the household, the fuel or fuel mix used for heating, the structure of the local supply market for this fuel, and the quantity demanded, such that it is unlikely that two households face the same price. Instead of relying on geographical averages, we therefore calculate the fuel price for heating for each household using the unit value of one MBtu. Thus, the fuel price of each household i is defined as $p_i = \frac{x_i}{q_i}$, where x_i gives the household's expenditures on fuel used for space heating in 2009 US Dollars, and q_i is the energy used for space heating in MBtus.

Similarly, the actual conversion of energy into thermal comfort depends on a wide range of dwelling characteristics aside from the efficiency of heating system itself like solar gain, envelope U-values, indoor-outdoor air exchange or the level of human activity in the building (Galvin, 2015). To account for this complexity, we follow Galvin (2015) in defining energy efficiency, ε_i, by its inverse energy intensity, ι_i, that is by the quantity of energy necessary to heat a given area to a comfortable temperature. In our case, intensity describes the fuel use of each household per square feet of heated floor area and 65°F heating degree days

Figure 2: Histogram of Energy Use in US Households



(HDD), $\iota_i = \frac{q_i}{f_i^2 \times HDD_i}$. Energy efficiency is then simply given by its inverse, such that $\varepsilon_i = \frac{1}{\iota_i} = \frac{f_i^2 \times HDD_i}{q_i}$.[1]

Table 1 provides summary statistics for energy price and energy efficiency. The average price for a MBtu of space heating energy is about US$ 0.02. This corresponds well to the energy prices as taken from annual averages for the US.[2] The efficiency measure indicates that households on average use one MBtu to heat about 290 heating degree days square feet which corresponds to 0.07 square feet if evaluated at mean heating degree days. Spread is substantial with the most efficient households heating up to 0.7 square feet with this amount of energy, while least efficient households only manage to heat 0.003 square feet.

The RECS data provide a rich set of household and dwelling characteristics. Therefore, we are able to control for a wide range of characteristics of the dwelling and the family living inside it. Socio-economic characteristics include the sex, age and race (4 dummies) of the household head, as well as her level of educational attainment (9 dummies) and employment status (3 dummies). Moreover, it contains

[1] Results substituting current HDD by the 30 average of HDD are indistinguishable from the ones presented below. They are available from the author upon request.

[2] For instance, according to the US Energy Information Administration US average prices were US$ 0.1151 per kwH of electricity and US$ 0.0133 per cubic foot of natural gas in 2009. Using standard conversion measures then yields prices per MBtu of US$ 0.03 for electricity and US$ 0.01 for natural gas.

Table 1: Summary statistics for Efficiency and Price

Variables	(1) Mean	(2) SD	(3) Min	(4) Max	(5) Median
Heating Efficiency	286.755	303.828	14.182	3040.182	190.240
Price in US$ per MBtu	0.021	0.011	0.004	0.084	0.017

Sample $N = 11'396$, Population $N = 107'815'430$.

information on household size (in logs), the share of household members aged less than 5 years and the share of household members aged 69 years or older. Aside from employment status of the householder, several variables account for the economic situation of the household. The most relevant are gross annual household income in US$ (in logs),[3] and whether the individual is the owner of her dwelling or a renter. A set of 5 dummies controls for the source of income, by measuring whether any household member received work income (self-employed or employed), retirement income, investment income, income from welfare cash benefits and supplemental security income.

Dwelling characteristics encompass the building type in which the dwelling is located (mobile home, single-family detached, single family attached, apartment building with 2-4 units, apartment building with 5+ units), the size of the building measured by the number of floors, the size of the dwelling in square feet (log), its position on the rural-urban continuum (2 dummies), the age of the primary heating system (log), the type of this system (9 dummies) and the fuel used for it (6 dummies). Further characteristics include whether a secondary heating system was in place, whether the household heated the basement or the attic, whether there was a heated swimming pool on the premises and whether rooms had high ceilings. Characteristics of the construction encompass the major outside wall material (8 dummies), the major roofing material (9 dummies) and whether the house was constructed on a cement slap or over crawl space.

To account for varying climatic conditions, additional variables include the 65°F heating degree days (HDD) in 2009, the 30 year average of 65°F HDD and dummies for the five principal Building America climate regions as defined

[3] Household income in the RECS is given in 24 intervals ranging from "less than $2'500" to "$120'000 or more". In order to obtain a continuous measure for income, interval mid-points were used as a proxy of household income.

by the U.S. Department of Energy. Finally, to control for differences in the accuracy of measurement, we include dummies indicating whether the household energy bill included charges for purposes other than family use, whether household information was compared to supplier information on the five most widely used fuels and whether any of the answers were imputed rather than recorded. A detailed summary statistics for all variables can be found in Table A1 the Appendix.

4 Empirical strategy

In order to empirically identify the rebound effect in space heating, we estimate the elasticity of energy consumption for space heating with respect to heating efficiency, $\frac{\partial q}{\partial \varepsilon} \times \frac{\varepsilon}{q}$, and then follow the definition provided in equation (2) to obtain the corresponding rebound effect. The econometric model used for this purpose is given by:

$$ln(q_i) = \beta_0 + \beta_1 ln(\varepsilon_i) + \beta_2 ln(p_i) + \sum_{l=3}^{l} \beta_l X_{li} + \zeta_i, \quad (4)$$

where q_i is the energy consumption of household i devoted to space heating (measured in MBtu) and ε_i is this household's heating efficiency. p_i gives the overall price of the household's heating energy as measured in US$ per MBtu. Finally, X_i is a vector of observed control variables and ζ_i is the error term, assumed to be correlated across households living in the same type of building within the same geographical region yielding a total of 135 clusters, with an average cluster size of about 285 households.[4] All estimations apply sample weights in order to obtain results that are representative for the US housing population.

[4] The sampling procedure of the RECS involves repeated stratified random sampling, where primary sampling units (PSU) are counties rather than the geographic domains provided in the data set. While sample weights are provided, information on PSU is not available. We therefore opted for emulating the sampling design by creating clusters that combine the highest and the lowest sampling strata, i.e. geographical information and type of housing unit. Standard errors based solely clustering at the level of the 27 geographic domains given in the data set are very similar to the ones reported below. Both are considerably more conservative than the ones obtained by estimating standard errors based on the non-clustered heteroskedasicity-robust White Variance-Covariance matrix.

The rebound effect of space heating is then given by:

$$\eta_{\varepsilon}(S) = \beta_1 + 1. \tag{5}$$

Coefficients of model (4) are identified using two econometric strategies. In a first step, we use ordinary least squares (OLS) assuming that ε_i is independent of ζ_i. In a second step, we relax this assumption in order to address several shortcomings of our data set and estimation strategy.

A major concern of regression-based estimations of the rebound effect in cross-sectional data is that energy efficiency is not exogenous to energy use, but rather that both are determined simultaneously as households with high energy requirements opt for living in energy-efficient dwellings (Sorrell and Dimitropoulos, 2008). In the presence of this type of sorting, OLS will underestimate β_1 (in absolute terms) and therefore overestimate $\eta_{\varepsilon}(S)$. To check for the extent of this problem in the OLS estimations, we apply an instrumental variable (IV) approach. Following Aydin et al. (2014) we use the age of the dwelling in years as instrument for energy efficiency and identify parameters applying a two-stage least squares estimator (2SLS). In using this instrument we assume that dwelling age is relevant for determining energy efficiency and that, conditional on other included predictors, dwelling age affects energy use only via energy efficiency. In a series of preliminary experiments applying reduced form models it was determined that dwelling age is a significant predictor of energy efficiency and that linear and cubic specifications yield minimal Information Criteria.

More importantly, we used these models to test for the mediation of dwelling age by energy efficiency. That is, we augmented the reduced form model by our measure of energy efficiency and then compared the coefficient of the variable dwelling age from the reduced and the augmented reduced form models.[5] Figure 3 plots the marginal effects and 90% confidence intervals of an additional year of dwelling age on household energy use from estimations including and excluding energy efficiency as a an additional predictor. Both estimations control for the full

[5] More formally, the reduced form model can be written as: $ln(q_i) = \beta_0 + \gamma ln(a_i) + \beta_1 ln(p_i) + \sum_{l=2}^{l} \beta_l X_{li} + \zeta_i$, where a_i is simply the age of household i's dwelling in years. The augmented reduced form model is then given by $ln(q_i) = \beta_0 + \gamma ln(a_i) + \beta_1 ln(\varepsilon_i) + \beta_2 ln(p_i) + \sum_{l=3}^{l} \beta_l X_{li} + \zeta_i$.

set of co-variates discussed in section 3. It shows that, dwelling age is a significant predictor of energy use for space heating when energy efficiency is not included among the regressors. In this specification, energy use increases by roughly 0.3% with each additional year of dwelling age. Yet, after including energy efficiency the coefficient on dwelling age drops substantially in size and losses any statistical significance.[6] Once we control for a dwelling's energy efficiency, the relationship between energy use and dwelling age becomes both statistically and substantially indistinguishable from zero. The correlation observed in the reduced form model must have been absorbed by the energy efficiency measure, suggesting that the conditional impact of dwelling age on energy use for space heating is mediated by the energy efficiency of the dwelling. Stated in simpler terms, this experiment shows that a dwelling's age affects its energy efficiency which in turns drives energy demand. It also shows that conditional on energy efficiency and other controls there is no quantifiable effect of dwelling age on household energy use for space heating, which suggests that the exclusion restriction holds when instrumenting energy efficiency by dwelling age.

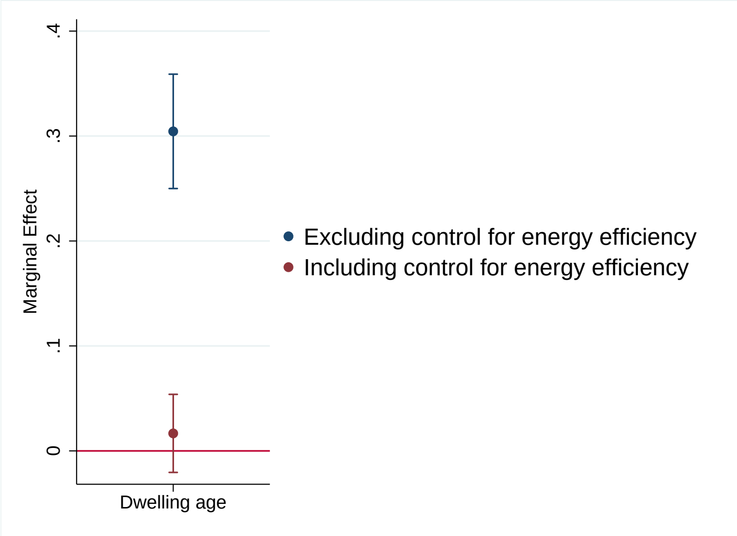
5 Results

5.1 Direct rebound in space heating

Table 2 presents results using OLS and IV estimators and applying a number of different specifications of the control variables. Columns (1) to (3) give results obtained using OLS, while columns (4) to (7) pertain to estimates obtained using IV. Columns (1) and (4) give results for models additionally controlling for household income (log), dwelling size (log) and HDD in 2009 (log). In columns (2) and (5) characteristics of the household and the household head are added, as well as state fixed effects and imputation controls. Finally, columns (3) and (6) to (8)

[6] In the augmented reduced from model, the coefficient on dwelling age indicates that an additional year of age increases energy use for space heating by about 0.017%, implying a reduction in coefficient size of about 95% compared to the reduced form model. Results from these estimations are available from the author upon request.

Figure 3: Marginal Effects and 90% Confidence Intervals of Dwelling Age on Energy Use



Notes: Estimations control for the full set of independents described above. Sample weights are applied.

give results additionally including dwelling characteristics. In order to assess the robustness of IV results with respect to the instrument applied, columns (7) and (8) provide results using alternative instruments. In column (7) we make use of the fact that previous literature has identified a strong relationship between the ownership status of a dwelling and the probability to invest in energy-efficient home improvements (International Energy Agency, 2007; Davis, 2010) and instrument household energy efficiency by a dummy taking the value of one if the household owns its place of residence, and zero otherwise. Mediation analysis for this instrument similar to the one presented in Figure 3 provided support for both relevance and conditional exogeneity of this instrument. Finally, in column (8) we follow Datta and Filippini (2015) and use the average fraction of Democratic members in state house and senate in 2009 as an instrument for energy efficiency.[7] Like Datta and Filippini (2015) we assume that these variables capture state policy towards energy-efficient home improvements without directly affecting energy use.

[7] As can be seen from Table A1 geographic domains are not generally congruent with US states in the RECS. If geographic domains comprise more than one state, we use population-adjusted average values of Democratic seat share in both chambers. Results restricting the sample to households for which geographic domain is equivalent with a single US state are very similar to the ones presented in Table 2. They are available upon request.

Since legislature composition is invariant within geographic units, we substitute state fixed effects by a set of average state outcomes in this specification. In particular, this control set contains median household income, average household size, fraction of households residing in a single-family home, fraction of households receiving social security income, fraction of households whose head is white, fraction of households whose head has completed tertiary education and the fraction of households whose head is currently employed. Due to limited variation both alternative instrument sets turn out to be weak, which is why model parameters are identified using Fuller's (1977) bias adjusted version of the limited information maximum likelihood estimator (LIML). This estimator has been found to perform reasonably well in the presence of weak instruments (Murray, 2006).[8]

For each model, we estimate rebound using the efficiency elasticity of energy demand based on definition (5). For the sake of brevity, we focus the presentation and discussion of results on the five most relevant out of 116 co-variates.

Table 2: Estimation Results: The Dependent is the log of household energy use for space heating

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	LIML	LIML
Instrument				Dwelling age	Dwelling age	Dwelling age	Ownership of dwelling	Partisanship of state chambers
Heating Efficiency (log)	-0.7653***	-0.7277***	-0.6851***	-0.7447***	-0.6939***	-0.7235***	-0.5787***	-0.7051***
	(0.0114)	(0.0116)	(0.0131)	(0.0264)	(0.0280)	(0.0390)	(0.1665)	(0.0942)
Price (log)	-0.2688***	-0.3696***	-0.3495***	-0.2907***	-0.4093***	-0.3140***	-0.4480***	-0.2899***
	(0.0198)	(0.0145)	(0.0217)	(0.0318)	(0.0387)	(0.0425)	(0.1580)	(0.0718)
Dwelling Size (log)	0.7209***	0.6696***	0.6398***	0.7096***	0.6504***	0.6656***	0.5683***	0.6531***
	(0.0138)	(0.0081)	(0.0128)	(0.0175)	(0.0185)	(0.0294)	(0.1131)	(0.0659)
Household Income (log)	0.0165***	0.0169***	0.0137***	0.0158***	0.0159***	0.0144***	0.0118**	0.0140***
	(0.0053)	(0.0051)	(0.0043)	(0.0052)	(0.005)	(0.0043)	(0.0054)	(0.0042)
Heating Degree Days (log)	0.9179***	0.8510***	0.8259***	0.9116***	0.8356***	0.8474***	0.7663***	0.8414***
	(0.0194)	(0.0114)	(0.0384)	(0.0201)	(0.0184)	(0.049)	(0.0983)	(0.0671)
Household Size (log)		0.0378***	0.0353***		0.0358***	0.0386***	0.0261*	0.0394***
		(0.0069)	(0.0065)		(0.0067)	(0.0069)	(0.015)	(0.0109)
Household Characteristics	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Dwelling Characteristics	No	No	Yes	No	No	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	No	Yes	Yes	Yes	No
Imputation Controls	No	Yes	Yes	No	No	Yes	Yes	Yes
$\eta_{\varepsilon}(S)$	0.2347***	0.2723***	0.3149***	0.2553***	0.3061***	0.2765***	0.4213***	0.2945***
	(0.0114)	(0.0116)	(0.0131)	(0.0264)	(0.028)	(0.039)	(0.1665)	(0.0942)
Adjusted R^2	0.934	0.941	0.948					
Centered R^2				0.934	0.94	0.947	0.945	0.946
First stage F-statistic				326.45	351.67	210.71	6.13	6.26
First stage instrument coefficient				-0.0076***	-0.0059***	-0.0042***	0.0518**	F-test[a]
				(0.0004)	(0.0003)	(0.0003)	(0.021)	

Notes: Sample $N = 11'396$, Population $N = 107'815'430$. All estimations contain a constant and apply sample weights. (Heteroskedasticity-robust standard errors clustered at the level of building type within each geographical region in parentheses). *** p<0.01, ** p<0.05, * p<0.1
[a] F-test for the two instruments (fraction of democrats in state house and fraction of democrats in state senate): p-value of 0.0025.

Signs and magnitudes of the coefficients of the presented control variables are in line with previous results. We find that energy use for space heating increases

8 All IV estimations were performed in Stata using the ivreg2 command by Baum et al. (2007).

substantially in dwelling size, with point estimates ranging between 0.64 and 0.72. Notably, holding dwelling size constant, point estimates of household size as measured by (the log of) the number of persons in the household take values below 0.04. This is substantially smaller than estimates reported in earlier work (e.g. by Schroder et al., 2015). However, these studies commonly lack detailed information on dwelling size, suggesting that the household-based scale economies identified in these studies are mainly driven by household differences in dwelling size. That is, larger households tend to live in bigger dwellings and energy demand for space heating increases under-proportionally in dwelling size. Yet, holding dwelling size constant, the number of people in a household has little impact on energy demand for space heating.

Consistent with prior literature, we also find that climatic conditions are important for determining energy use for space heating. Coefficient estimates show that a 1% increase in heating degree days yields an almost unitary increase in energy use for space heating. Income elasticities for space heating energy are estimated to be around 1.6%, clearly demonstrating that space heating energy is a necessary good. Although comparable to early studies using US data (Dubin and McFadden, 1984), this estimate is situated on the lower end of the scale of income elasticities found in most previous studies. One reason could be that income in the RECS is measured in intervals and is therefore subject to measurement error yielding downward biased point estimates.

Price elasticities for energy demand in space heating take values of -0.38 to -0.26. These estimates are in line with long-run price estimates identified in the previous literature (see Azevedo, 2014).

Finally, Table 2 reports estimates for the efficiency elasticity of energy demand in space heating (β_1 coefficients). In general point estimates of β_1 obtained using OLS are only slightly smaller than IV estimates, suggesting that bias in OLS coefficients is limited in our estimations. Note, however, that differences between IV and OLS estimates are significant as judged by the χ^2 values from the Durbin-Wu-Hausman endogeneity test. Dwelling age is a strong instrument with first stage F-statistics exceeding the critical value of 10 by at least an order of magnitude and first stage coefficients being highly significant. Point estimates of β_1 range between -0.77 and -0.69 in OLS estimations and -0.74 and -0.58 in IV estimations.

Using definition (5) they translate into rebound effects in the range between 23% and 31% in OLS and 25% to 42% in IV estimations.[9] We also find that using different instruments yields comparable point estimates of the rebound effect. While, the estimated β_1 coefficient is somewhat larger when using ownership status as instrument, standard errors are also substantially larger than in the other two specifications. As a result ensuing Wald tests do not provide sufficient evidence to reject the Null that the rebound estimate from this specification is significantly different from rebound estimates of the other two.

Our estimates correspond surprisingly well to earlier rebound estimates from the U.S. and Northern Europe relying on price-elasticities as proxies for the rebound effect (e.g. Dubin and McFadden, 1984; Nesbakken, 2001), and roughly take a middling value in the range of most previous results (cf. Sorrell et al., 2009; Azevedo, 2014). Moreover, they are similar to the ones presented by Aydin et al. (2014) who use a very similar identification strategy to obtain rebound effects between 28% and 42% for a large Panel of gas-heating Dutch households.

In summary, our results suggest that as energy efficiency of U.S. dwellings increases, energy savings increase under-proportionally with only about 70% of potential savings from efficiency improvements actually being realized. This shows that rebound in domestic space heating is substantial among US households.

However, caution is advised when interpreting these values with respect to the expected change in household energy use as levels of efficiency increase. While, rebound estimates are significantly larger than zero, they are also significantly smaller than one. Thus, despite the fact that households 'takeback' some of the energy saving accrued from improvements in heating efficiency, these improvements nevertheless imply clear reductions in energy use. For example, an intervention that would improve the heating efficiency of a median efficient household to match the efficiency of a household at the 60% decile, would imply energy savings of 20% despite rebound. This corresponds to the effect of a 64% price increase, and is thus substantial compared to an important policy instrument like taxation.

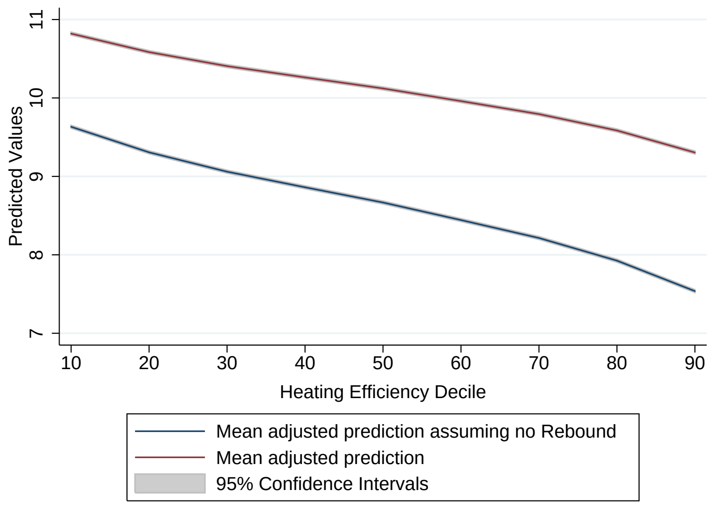
To illustrate this further, Figure 4 plots average predicted values of household energy demand for space heating over the deciles of the energy efficiency distribution. The upper line depicts predicted values using the coefficient estimates

[9] Point estimates and standard errors for these values are given in the row labeled $\eta_\varepsilon(S)$.

presented in column (6) of Table 2. The lower line depicts average predictions assuming that there was in fact no rebound, i.e. $\beta_1 = -1$.

The vertical distance between the two lines gives the difference between expected energy demand for space heating given unit-elasticity of demand with respect to energy efficiency and realized energy demand as predicted from the estimation presented in Table 2. That is, assuming that the marginal effect at the mean applies to the entire range of observable efficiency values, it gives the amount of space heating energy that can be attributed to rebound and thus provides a visual interpretation for the β_1 coefficient from Table 2. A second, equally important insight that can be gained from Figure 4 is that both lines are downward sloping. That is, that as energy efficiency increases predicted demand declines, even in the presence of a rebound effect. Put differently, despite a non-negligible degree of 'takeback' among US households, improvements in energy efficiency yield considerable energy savings.

Figure 4: Average predicted values of energy consumption for space heating



A notable feature of the results presented in Table 2 is that in absolute size efficiency elasticities and price elasticities of energy demand are fairly similar. Using definition (3) would yield estimates of the rebound effect between 27% and 45%, and thus values that are on average about 5% above the rebound effects obtained from efficiency elasticities. This result could thus be interpreted as empirical support for the argument by Henly et al. (1988) and Hunt and Ryan (2014) that once controlling for differences in energy efficiency, energy price elasticities can be used to proxy direct rebound effects.

However, it should also be noted that despite the apparent similarities in rebound estimates based on energy price and energy efficiency, a series of ensuing Wald tests suggested that differences between these estimates are statistically significant in all estimations presented in Table 2. Moreover, additional experiments aiming to evaluate the robustness of price elasticities to changes in the measure of energy efficiency showed that price elasticities reacted extremely sensitive to changes in specification. In particular, we found that when emulating the empirical strategies applied in the previous literature by substituting energy efficiency by different specifications of dwelling age or by the state-level price development of the household's main heating fuel in the 10 years prior to 2009 (as in Hunt and Ryan, 2014) as well as by interactions between energy-related dwelling characteristics (as in Hsueh and Gerner, 1993) point estimates were very close to negative unity, implying 'takeback' rates that are about three times the size of the ones identified in Table 2.[10] Results, thus, show that even when controlling for characteristics that proxy energy efficiency, bias in rebound estimates based on price elasticities can be substantial. Researchers relying on such an identification strategy for rebound should therefore exercise great caution.

5.2 The effect of energy price on rebound

An important finding from previous research is that the degree of 'takeback' is not homogeneous across the population, but varies systematically along several socio-economic dimensions. For instance, Guertin et al. (2003), Madlener and Hauertmann (2011) or Aydin et al. (2014) all find that the rebound effect in space heating changes with household position along the income distribution as well as with ownership status of the dwelling. Poorer households and renters show higher rates of 'takeback'. These findings are important in order to understand

[10] Results are given in Table A2 in the Appendix.

heterogeneity in rebound in space heating and to improve predictions on the effectiveness of policy interventions tailored to sub-populations in the population.[11]

Another important question with respect to the heterogeneity in rebound, is whether household responses to efficiency improvements depend on the level of energy prices as well. Most policies aiming to reduce household-level energy demand rely on a mix of different instruments, commonly combining price regulation of energy sources through taxation and stimulating efficiency-improvements through subsidies and tax exceptions. However, it is not a priori clear whether these measures have a purely additive effect on household energy demand.

While - as shown in Table 2 - increasing energy prices lead to a decrease in demand, they also entail increasing cost savings from investments in energy efficiency improvements . That is, cost savings for the same energy efficiency improvement will be higher in a high price environment than in a low price environment. Yet, larger cost savings may provoke stronger rebound effects, if consumer responses to cost savings are non-linear. In fact, the literature on real-time pricing of electricity indicates that sensitivity to price changes depends on price levels, with a majority of studies showing that price elasticities of energy demand increase in prices (Aigner et al., 1994; Filippini, 2011). Hence, one should expect higher 'takeback' rates among households facing higher prices if efficiency changes yield similar behavioral responses as relative price changes. Moreover, households facing high energy prices may be forced to cut-back more on energy consumption and may thus be further away from a point of optimal thermal comfort. Consequently, the marginal utility of spending an extra Dollar on heating energy could be higher among them, such that they re-spend a larger share of efficiency-induced costs savings on heating energy.

To assess whether price increases and efficiency efficiency improvements counteract each other, I expand model (4) by a term interacting household heating efficiency ε_i with the price of heating energy p_i. The extended regression is then given by:

[11] In a set of additional estimations (not reported, but available upon request) we were able to reproduce these findings for the RECS 2009 data set.

$$ln(q_i) = \beta_0 + \beta_1 ln(\varepsilon_i) + \beta_2 ln(p_i) + \beta_3 \left(ln(\varepsilon_i) \times ln(p_i)\right) + \sum_{l=4}^{l} \beta_l X_{li} + \zeta_i, \qquad (6)$$

where $ln(\varepsilon_i)$ and $ln(p_i)$ are centered at their respective median values in order to retain interpretable base effects. Thus, $\beta_1 + \beta_3 ln(p_i)$ gives the marginal effect of heating efficiency on energy consumption at different price levels, with β_1 denoting this effect at median energy prices, i.e. at the price of about 1.7 US Dollar cents for one MBtu of primary heating energy. Analogously, $\beta_2 + \beta_3 ln(\varepsilon_i)$ gives the marginal effect of energy prices at different levels of efficiency, with β_2 denoting this effect at median efficiency values, meaning that a household manages to heat roughly 193 heating degree days square feet per MBtu.

Endogeneity of energy efficiency is again accounted for by the age of the dwelling. Moreover, following Wooldridge (2002) the interaction is instrumented by an interaction between dwelling age and the price of energy.[12]

Results from these exercises are presented in Table 3. Mimicking the empirical strategy in section 5.1, the number of covariates increases from column (1) through to column (4). The final column additionally includes a squared price term in order to accommodate for the fact that price elasticities of energy may not be independent of price levels (Aigner et al., 1994; Filippini, 2011). Base effects for efficiency and price correspond well with marginal effects at the mean presented in Table 2, suggesting that our main results are not driven by outliers.

We find that both energy price and its square term have a significant, negative effect on household energy demand, providing evidence for a strong and non-linear increase of own-price elasticities of energy consumption in prices. This finding is in line with earlier results on real time pricing of electricity (Aigner et al., 1994; Filippini, 2011), and suggests that price-based differences in sensitivity to price

[12] A word of caution concerning our estimation strategy is advised here. By using the interaction between dwelling age and the price of energy as an instrument for the interaction between energy efficiency and the price of energy, we have to assume that energy prices are exogenous regressors. While this assumption is unlikely to hold, we have not been able to identify suitable instruments for energy prices. Experiments using the changes in regional prices of the main heating fuel in the 10 years prior to 2009 did not yield plausible results.

Table 3: Estimation Results: The Dependent is the log of household energy use for space heating

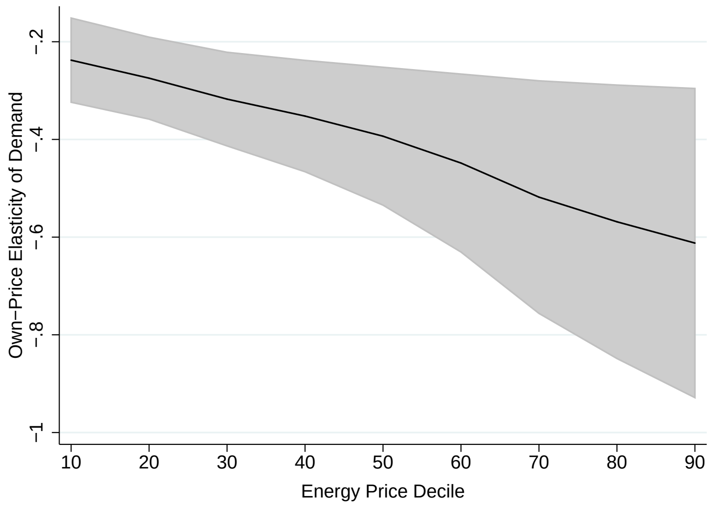
	(1)	(2)	(3)	(4)
Estimator	2SLS	2SLS	2SLS	2SLS
Instrument	Dwelling age	Dwelling age	Dwelling age	Dwelling age
Heating Efficiency (log)	-0.7395***	-0.6576***	-0.6785***	-0.6774***
	(0.0350)	(0.0366)	(0.0516)	(0.0526)
Price (log)	-0.3710***	-0.5713***	-0.4619***	-0.3961***
	(0.0493)	(0.0748)	(0.0999)	(0.0728)
Heating Efficiency (log) × Price (log)	0.2348***	0.2406***	0.2132**	0.1921**
	(0.0666)	(0.0680)	(0.0856)	(0.0769)
Price (log) × Price (log)				-0.1420**
				(0.0634)
Household Income (log)	0.0124**	0.0101*	0.0104**	0.0112**
	(0.0059)	(0.0052)	(0.0048)	(0.0046)
Dwelling Size (log)	0.7005***	0.6030***	0.6187***	0.6219***
	(0.0233)	(0.0287)	(0.0418)	(0.0410)
Heating Degree Days (log)	0.8932***	0.7720***	0.8222***	0.8240***
	(0.0260)	(0.0339)	(0.0622)	(0.0578)
Household Size (log)		0.0320***	0.0332***	0.0339***
		(0.0071)	(0.0076)	(0.0074)
Household Characteristics	No	Yes	Yes	Yes
Dwelling Characteristics	No	No	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes
Imputation Controls	No	No	Yes	Yes
Centered R2	0.921	0.929	0.940	0.942

Notes: Sample $N = 11'396$, Population $N = 107'815'430$. All estimations contain a constant and apply sample weights. (Heteroskedasticity-robust standard errors clustered at the level of building type within each geographical region in parentheses). *** p<0.01, ** p<0.05, * p<0.1

changes are likely to extend to other energy sources as well. Figure 5 plots own-price elasticities at different deciles of the observed price distribution, based on the estimates provided in column 4. It shows that own-price elasticities change substantially over the observed price distribution, rising from -0.24 at the 10% decile (corresponding to a price of US$ 0.0097 per MBtu) to -0.61 at the 90% decile (about US$ 0.036 per MBtu). Note that due to inherent problems of efficiency in regressions using interaction terms, confidence bounds are wide for these estimates. Nevertheless, a set of ensuing Wald tests (not reported but available upon request) suggest significant differences between price elasticities at the median and other deciles of the price distribution.

Results from Table 3 also show a positive and significant coefficient on the interaction term, suggesting that an increase in prices leads to a decrease in the efficiency elasticity of energy consumption and thus to an increase in rebound.

Figure 5: Own-price Elasticity of Energy Demand by Price Level

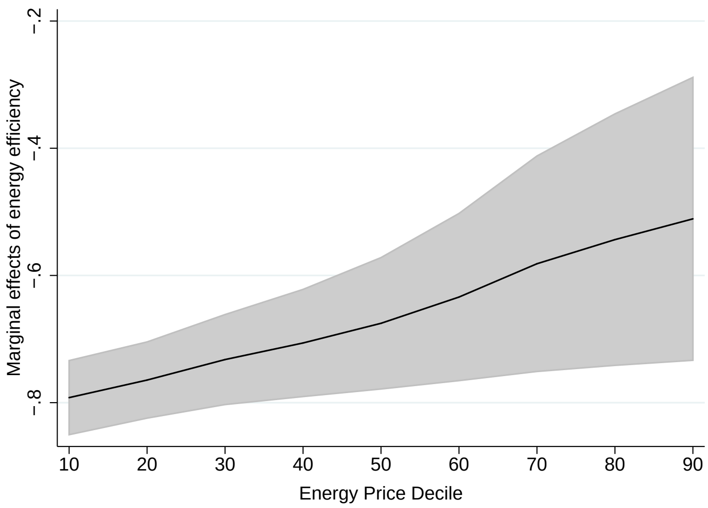


Point estimates take values around 0.2 in all models, indicating that doubling prices will increase average 'takeback' by about 20%. This is substantial, given that rebound is just over 30% at median price levels. Moreover, estimates predict that efficiency improvements may actually backfire (i.e. $\eta_{\varepsilon}(S) \geq 1$) once energy prices exceed a certain threshold. In our estimations this threshold ranges from US$0.25 to US$0.57 per MBtu, depending on the specification. While these values exceed observed prices by at least a factor three,[13] they nevertheless underline that an increase in energy prices with the aim of encouraging energy conservation may produce unintended side effects by decreasing the effectiveness of energy efficiency improvements.

In order to get a more realistic impression on the change in 'takeback' across price levels, Figure 6 plots estimated rebound effects for different deciles of observable energy prices. Estimates are based on the results presented in column 4 of Table 3. It shows that rebound effects more than double from about 22% at the 10% price decile to just over 47% at the 90% price decile. Again a series of ensuing Wald tests indicate that differences between rebound effects at the median

[13] The average price per MBtu in the population is US$ 0.021, ranging from a minimum of US$ 0.004 to a maximum of US$ 0.084.

Figure 6: Rebound Effect by Price Level



and other deciles of the price distribution are significant at commonly accepted levels of error.

From an individual perspective, these results are intuitive. Rising energy prices are likely to force households to cut back demand, depriving the household of thermal comfort and thus increasing the marginal utility of an additional Dollar spent on heating. Consequently, savings from improvements in energy efficiency will be re-spend on heating energy in order to reduce deprivation of thermal comfort. That is, households use efficiency improvements to mitigate the effect of rising energy prices on their energy consumption.

From a policy perspective, this is a somewhat unfortunate finding. As rebound depends on energy prices, price-based and efficiency-based policy instruments aiming at energy conservation may at least partially offset one another. Hence, policies combining both instruments need to take these interactions into account when trying to predict effectiveness of overall energy policy. In particular, results suggest that beyond certain energy price levels, efficiency policies will fail to contribute to energy savings in domestic space heating. However, they may nevertheless be important tools to improve households' well-being by enabling them to achieve higher levels of thermal comfort despite high price levels.[14]

[14] Moreover, as price elasticities also increase in prices and do so stronger than rebound effects, the net effect of both efficiency and price increases on energy demand remains negative even when

5.3 Indirect Rebound

Another common cause for concern when discussing estimations of the direct rebound effect is that they provide only a partial picture of the effect of increases in energy efficiency on household total energy use. The reason is that by decreasing the costs of a particular service (in our case space heating), efficiency increases induce substitution and income effects that go above and beyond the demand adaptations for the primarily affected service (Sorrell and Dimitropoulos, 2008; Azevedo, 2014). For example, increases in household space heating efficiency decrease the cost of space heating and will (as demonstrated above) lead to increases in energy demand for space heating that partially offset the energy savings from the efficiency improvements. That is, it will produce a direct rebound effect. However, energy savings also increase the disposable income of a household which in turn will increase demand for all normal goods including energy used for services other than space heating, like water heating or refrigerating.

This is particularly problematic in our case as the dependent variable in estimations presented in sections 5.1 and 5.2 is household energy use for space heating, rather than total energy use. As previous studies have suggested that the size of the indirect rebound effect may be substantially larger than the one of the direct rebound effect (see reviews by Thomas and Azevedo, 2013a; Chitnis et al., 2013), estimates given above may present only a small share of total household reactions to improvements in space heating efficiency. To check whether this is a likely scenario in the current setting, Table 4 presents a set of estimations where the dependent variable is household energy use (in MBtu) for all services other than space heating, i.e. water heating, space cooling, cooking, and the use of electric appliances. Again energy efficiency is instrumented using dwelling age.

Results show that all in all energy demand for services other than space heating seems to be unaffected by changes in energy efficiency for space heating. While excluding most covariates yields a moderate indirect rebound effect of 11%, this effect quickly disappears as additional controls are added, with coefficient size

predicting demand at price levels where efficiency improvements can be predicted to 'backfire' (i.e. rebound in excess of 100%).

Table 4: Estimation Results: The dependent is the log of household energy use for purposes other than space heating

	(1)	(2)	(3)
Estimator	2SLS	2SLS	2SLS
Instrument	Dwelling age	Dwelling age	Dwelling age
Heating Efficiency (log)	0.1101***	0.0117	-0.0193
	(0.0471)	(0.0498)	(0.0685)
Price (log)	-0.2348***	-0.1554***	-0.2493***
	(0.0623)	(0.0651)	(0.0714)
Household Income (log)	0.0443***	0.0332***	0.0333***
	(0.0113)	(0.0071)	(0.0061)
Dwelling Size (log)	0.4554***	0.3490***	0.2898***
	(0.0455)	(0.0356)	(0.0478)
Heating Degree Days (log)	-0.1368***	-0.0914***	-0.0272
	(0.0374)	(0.0298)	(0.0705)
Household Size (log)		0.4102***	0.3842***
		(0.0119)	(0.0108)
Household Characteristics	No	Yes	Yes
Dwelling Characteristics	No	No	Yes
State Fixed Effects	No	Yes	Yes
Imputation Controls	No	No	Yes
Centered R2	0.335	0.543	0.608

Notes: Sample $N = 11'396$, Population $N = 107'815'430$. All estimations contain a constant and apply sample weights. (Heteroskedasticity-robust standard errors clustered at the level of building type within each geographical region in parentheses). *** p<0.01, ** p<0.05, * p<0.1

approaching zero and p-values approaching one. As the exogeneity of the instrument for energy efficiency is likely to be violated when excluding other dwelling characteristics, results in columns (2) and (3) are more reliable than the result from column (1). We, thus, find no evidence for the fact that energy efficiency changes in space heating affect energy demand for other services, which contradicts most previous findings (e.g. Thomas and Azevedo, 2013b).

It is important to note, however, that this analysis does not cover all aspects of energy use. In particular, we do not assess whether changes in energy efficiency are correlated to changes in household expenditures for goods and services that require embodied energy. This may also explain the difference between the results of Table 4 and the findings from previous literature. Yet, our results are nevertheless important with respect to the structure of the indirect rebound effect. They show that beyond the direct rebound effect, changes in energy efficiency for space heating do not affect changes in energy demand for other services and thus suggest that this particular channel of indirect rebound may be less problematic than commonly assumed.

6 Conclusion

Improving energy efficiency in the domestic sector is increasingly seen as a key strategy in the quest to reduce (externalities from) global carbon emissions and to move towards a more sustainable energy system. While the scope for such improvements is indeed substantial (Dietz et al., 2009; Stern, 2014), economists have long noted that technological measures of this type are tantamount to decreasing the relative costs of energy and thus are likely to stimulate households to increase their demand (Khazzoom, 1980; Brookes, 1990; Berkhout et al., 2000; Greening et al., 2000). From a policy perspective this phenomenon known as the 'rebound' or 'takeback' effect has several important implications. It determines how effective policy measures targeting energy efficiency are in reducing energy demand. A rebound effect of 25% implies that an efficiency improvement predicted to reduce energy demand by 1 tonne of oil equivalent (toe), will in fact reduce demand only by 0.75 toe. Moreover, the difference between expected and realized energy savings affects the cost-effectiveness of these policy measures. If original predictions estimated the costs of saving one toe to be \$100, realized costs would be as high as \$133 (see Azevedo, 2014, for a similar example). Quantifying the scope of the rebound effect is therefore an important step in improving models predicting energy savings from efficiency measures as well as their cost-effectiveness.

The current study investigates the rebound effect in space heating using the 2009 wave of the US Residential Energy Consumption Survey. Contrary to much earlier work, it uses household level measures of energy efficiency and therefore does not have to rely on the problematic assumption that consumer reactions to energy improvements can be equated with consumer reactions to price changes. Moreover, we address the problem of endogeneity in energy efficiency by using an instrumental variable approach.

For evaluating the effectiveness of efficiency improvements in domestic space heating, this study provides some important insights. First and foremost, we find that on average U.S. households 'takeback' about 30% of the energy savings from improvements in energy efficiency. That is, US households only manage to realize 70% of expected savings. Thus, an intervention that would have been planned based on assuming perfect elasticity would have the realized a 43% lower cost-effectiveness than initially estimated. Rebound in space heating is thus non-negligible in the US domestic sector. Consequently, including these behavioral responses into models of projected energy savings and use may provide more a realistic picture on the effectiveness of policy interventions and thus help to improve decisions over competing strategies. On the other hand, it needs to be pointed out that our empirical estimate of the rebound effect is well below the 60% mark quoted in earlier literature (Sorrell and Dimitropoulos, 2008). That is, despite a non-negligible degree of 'takeback', energy efficiency improvements in domestic heating yield considerable reductions in energy demand, suggesting that measures to improve domestic heating efficiency are valuable policy instruments for curbing domestic energy use. This clearly underlines the argument by Gillingham et al. (2013) that the existence of rebound effects alone is not sufficient to justify the rejection of energy efficiency policies.

This argument is further supported by the fact that we fail to find evidence for an impact of energy efficiency improvements in space heating on demand for other energy uses like water heating, cooking or space cooling. That is we find no evidence for an indirect rebound effect, which has been asserted to further undermine the effectiveness of energy efficiency policies (cf. Sorrell and Dimitropoulos, 2008; Chitnis et al., 2013). Clearly, by focusing on other household energy uses, the scope of this analysis is limited. For instance, due to the absence of suitable data we can make no statements about the effect of these improvements on demand for transport or the energy intensity of products and services acquired. Hence, a study including a comprehensive assessment of household energy demand may prove to be an important complement to this investigation. However, it is often assumed that re-spending on other fuels is an important source of indirect rebound (Thomas and Azevedo, 2013b). Thus, our failure to identify such an effect suggests that at least this channel of indirect rebound may be less problematic than previously assumed.

We further assess the change in rebound with respect to changes in prices for heating energy, using interactions between energy efficiency and energy prices. Coherent with prior findings on the dependence of price-elasticities on price levels (Aigner et al., 1994; Filippini, 2011), we identify both increasing own-price elasticities of demand and rising degrees of rebound as energy prices surge. Hence, households facing higher energy prices tend to 'takeback' larger shares of potential energy savings, then households in a low price environment. This phenomenon likely originates from the fact that households make use of energy efficiency improvements to mitigate the effect of high energy prices on their level of thermal comfort.

From a policy perspective this result has the somewhat unfortunate implication that price-based and efficiency-based instruments partially, albeit not completely, offset one another. In particular, it suggests that efficiency policies will contribute little in terms of energy savings, once energy prices have passed a certain threshold. Indeed, our estimates even indicate that rebound effects in excess of 100% can be expected at price levels beyond a range of US$ 0.26 to US$ 0.57 per MBtu. While these values exceed observed average sample prices by at least a factor 14, models predicting energy consumption and savings from energy policies combining price-based and efficiency-based tools need to account for the fact that both instruments are not simply additive. However, as rebound entails improvements in well-being by enabling households to achieve better levels of thermal comfort (Borenstein, 2014), energy efficiency policies should remain important tools for public policy even in high energy price environments.

In summary, we believe that results presented in this study are encouraging from a policy perspective. While they clearly demonstrate that there is substantial rebound in space heating among US households, they also show that this effect is by far too small to dominate the energy savings that can be accrued from improvements in efficiency. In other words, improving household efficiency in domestic heating can be predicted to save energy, despite 'takeback'.

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A Appendix

Table A1: Summary Statistics.

	(1)	(2)	(3)	(4)
VARIABLES	Mean	SD	Min	Max
Main variables of Interest:				
Heating Efficiency (log)	5.298	0.829	2.652	8.020
Price (log)	-4.003	0.507	-5.425	-2.473
Household head charcteristics:				
Sex (1 = male)	0.466	0.499	0	1
Age in years (log)	3.860	0.358	2.773	4.443
Race				
White	0.790	0.407	0	1
Black	0.137	0.343	0	1
Hispanic	0.118	0.323	0	1
Asian	0.032	0.175	0	1
Other	0.042	0.200	0	1
Educational attainment				
No completed schooling	0.017	0.130	0	1
Grade 12	0.087	0.282	0	1
High school diploma	0.271	0.444	0	1
Some college, no degree	0.225	0.418	0	1
Associate degree	0.096	0.294	0	1

VARIABLES	Mean	SD	Min	Max
Bachelor degree	0.197	0.397	0	1
Master degree	0.079	0.269	0	1
Professional degree	0.017	0.128	0	1
Doctorate degree	0.011	0.107	0	1
Occupational attainment				
Unemployed	0.396	0.489	0	1
Part time employed	0.497	0.500	0	1
Full time employed	0.107	0.309	0	1
Household characteristics:				
Household size (log)	0.775	0.578	0	2.639
Share of members younger than 5 years	0.041	0.115	0	0.800
Share of members older than 69 years	0.032	0.118	0	0.667
Owns dwelling	0.682	0.466	0	1
Rents dwelling	0.306	0.461	0	1
Lives rent-free in dwelling	0.012	0.110	0	1
Household annual gross income (log)	10.559	0.993	7.313	11.849
Any household member receives:				
Employment income	0.747	0.435	0	1
Retirement income	0.310	0.462	0	1
Supplemental security income	0.079	0.270	0	1
Welfare benefits or cash assistance	0.023	0.150	0	1
Income from investments	0.225	0.418	0	1
HH receives food stamps	0.108	0.311	0	1
Dwelling characteristics:				
Size in square feet (log)	7.461	0.654	4.787	9.688
Age in years	37.683	24.998	0	89
Mobile home	0.061	0.240	0	1
Single-family detached	0.640	0.480	0	1
Single-family attached	0.060	0.238	0	1
Apartment in building with 2 - 4 units	0.079	0.270	0	1
Apartment in building with 5+ units	0.160	0.366	0	1
Number of floors in Single-family home (0 otherwise)	0.263	0.494	0	3
Number of floors in Apartment (0 otherwise)	10.910	8.125	0	40
Major outside wall material:				
Brick	0.273	0.445	0	1
Wood	0.172	0.377	0	1
Siding (Aluminium, Vinyl, Steel)	0.370	0.483	0	1

VARIABLES	Mean	SD	Min	Max
Stucco	0.119	0.324	0	1
Composition (shingle)	0.014	0.117	0	1
Stone	0.012	0.107	0	1
Concrete, Concrete Block	0.035	0.184	0	1
Other	0.005	0.073	0	1
Major outside roofing material:				
No direct roof in dwelling	0.160	0.366	0	1
Ceramic or clay tiles	0.028	0.166	0	1
Wood shingles or shakes	0.057	0.231	0	1
Metal	0.071	0.257	0	1
Slate or synthetic slate	0.011	0.105	0	1
Composition shingles	0.485	0.500	0	1
Asphalt	0.166	0.372	0	1
Concrete tiles	0.011	0.104	0	1
Other	0.011	0.102	0	1
Built on cement slap	0.359	0.480	0	1
Built over crawl space	0.231	0.421	0	1
High ceilings	0.274	0.446	0	1
Major heating system:				
Steam or hot water system	0.107	0.309	0	1
Central warm air	0.649	0.477	0	1
Heat pump	0.094	0.292	0	1
Electric units (bulit in or portable)	0.077	0.267	0	1
Floor or wall pipeless furnace	0.015	0.121	0	1
Built-in room heater	0.030	0.171	0	1
Heating stove	0.012	0.111	0	1
Other	0.014	0.120	0	1
Major heating fuel:				
Natural Gas	0.512	0.500	0	1
Propane/LPG	0.052	0.221	0	1
Fuel Oil	0.064	0.245	0	1
Electricity	0.352	0.477	0	1
Other	0.021	0.142	0	1
Age of main heating equipment	3.516	1.336	1	5
Secondary heating equipment	0.388	0.487	0	1
Energy bill covers charges other than family use	0.078	0.269	0	1
Heated pool	0.066	0.248	0	1
Heated basement	0.050	0.218	0	1
Heated attic	0.003	0.054	0	1

VARIABLES	Mean	SD	Min	Max
Geographic characteristics:				
Urban environment	0.776	0.417	0	1
Building America Climate Region:				
Very cold/cold	0.350	0.477	0	1
Hot-dry/mixed-dry	0.113	0.317	0	1
Hot-humid	0.162	0.369	0	1
Mixed-humid	0.321	0.467	0	1
Marine	0.054	0.226	0	1
Heating Degree Days 2009 (log)	8.169	0.724	3.970	9.435
Heating Degree Days 30 year average (log)	8.176	0.710	4.290	9.499
Geographic domain:				
Connecticut, Maine, New Hampshire, Rhode Island, Vermont	0.027	0.162	0	1
Massachusetts	0.023	0.149	0	1
New York	0.064	0.245	0	1
New Jersey	0.029	0.168	0	1
Pennsylvania	0.045	0.207	0	1
Illinois	0.043	0.202	0	1
Indiana, Ohio	0.064	0.245	0	1
Michigan	0.034	0.181	0	1
Wisconsin	0.020	0.141	0	1
Iowa, Minnesota, North Dakota, South Dakota	0.035	0.184	0	1
Kansas, Nebraska	0.017	0.128	0	1
Missouri	0.021	0.143	0	1
Virginia	0.027	0.163	0	1
Delaware, District of Columbia, Maryland, West Virginia	0.031	0.174	0	1
Georgia	0.032	0.176	0	1
North Carolina, South Carolina	0.049	0.216	0	1
Florida	0.057	0.231	0	1
Alabama, Kentucky, Mississippi	0.041	0.199	0	1
Tennessee	0.023	0.148	0	1
Arkansas, Louisiana, Oklahoma	0.038	0.192	0	1
Texas	0.077	0.266	0	1
Colorado	0.017	0.131	0	1
Idaho, Montana, Utah, Wyoming	0.018	0.134	0	1
Arizona	0.020	0.140	0	1
Nevada, New Mexico	0.016	0.124	0	1
California	0.095	0.293	0	1

VARIABLES	Mean	SD	Min	Max
Alaska, Hawaii, Oregon, Washington	0.037	0.190	0	1

Sample $N = 11'396$, Population $N = 107'815'430$.

Table A2: Robustness checks for own-price elasticities

	(1)	(2)	(3)	(4)	(5)	(6)
Proxy for energy efficiency in space heating	None	Age of dwelling	Age of dwelling (log)	Age of dwelling (squared)	Develop-ment of heating fuel prices 1999 to 2009	Interactions of dwelling characteristics[a]
Price (log)	-0.9544***	-0.9582***	-0.9600***	-0.9588***	-0.9896***	-0.9475***
	(0.0267)	(0.0266)	(0.0266)	(0.0266)	(0.0272)	(0.0274)
Adjusted R^2	0.859	0.862	0.861	0.862	0.86	0.868

Notes: Sample $N = 11'396$, Population $N = 107'815'430$. Controls in all estimations correspond to the ones used in Table 2 column 6. (Heteroskedasticity-robust standard errors clustered at the level of building type within each geographical region in parentheses). *** p<0.01, ** p<0.05, * p<0.1

[a] We have tested a number of different models and have opted to present only the one that minimizes BIC. In this model, we include a set of interactions between house type, heating system type, main heating fuel, age of the heating system, major outside wall material and major roofing material yielding an additional 1'035 interaction terms.