Energy Policy 118 (2018) 149–159

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Why are rented dwellings less energy-efficient? Evidence from a representative sample of the U.S. housing stock

M.N.M. Souza

University of Illinois at Urbana-Champaign, 414 Mumford Hall, 1301 W Gregory Drive, Urbana, IL, USA

ARTICLE INFO

Keywords:
Energy efficiency
Technology adoption
Asymmetric information
Housing markets
Landlord-tenant problem

ABSTRACT

This paper compares energy-efficient appliance adoption rates across U.S. residential markets. The focus is to explore variation across tenure modes (rented or owner-occupied residences). Bivariate probits are used to correct for endogenous determination of tenure mode and energy efficiency outcomes. Results suggest that, when compared to renters, homeowners are significantly more likely to have energy-efficient appliances. The mechanisms that could be driving those differences are also investigated. Heterogeneity analyses reveal that rented dwellings are more likely to have efficient appliances when landlords incur utility payments. Adoption rate differences are also shown to be inversely related to energy prices. Those findings are consistent with a problem of asymmetric information in the housing market, typically referred to as the "landlord-tenant problem." This paper is also the first to assess how tenancy duration influences efficiency investments in this context. Results suggest that investments in rented homes are more likely to occur at later periods of tenancy, when relations between landlords and tenants might be better established.

1. Introduction

The Energy Information Agency (EIA) estimates that approximately 20.6% of U.S. energy-related carbon emissions can be attributed to the residential sector (EIA, 2015). Space heating, water heating, and air conditioning collectively account for almost 65% of the energy consumption in U.S. homes. Other appliances, electronics and lighting account for the remaining 35% (EIA, 2009). Many engineering estimates from the late 2000 s (Chandler and Brown, 2009; EPRI, 2009; McKinsey, 2009) suggest that improving fuel and energy efficiency in homes may be cost-effective for carbon abatement, since future energy savings may exceed the upfront installation costs of new, more efficient technologies. However, recent environmental economics literature provides evidence that those technologies are being adopted at low or even sub-optimal rates (for reviews, see: Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). This disconnect between an optimal and the current level of energy efficiency investments is often referred to as the energy efficiency "gap" or "paradox"

Jaffe and Stavins (1994) recognize that the extent of that gap depends on the definition of optimality being considered by the researcher. For example, if the social optimum takes into account environmental externalities, then the gap is likely to be wider. A discussion of optimality is omitted from this paper, which rather focuses on identifying mechanisms that might be causing energy efficiency investments to vary across U.S residences. Adoption rates of a broad set of Energy Star[1] (ES) rated appliances are compared, exploiting variations in tenure mode (rented or owner-occupied residences). First, with data from the 2011 American Housing Survey,[2] linear probability models (LPM) are estimated for ES appliance adoption, controlling for degree of urbanization, climate, household demographics, and housing amenities and structure. Second, alternative specifications are used to identify mechanisms that could be driving heterogeneity in technology adoption rates. Finally, bivariate probits are estimated, in order to correct for the endogenous determination of energy efficiency outcomes and tenure mode.

Initial LPM estimates show that rented homes are less likely to have efficient room air-conditioners (– 6.73%), central air conditioners (– 8.08%), dishwashers (– 14.85%), clothes washers (– 6.23%), refrigerators (– 12.96%), electric central heating (– 5.16%), gas central heating (– 7.41%), and oil central heating (– 7.56%). When compared to estimates from previous literature (Davis, 2012), these results suggest that the gap between rented and owner-occupied units became significantly wider between 2005 and 2011. The linear estimates, however, might be biased due to classic endogeneity: there might be unobserved household preferences that simultaneously affect both tenure

E-mail address: nogueir2@illinois.edu.

[1] Energy Star is a voluntary program established in 1992 by the U.S. Environmental Protection Agency (EPA). To earn a label that attests high energy efficiency, a product must be certified by EPA-recognized third-party laboratories (EPA, 2016).

[2] The AHS is conducted every 2 years by the Department of Housing and Urban Development (HUD) and the U.S. Census Bureau. It comprises a nationally representative sample of the U.S. housing stock.

https://doi.org/10.1016/j.enpol.2018.03.013
Received 25 July 2017; Received in revised form 6 February 2018; Accepted 5 March 2018

mode and energy efficiency outcomes.

To attenuate that type of endogeneity, bivariate probit (or biprobit) models are estimated. Han and Vytlacil (2017) demonstrate that the nonlinear nature of biprobits allows identification of systems in which a binary variable (e.g. ownership of Energy Star appliances) is regressed on another endogenous binary variable (e.g. tenure mode). Estimation for each appliance consists of a system of two-equations: one which describes the adoption of ES appliances, and another which describes tenure mode. The endogeneity-corrected estimates reveal that linear models overestimate the effects of tenure mode on energy efficiency. For example, biprobit estimates suggest that renters are 8.98% less likely than homeowners to have Energy Star refrigerators. That estimate was closer to 13% with a linear model.

It was also possible to identify a few mechanisms that lead to ES appliance adoption heterogenenity across tenure modes. By exploiting variation in who pays (landlord or tenant) for the utility bills of rented dwellings, it is possible to test for the effects of split incentives ("landlord-tenant problem"), which previous literature has explored in similar contexts (see, for example: Myers, 2015; Gillingham et al., 2012; Levinson and Niemann, 2004). Since landlords often do not pay for utility bills, they have less incentives to invest in energy efficiency. Biprobit estimates are consistent with that scenario, indicating that, for some appliances, the adoption gap between homeowners and renters becomes significantly narrower when landlords do pay utility bills. For example, point estimates of the gap drop from 8.98% to 3.69% for refrigerators, and from 10.09% to 3.73% for dishwashers.

To explore further heterogeneity, the effects of tenancy duration[3] on ES appliance adoption are tested for, by estimating alternative LPM specifications. Even though data on ownership of Energy Star appliances are only available for the survey year of 2011, the panel structure of the AHS allows the construction of variables that identify how long a given household has resided in the same unit. Results from regressions with those variables suggest that tenancy duration does not significantly affect homeowners' decisions to adopt small ES appliances. This is expected, since homeownership implies no asymmetric information problem. On the other hand, saturations of small ES appliances are significantly lower for short-duration renters, when compared to long-duration renters (which have been in the dwelling for more than 10 years). For large appliances (central AC and heating), the effects are reversed: renters are unaffected by tenancy duration, but homeowners are. It could be that homeowners choose to postpone investments in large appliances due to liquidity constraints right after the purchase of their homes.

Finally, it was possible to assess if ES appliance adoption is heterogeneous across U.S. census divisions. That is implicitly a test for heterogeneity across energy prices. It can be shown that saturation differences between renters and homeowners are smaller in areas with higher energy prices (especially New England and Middle Atlantic). This suggests that renters in those areas are more attentive to energy costs, thus demanding dwellings with more energy-efficient appliances.

Overall, the gap between rented and owner-occupied units is evident. Incentives for investments in energy efficiency are misaligned especially in the rental markets. Therefore, it may be more cost-effective to provide energy efficiency subsidies to renters or landlords, rather than to owner-occupants. Policies that encourage homeownership might simultaneously address this issue. Those findings also reinforce the importance of policies, such as appliance labeling, energy consumption audits, and disclosure requirements that address information asymmetries in rental markets.

The remainder of the paper is organized as follows: Section 2 presents the data and descriptive statistics; in Section 3, empirical strategy and results are presented; concluding remarks and policy recommendations are in Section 4.

[3] Throughout this paper, "tenancy duration" or "household duration" refers to how long a given household has been occupying the same residential unit.

2. Data and descriptive statistics

The American Housing Survey (AHS) comprises a nationally representative sample of the U.S. housing stock. It includes several variables which were used as controls in the regression specifications: number of bathrooms, half bathrooms, bedrooms, and overall rooms in the residence; year or decade that the unit was built; age of householder; education level; householder's works status; household income; number of family members; indicator for who pays for the utility bills; year in which the household moved into the dwelling. Available geographic information includes: broad climate classifications, based on heating degree days (HDD) and cooling degree days (CDD)[4]; degree of urbanization (city, suburb, small town, and rural); census division and state (when available).[5]

In survey year 2011, a supplemental module of the AHS included questions to identify if the appliances in the dwellings are rated as Energy Star.[6] For this study, the following appliances were considered: room air conditioner, dishwasher, clothes washer, clothes dryer, refrigerator, central air conditioning, central electric heating, central gas heating, and central oil heating.[7] That is a comprehensive list of appliances for which it is possible to identify Energy Star rating.[8] The full survey collected data for 186, 448 residences. However, this study restricts the sample to residences that were not vacant during the survey year of 2011, and for which it is possible to identify tenancy (otherwise, crucial variables of interest would be lacking). The final sample for this study therefore consists of 132, 995 housing units.

Descriptive statistics of the control variables were computed using the 2011 AHS data. Table 1 presents differences in means of the demographic variables for owner-occupied units, tenant-pay and landlord-pay rented units. The p-values indicate if the differences in means are statistically significant (based on Welch *t*-tests). It is clear that the groups are unbalanced in terms of demographics. For example, compared to renters, homeowners on average have higher income, are older, and are more likely to be white. Furthermore, tenant-pay dwellings are in general occupied by lower income families than landlord-pay dwellings. Table 2 also reveals significant imbalance, by comparing means for geographic and climactic variables. Owner-occupied homes tend to be in suburban areas, while rented homes are more likely to be closer to city centers, especially when under a tenant-pay regime.

Table 3 presents mean comparisons for variables related to housing amenities and structure. It can be noted that homeowners are more likely to live in single-unit buildings (houses), with large square footage. Renters, on the other hand, are more likely to live in smaller apartments that have less rooms. The variables for decade built provide evidence that older constructions are more likely to be put up for rental.

Fig. 1 illustrates densities for the years in which tenants moved into their dwellings. The graph suggests that homeowners tend to stay in the

[4] Climates are identified as: Coldest (more than 7001 HDD and less than 2000 CDD), Cold (5500–7000 HDD and less than 2000 CDD), Cool (4000–5499 HDD and less than 2000 CDD), Mild (less than 4000 HDD and less than 2000 CDD), Mixed (2000–3999 HDD and more than 2000 CDD), and Hot (less than 2000 HDD and more than 2000 CDD).

[5] Due to confidentiality, states are not identified for some housing units in the dataset.

[6] Householders are first asked if the unit has a particular appliance. Then they are asked if the appliance is Energy Star rated. Responses include 'Yes', 'No' and 'Do not know'.

[7] "Central heating" refers to large appliances intended to heat all the rooms of a dwelling. Over 96% of the survey respondents reported using those as their main heating equipment. The remaining 4% reported using portable or single-room heaters. Also, less than 0.5% of the sample reported using any supplemental (secondary) heating equipment. Water heaters (although widespread) have been omitted from this study, since the survey does not identify the efficiency rating for those appliances.

[8] Almost all the appliances for which it is possible to identify Energy Star rating were used. Due to sparsity of the data, the only omitted appliances were built-in trash compactors (less than 4% of sample), and heating equipment that do not use gas, electricity or oil (less than 2% of sample).

Table 1
Mean comparisons for demographic variables.

	Difference in means		Difference in means	
Householder's Characteristics	(Rented) - (Owner-occupied)	P-value of diff.	(Tenant-pay) - (Landlord-pay)	P-value of diff.
Income ($1000 per year)	− 44.391	0.000	− 14.367	0.000
Has job	0.56%	0.042	− 19.65%	0.000
Family size	− 0.237	0.000	− 0.602	0.000
Age	− 10.522	0.000	8.075	0.000
Has child	− 0.69%	0.006	− 17.25%	0.000
White	− 16.13%	0.000	0.22%	0.677
Black	12.95%	0.000	0.02%	0.960
Indigenous	0.67%	0.000	− 0.13%	0.286
Asian	1.45%	0.000	0.08%	0.784
Other race	1.07%	0.000	− 0.19%	0.246
Less than high-school	9.35%	0.000	6.94%	0.000
Completed high-school	3.47%	0.000	1.55%	0.002
Incomplete college	3.17%	0.000	− 2.05%	0.000
Completed college	− 8.46%	0.000	− 5.41%	0.000
Graduate degree	− 7.53%	0.000	− 1.03%	0.000
Sample Size	132,995		50,574	

Notes: Means calculated with the 2011 American Housing Survey. P-values of differences in means are based on Welch *t*-tests.

Table 2
Mean comparisons for geographic variables.

	Difference in means		Difference in means	
Geographic Variables	(Rented) - (Owner-occupied)	P-value of diff.	(Tenant-pay) - (Landlord-pay)	P-value of diff.
Urban	20.85%	0.000	12.27%	0.000
Suburban	− 13.69%	0.000	− 12.31%	0.000
Small town	0.72%	0.000	1.24%	0.000
Rural	− 7.88%	0.000	− 1.20%	0.000
Coldest Climate	− 0.37%	0.010	4.76%	0.000
Cold Climate	− 1.98%	0.000	16.41%	0.000
Cool Climate	− 1.13%	0.000	3.17%	0.000
Mild Climate	3.83%	0.000	− 15.05%	0.000
Mixed Climate	− 0.35%	0.016	− 4.28%	0.000
Hot Climate	0.00%	0.986	− 5.01%	0.000
New England	0.57%	0.000	8.99%	0.000
Middle Atlantic	0.10%	0.513	14.07%	0.000
East North Central	− 2.11%	0.000	2.80%	0.000
West North Central	− 1.39%	0.000	0.09%	0.734
South Atlantic and East South Central	− 0.24%	0.127	− 4.67%	0.000
West South Central	− 3.50%	0.000	− 7.42%	0.000
Mountain and Pacific	6.57%	0.000	− 13.85%	0.000
Sample Size	132,995		50,574	

Notes: Means calculated with the 2011 American Housing Survey. P-values of differences in means are based on Welch *t*-tests.

same unit for longer, since almost 50% had moved in before the year 2000. On the other hand, close so 40% of renters moved into their dwelling during the survey year 2011 or 2010. Only about 10% of renters had been living in the same unit since before the year 2000.

Finally, Table 4 compares appliance and ES appliance saturations between owner-occupied and rented units. Rented units only have higher saturations of standard room air-conditioners and standard electric heating, which are typically more common in apartment buildings. It can also be noted that renters have lower saturations of all energy-efficient appliances. However, ES appliance saturation differences between landlord-pay and tenant-pay dwellings are not so straightforward, and should be better analyzed under a regression framework.

Demographic and housing structure imbalance between renters/homeowners, and landlord-pay/tenant-pay dwellings will be controlled for in the following analysis section, by including all the variables from Tables 1–3 in the regression specifications. With that, it will be possible to more rigorously test for the mechanisms that could be driving differences in ES appliance saturations across U.S. homes. Variation in the following factors will be explored: tenancy modes, utility payment regimes, tenancy duration, and finally geographic location (which implies variation in energy prices).

3. Empirical strategy and results

3.1. Heterogeneity by tenancy modes and utility payment regimes

Section 2 reveals that renters and homeowners are significantly disparate in terms of demographic and housing characteristics, which could be correlated with adoption of efficient appliances. A robust analysis of adoption should, therefore, control for those variables. Furthermore, previous literature suggests that rental units face a problem of split incentives (“landlord-tenant problem”), which can translate into sub-optimal energy efficiency decisions (Gillingham et al.,

Table 3
Mean comparisons for housing characteristics.

Housing Characteristics	Difference in means (Rented) - (Owner-occupied)	P-value of diff.	Difference in means (Tenant-pay) - (Landlord-pay)	P-value of diff.
Built before 1950	− 0.56%	0.021	5.79%	0.000
Built in 1950 s	− 1.44%	0.000	− 0.41%	0.199
Built in 1960 s	1.96%	0.000	2.49%	0.000
Built in 1970 s	5.54%	0.000	6.20%	0.000
Built in 1980 s	2.84%	0.000	− 4.66%	0.000
Built in 1990 s	− 3.47%	0.000	− 3.78%	0.000
Built in 2000 s	− 4.62%	0.000	− 5.45%	0.000
Built in 2010 s	− 0.25%	0.000	− 0.17%	0.002
Single-unit building	− 57.33%	0.000	− 24.55%	0.000
Apartment building	60.18%	0.000	25.18%	0.000
Mobile home	− 2.85%	0.000	− 0.63%	0.000
Square footage	− 1156.638	0.000	− 332.524	0.000
# Bedrooms	− 1.160	0.000	− 0.585	0.000
# Half-bathrooms	− 0.284	0.000	− 0.085	0.000
# Bathrooms	− 0.599	0.000	− 0.238	0.000
# Overall rooms	− 2.077	0.000	− 0.884	0.000
Sample Size	132,995		50,574	

Notes: Means calculated with the 2011 American Housing Survey. P-values of differences in means are based on Welch *t*-tests.

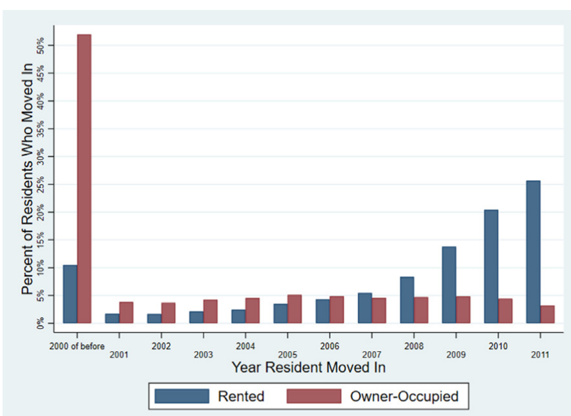

Fig. 1. Density for year in which tenant moved into the dwelling.

2012). It is hypothesized that, especially when tenants pay utility bills, landlords have little incentive to invest in efficiency,[9] because they are unlikely to accrue the energy savings. Efficiency investments might not always translate into higher rents, due to information asymmetries that limit prospective tenants' abilities to fully compare rental units in the market (Myers, 2015).

To test if those problems can lead to differences in adoption rates of Energy Star appliances, the following latent variable model can be considered:

$$y_i^* = \beta_0 + \beta_1[rented]_i + \beta_2[lpu]_i + \gamma\mathbf{X}_i + \varepsilon_i \qquad (1)$$

where y_i^* is a latent variable that determines if residential unit i adopts either a standard appliance, or an Energy Star appliance; $[rented]_i$ is an indicator variable equal to one if the unit is rented, and equal to zero if the unit is owner-occupied; $[lpu]_i$ is an indicator equal to one if the landlord pays the utility bills, and equal to zero otherwise; $\mathbf{X}_i$ is a vector including a constant and controls; and ε_i is an idiosyncratic error term. Note that y_i^* may not be directly observable. Rather, the following indicator variable, y_i, can be observed:

$$y_i = \begin{cases} 0, & \text{if } y_i^* < 0 \\ 1, & \text{if } y_i^* \geq 0 \end{cases}$$

where adoption of the ES appliance is indicated by $y_i = 1$, and adoption of the standard appliance is indicated by $y_i = 0$. A linear probability model (LPM) can be constructed by replacing y_i^* by the indicator y_i in Eq. (1). Letting $\mathbf{Z}$ denote the vector of all covariates included in the model, and assuming that no functional relation exists between any covariates, the coefficients of interest for this research can be written as: $\beta_1 = \frac{\partial P(y=1\mid\mathbf{Z})}{\partial[rented]}$ and $\beta_2 = \frac{\partial P(y=1\mid\mathbf{Z})}{\partial[lpu]}$. The coefficient β_1 compares rented and owner-occupied units in terms of probabilities of having a given Energy Star appliance, holding all other factors fixed. Coefficient β_2 captures heterogeneity of those probabilities for when landlords, rather than tenants, pay the utility bills.

Using data from the 2011 AHS, the above model was estimated for 6 types of electric appliances and 3 types of central heating equipment. For all the regressions throughout this paper, the samples were restricted to only residences that have the respective appliance, either in standard form, or rated as Energy Star. Non-adoption whatsoever of the appliances is, therefore, out of the scope of this research.

Table 5 reports β_1 and β_2 LPM estimates for small appliances, while Table 6 reports estimates for large appliances. All regressions control for the covariates presented in Tables 1 and 2: household demographics, such as income, education, work status of householder, household size, age of householder, if householder has children, and if householder is non-white; degree of urbanization (city, suburb, small town, and rural); type of climate (based on degree days); census division and state (when available). Specifications marked with a 'b' (second column of each appliance), report estimates that also control for housing characteristics presented in Table 3: decade built, housing structure (single-family unit, apartment unit, or mobile home), square footage, and number of bedrooms, half-bathrooms, bathrooms, and overall rooms. All of the control variables are flexibly (indicator variables for each category) included in the regressions. For example, household size (hhsize) is accounted for with one indicator for hhsize = 1, another for hhsize = 2, and so on.

The β_1 estimates from specifications in Tables 5 and 6 are generally negative and statistically significant (with the exception of ES Clothes

[9] Depending on the appliance, efficiency investments can be substantial. Table A2 from the appendix shows that the price premium for Energy Star rating can range from \$50 (for Clothes Washers), to over \$2000 (for Central AC).

Table 4
Appliance and ES Appliance Adoption Comparisons, Across Tenure Modes and Utility Payment Regimes.

	Difference in adoption %		Difference in adoption %	
	(Rented) - (Owner-occupied)	P-value of diff.	(Tenant-pay) - (Landlord-pay)	P-value of diff.
Room AC	10.11%	0.000	18.06%	0.000
ES Room AC	− 8.70%	0.000	4.53%	0.000
Central AC	− 20.97%	0.000	− 20.63%	0.000
ES Central AC	− 16.47%	0.000	− 0.90%	0.144
Dishwasher	− 28.37%	0.000	− 29.36%	0.000
ES Dishwasher	− 21.79%	0.000	− 2.96%	0.000
Clothes Washer	− 43.87%	0.000	− 35.07%	0.000
ES Clothes Washer	− 22.11%	0.000	− 6.84%	0.000
Clothes Dryer	− 45.33%	0.000	− 36.04%	0.000
ES Clothes Dryer	− 5.58%	0.000	− 3.84%	0.000
Refrigerator	− 0.18%	0.000	− 0.49%	0.000
ES Refrigerator	− 24.26%	0.000	− 1.05%	0.045
Electric Central Heat	19.70%	0.000	− 19.21%	0.000
ES Electric Central Heat	− 12.17%	0.000	0.66%	0.243
Gas Central Heat	− 13.02%	0.000	7.35%	0.000
ES Gas Central Heat	− 16.27%	0.000	− 2.90%	0.000
Oil Central Heat	− 0.69%	0.000	11.87%	0.000
ES Oil Central Heat	− 12.71%	0.000	− 3.83%	0.024
Sample Size	132,995		50,577	

Notes: Adoption rates were calculated with the 2011 American Housing Survey. To compare adoption rates of Energy Star appliances, the samples were first restricted to homes that have the respective appliances (in standard or ES form). P-values of differences in means are based on Welch *t*-tests.

Table 5
LPM estimates of the effects of tenure mode and payment regimes on adoption of small Energy Star appliances.

ES Appliance:	Room AC		Dishwasher		Clothes Washer		Clothes Dryer		Refrigerator	
Regression Specification:	(1.a)	(1.b)	(2.a)	(2.b)	(3.a)	(3.b)	(4.a)	(4.b)	(5.a)	(5.b)
Owner-Occupied Mean Adoption	[0.3811]	[0.3843]	[0.4468]	[0.4507]	[0.4651]	[0.4722]	[0.1920]	[0.1917]	[0.4885]	[0.4960]
Rented (β_1)	− 0.0545**	− 0.0577**	− 0.1609***	− 0.1470***	− 0.0587*	− 0.0494	− 0.0051	− 0.0036	− 0.1440***	− 0.1154***
	(0.0171)	(0.0184)	(0.0165)	(0.0265)	(0.0242)	(0.0266)	(0.0178)	(0.0208)	(0.0148)	(0.0094)
Landlord Pays Electricity (β_2)	− 0.0092	− 0.0157	0.0169	0.0107	0.0636**	0.0537	0.0149	0.0163	0.0245**	0.0150
	(0.0167)	(0.0224)	(0.0160)	(0.0188)	(0.0256)	(0.0285)	(0.0210)	(0.0219)	(0.0099)	(0.0103)
Sample Size	27,765	22,419	82,037	76,345	97,104	87,882	94,857	86,224	119,088	104,877
Housing Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic and Climate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports LPM estimates of the effects of tenure mode and utility payment regimes on the likelihood of having a given Energy Star electric appliance. Variables presented in Tables 1, 2, and 3 are flexibly controlled for. Inverse probabilities of selection were used as sampling weights. Standard errors, presented in parentheses, are clustered by census division. Means of the dependent variable for the omitted comparison group (owner-occupied residences) are presented in brackets. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively. Samples are restricted to dwellings that have the appliance in question (either in standard or rated Energy Star).

Table 6
LPM estimates of the effects of tenure mode and payment regimes on adoption of large Energy Star appliances.

ES Appliance:	Central AC		Electric Central Heating		Gas Central Heating		Oil Central Heating	
Regression Specification:	(1.a)	(1.b)	(2.a)	(2.b)	(3.a)	(3.b)	(4.a)	(4.b)
Owner-Occupied Mean Adoption	[0.2814]	[0.2844]	[0.1908]	[0.1951]	[0.2567]	[0.2608]	[0.2085]	[0.2137]
Rented (β_1)	− 0.0988***	− 0.0877***	− 0.0672***	− 0.0537***	− 0.1068***	− 0.0737***	− 0.0916***	− 0.0793***
	(0.0127)	(0.0135)	(0.0070)	(0.0095)	(0.0027)	(0.0093)	(0.0077)	(0.0085)
Landlord Pays Utilities (β_2)	.0173*	0.0088	0.0235**	0.0206	0.0088	0.0089	0.0290**	0.0295**
	(0.0088)	(0.0084)	(0.0088)	(0.0106)	(0.0080)	(0.0095)	(0.0110)	(0.0095)
Sample Size	79,488	72,543	39,156	34,361	70,671	62,711	5072	4201
Housing Controls	No	Yes	No	Yes	No	Yes	No	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic and Climate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports LPM estimates of the effects of tenure mode and utility payment regimes on the likelihood of having a given Energy Star electric appliance. Variables presented in Tables 1, 2, and 3 are flexibly controlled for. Inverse probabilities of selection were used as sampling weights. Standard errors, presented in parentheses, are clustered by census division. Means of the dependent variable for the omitted comparison group (owner-occupied residences) are presented in brackets. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively. Samples are restricted to dwellings that have the appliance in question (either in standard or rated Energy Star).

Table 7
Probit estimates of the effects of tenure mode and payment regimes on adoption of Energy Star appliances.

ES Appliance: Regression Specification:	Room AC (1)	Dishwasher (2)	Clothes Washer (3)	Clothes Dryer (4)	Refrigerator (5)	Central AC (6)	Electric Central Heating (7)	Gas Central Heating (8)
Owner-Occupied Mean Adoption	[0.3843]	[0.4507]	[0.4722]	[0.1917]	[0.4960]	[0.2844]	[0.1951]	[0.2608]
Rented (β_1)	-0.0686^{***}	-0.1526^{***}	-0.0572^{**}	-0.0189^{**}	-0.1297^{***}	-0.0970^{***}	-0.0526^{***}	-0.0954^{***}
	(0.0136)	(0.0280)	(0.0267)	(0.0071)	(0.0114)	(0.0182)	(0.0124)	(0.0127)
Landlord Pays Utilities (β_2)	−0.0172	0.0183	0.0585^{**}	0.0040	0.0177^{*}	0.0112	0.0366^{***}	0.0038
	(0.0184)	(0.0210)	(0.0275)	(0.0053)	(0.0092)	(0.0126)	(0.0130)	(0.0120)
Sample Size	22,419	76,345	87,882	86,224	104,877	72,543	34,361	62,711
Housing Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic and Climate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports Probit estimates of average marginal effects of tenure mode and utility payment regimes on the likelihood of having Energy Star electric appliances. Regressions include all the control variables described in Tables 1, 2 and 3. Delta method standard errors are presented in parentheses. Means of the dependent variable for the omitted comparison group (owner-occupied residences) are presented in brackets. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively. Samples are restricted to dwellings that have the appliance in question (either standard or rated Energy Star).

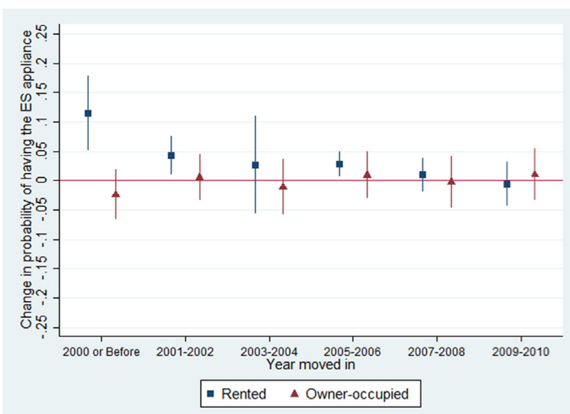

Fig. 2. Estimates for refrigerators.

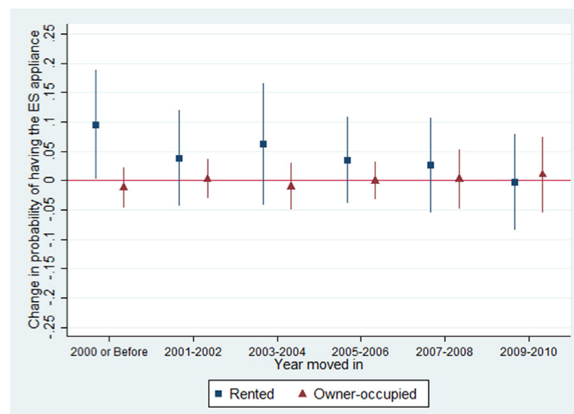

Fig. 3. Estimates for clothes washers.

Washers and Dryers),[10] indicating that renters are less likely to have the energy-efficient appliances. For the specifications without housing controls, the effects are particularly strong for ES dishwashers (− 16.09%) and ES refrigerators (− 14.4%). Estimates from similar specifications from previous literature (Davis, 2012) were only − 9.5% for ES dishwashers and − 6.7% for ES refrigerators, suggesting that the gap between rented and owner-occupied residences may have become wider between 2005 and 2011 (Davis, 2012 uses 2005 data, while this paper uses 2011 data). For Clothes Washers, Refrigerators, Central AC, Electric Heating, and Oil Heating, the β_2 estimates for the LPMs are statistically significant, and so there is evidence of attenuation of the gap when landlords pay the utility bills for rented homes.

It is reasonable to expect, however, that differences in housing characteristics might bias LPM estimates. Housing amenities could even affect tenure mode and energy efficiency outcomes simultaneously. For example, owner-occupied homes are more likely to have bigger rooms, and so they might require more potent air conditioners, which in turn could encourage efficiency investments. The second column for each appliance includes housing controls, to attenuate those types of biases. After including housing controls, β_1 point estimates become less negative. For example, for refrigerators, the estimates increased from − 14.5% to − 11.54%, and for Gas Heating they increased from 10.68% to 7.37%. Most of the β_2 estimates are no longer statistically significant after including the housing controls, with the exception of ES Oil Heating. For that appliance, β_2 remains significantly positive, which indicates attenuation of the landlord-tenant problem when landlords pay the utility bills.

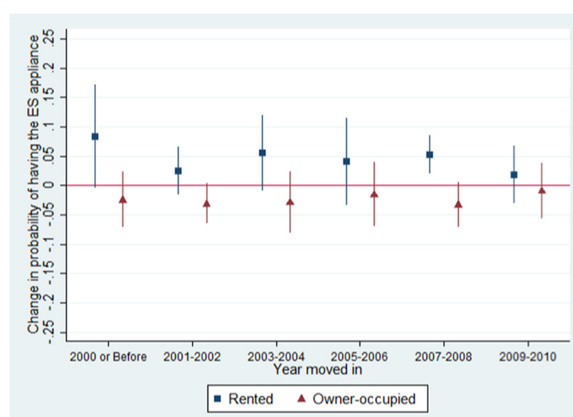

Fig. 4. Estimates for clothes dryers.

As a robustness check, probit models are estimated, also accounting for housing attributes.[11] Table 7 reports average marginal effects

[10] In some cases, clothes washers and dryers may be combined in the same appliance. The survey does not identify that. It is reasonable to assume, however, that clothes washers and dryers are complement goods, such that most residents would either have both, or none. Table A1 from the appendix presents regressions which pool those appliances (sample restricted to homes that have both).

[11] Convergence was not achieved for probit models with flexible controls. Income, family size, householder's age, unit's square footage and number of rooms were thus included as continuous control variables for the probit models. That reduces the number of parameters to be estimated, and facilitates convergence.

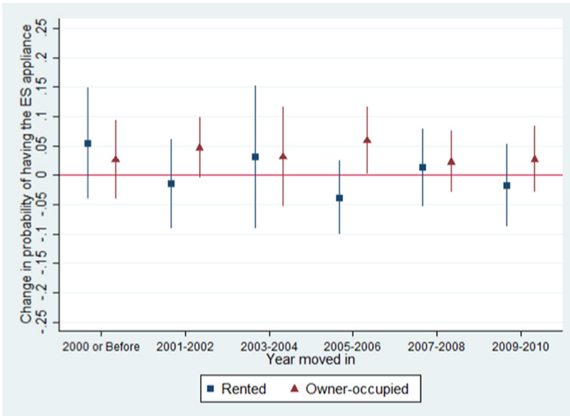

Fig. 5. Estimates for dishwashers.

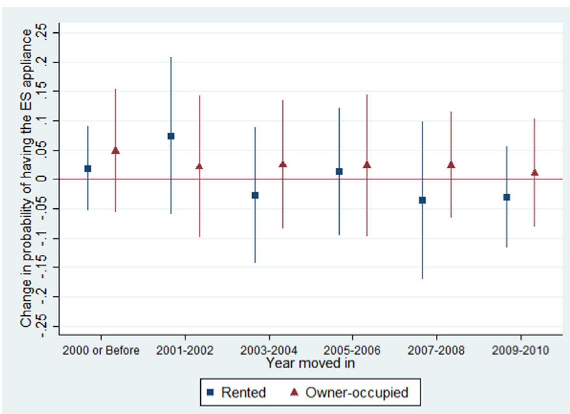

Fig. 6. Estimates for room AC.

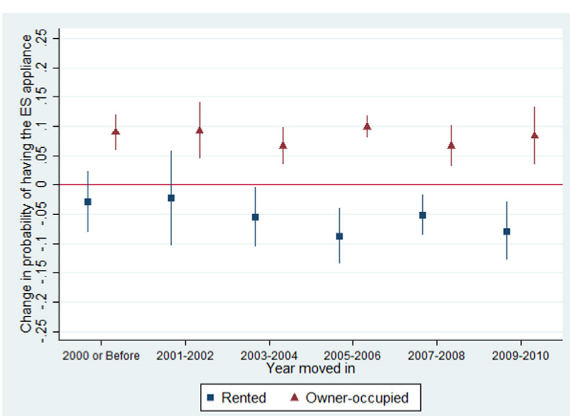

Fig. 7. Estimates for central AC.

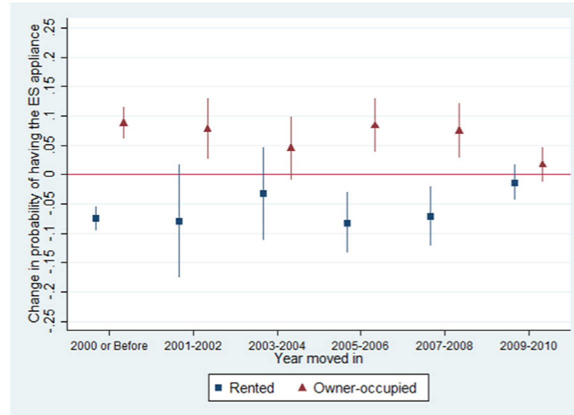

Fig. 8. Estimates for central electric heat.

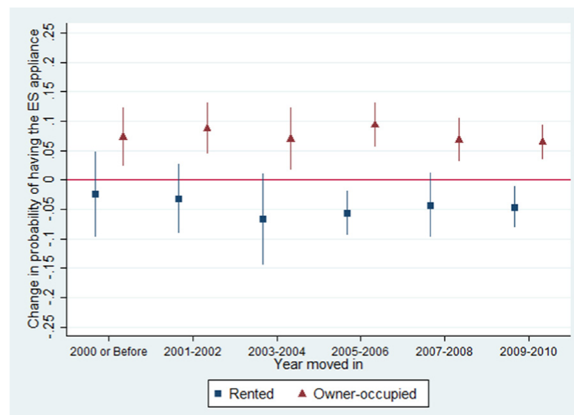

Fig. 9. Estimates for central gas heat.

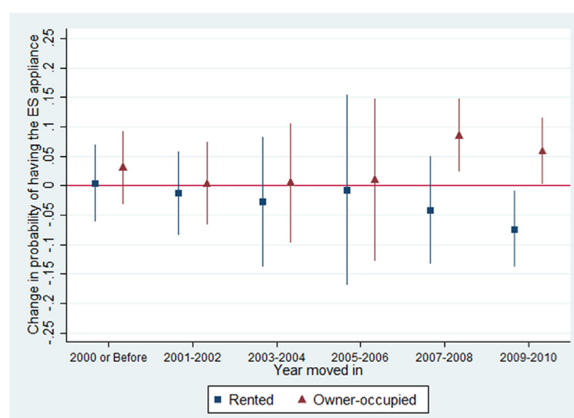

Fig. 10. Estimates for central oil heat.

analogous to the β_1 and β_2 LPM estimates. The probit marginal effects are generally statistically indistinguishable from the LPM point estimates. Results are therefore robust across distributional assumptions for single equation model specifications.

The estimates presented in this subsection also do not significantly differ between small and large appliances, which is surprising because larger appliances tend to also have longer payback periods (McKinsey, 2009). The following subsection exploits heterogeneity in tenancy duration to provide insight about other mechanisms that could discourage investments in energy efficiency.

3.2. Heterogeneity by tenancy duration

Assuming that energy efficiency is a measure of residential quality, some literature in urban economics provides insight about how tenancy duration could affect technology adoption. A dynamic optimization model from Sweeney (1974), for example, shows that the quality of owner-occupied residences tends to be higher than that of rented residences, because homeowners are more likely than landlords to engage in housing maintenance. One could argue that landlords are discouraged to invest in maintenance because they expect carelessness from tenants. Homeowners, on the other hand, might engage in upkeep more often because they face high moving costs, such as broker and legal fees, transfer taxes, lengthy search processes when trying to buy, and risks of bearing housing costs while unable to sell (Haurin and Gill, 2001; Montgomery, 1992; Potepan, 1989). Rather than moving out and facing those costs, homeowners might prefer to stay longer and invest more in a given residence. That also implies that owner-occupied units tend to have longer tenancy duration than rented units.

Halket and di Custoza (2015) show, with an equilibrium sorting model, that expected tenancy duration is a key determinant of the quality of residences, especially because short-duration renters (which will not stay for long in the unit) are associated with higher search costs for landlords. Their model suggests that uncertainty and asymmetric information about expected tenancy duration can produce distortions in the rental markets, in which high-quality residences may be under-provided. Home-ownership can resolve that problem of asymmetric information, causing owner-occupied homes to be of higher-quality, and more attractive to long-duration households. That produces a separating equilibrium, in which short-duration households are more likely to be renters, while long-duration households are more likely to be homeowners (Fig. 1 provides evidence of that for the AHS sample).

Assuming that investments in newer, more efficient appliances can essentially be considered as investments in unit quality, then it is reasonable to expect that efficiency investments will be affected by tenancy duration. It is possible to test for that, by estimating the effects of variables that identify the year in which tenants moved into their dwellings. The following linear probability models can be estimated:

$$y_i = \beta_1[rented]_i + \alpha_1^t[\text{Moved in year}t]_i + \alpha_2^t[rented]_i \times [\text{Moved in year}t]_i + \boldsymbol{\gamma}\mathbf{X}_i + \varepsilon_i \quad (2)$$

where y_i is an indicator variable equal to one if housing unit i's appliance is Energy Star, and equal to zero if it is standard; $[rented]_i$ is an indicator variable equal to one if the unit is rented, and zero if it is owner-occupied; $[lpu]_i$ is an indicator equal to one if the unit is under a landlord-pay regime, and zero otherwise; $[\text{Moved in year } t]_i$ is equal to one if household i moved into the unit in year t; X_i is a vector including a constant and control variables (full set of controls, including housing attributes); and ε_i is an idiosyncratic error term.

For each appliance, Eq. (2) was estimated through Ordinary Least Squares (OLS), using data from the 2011 AHS. Figs. 2 through 10 present estimates of the effects of tenancy duration on adoption of efficient appliances. For homeowners, the effects for having moved in year t are captured by α_1^t from Eq. (2). The effects for being a renter and having moved in year t are captured by $(\beta_1 + \alpha_1^t + \alpha_2^t)$. Note that, for all graphs, the omitted comparison group are homeowners who moved into their dwelling in 2011. The figures show point estimates, as well as 95% confidence intervals (based on standard errors clustered by census division).

Duration does not seem to significantly affect homeowners' investments in small ES appliances (Figs. 2 through 6). That means that recently purchased homes (short-duration) are, on average, at least as energy-efficient as homes that were purchased a long time before 2011 (long-duration). That might indicate that homeowners buy the small appliances around the time that they move into the home. For renters, on the other hand, duration has a positive effect (estimates become less negative) on adoption of small ES appliances. The estimates for year 2011 are generally lower than those for "2000 or Before." That means that long-term rentals are more likely to have those ES appliances. Long-duration renters may have chosen to move into units that were already efficient to begin with, or they may have invested in efficiency during their occupancy. Alternatively, landlords may have felt more encouraged to invest in efficiency once they learned that the tenants were likely to stay in the unit for longer periods. A long duration rental could be a sign that both the landlord and the tenant abide by contracts, payments or maintenance, all of which may be reflected in the overall quality of the residential unit.

Looking at larger appliances (Figs. 7 through 10), the effects seem to be reversed. Duration positively affects homeowners, but negatively affects renters. This is especially clear when comparing Figs. 6 and 7, which reveals that long-duration homeowners are more likely to have energy-efficient central air-conditioning, while the effects for room air-conditioners are null. Similar patterns can be noted for electric heating or gas heating. This could be because of liquidity constraints that discourage homeowners to make costly improvements right after buying a home.[12] The large investments may therefore be deferred to later periods of tenancy.

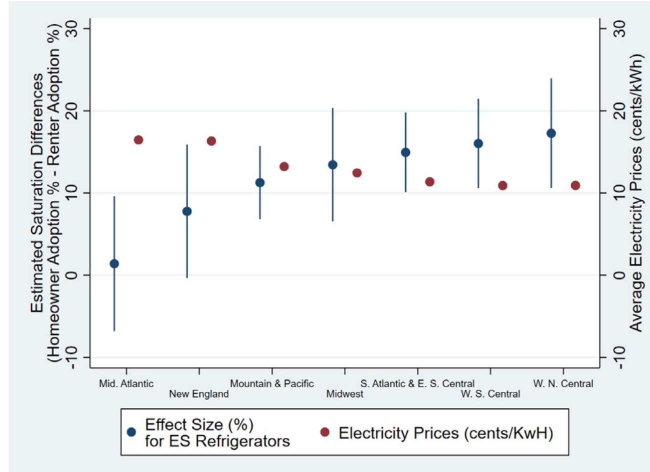

Fig. 11. Average electricity prices, and effect sizes for ES refrigerators, by census division.

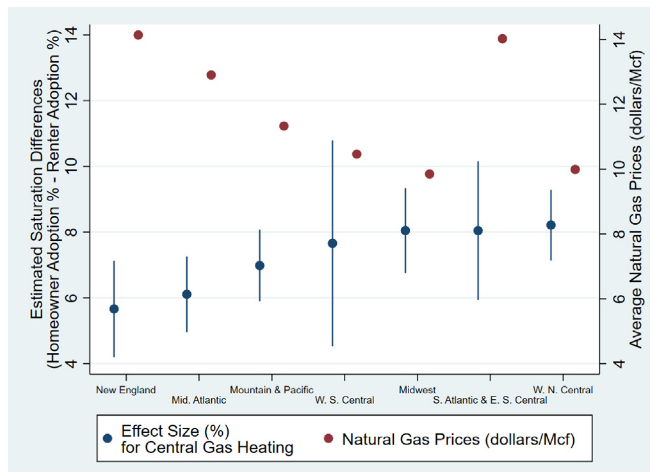

Fig. 12. Average natural gas prices, and effect sizes for ES gas heating, by census division.

3.3. Heterogeneity by energy prices

The American Housing Survey does not collect specific energy prices paid by each household. However, by looking at heterogeneity of effects by census division, it is possible to implicitly assess heterogeneity by energy prices. In this subsection, estimates from the following regression specification are presented:

$$y_i = \beta_1^d[rented]_i \times [\text{Census Division } d]_i + \boldsymbol{\gamma}\mathbf{X}_i + \varepsilon_i \quad (3)$$

where y_i is an indicator variable equal to one if housing unit i's

[12] As shown in Table A2 from the appendix, the price premium for large ES appliances is usually much higher than that for smaller appliances.

Table 8
Biprobit estimates of the effects of tenure mode and payment regimes on adoption of Energy Star appliances.

ES Appliance: Regression Specification:	Room AC (1)	Dishwasher (2)	Clothes Washer (3)	Clothes Dryer (4)	Refrigerator (5)	Central AC (6)	Electric Central Heating (7)	Gas Central Heating (8)
Owner-Occupied Mean Adoption	[0.3843]	[0.4507]	[0.4722]	[0.1917]	[0.4960]	[0.2844]	[0.1951]	[0.2608]
Rented	0.0010	−0.0793***	−0.0858***	0.0067	−0.0843***	−0.0568***	−0.0192	−0.0992***
	(0.0251)	(0.0300)	(0.0325)	(0.0294)	(0.0149)	(0.0195)	(0.0165)	(0.0135)
Landlord Pays Utilities	0.0286	0.0669**	0.0352	0.0291	0.0488***	0.0297**	0.0454***	−0.0128
	(0.0195)	(0.0270)	(0.0302)	(0.0252)	(0.0122)	(0.0176)	(0.0125)	(0.0114)
Sample Size	22,419	76,345	87,882	86,224	104,877	72,543	34,361	62,711
Housing Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic and Climate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports Biprobit estimates of average marginal effects of varying tenure mode and utility payment regimes on the likelihood of having Energy Star appliances. Delta method standard errors are presented in parentheses. Means of the dependent variable for the omitted comparison group (owner-occupied residences) are presented in brackets. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

appliance is Energy Star, and equal to zero if it is standard; $[rented]_i$ is an indicator variable equal to one if the unit is rented, and zero if it is owner-occupied; $[\text{Census Division } d]_i$ is an indicator equal to one if the unit is in Census Division d; X_i is a vector including a constant and control variables (full set of controls, including housing attributes); and ε_i is an idiosyncratic error term.

The coefficients β_1^d capture ES appliance saturation differences between renters and homeowners, across each of the following census divisions: New England; Middle Atlantic; Midwest; West North Central; South Atlantic and East South Central; West South Central; Mountain and Pacific.[13]

Fig. 11 plots the estimated percentage saturation differences between renters and homeowners, for each census division, and for a regression with adoption of ES refrigerators as the dependent variable. The same figure also plots population weighted average electricity prices by census division.[14] Fig. 12 is analogous to Fig. 11, but for a regressions on ES gas heating, and plotting average natural gas prices.[15]

Both plots are suggestive of an inverse relationship between the estimated effect sizes and energy prices. Therefore, saturation differences across homeowners and renters are smaller when energy prices are higher. The higher prices might increase the attentiveness of renters to a home's energy consumption, which can then get translated to higher demand for efficient homes, even in the rental market.

3.4. Bivariate probit estimation

It is reasonable to expect unobservable preferences to be correlated both with investments in efficiency and with tenure mode. For example, environmentally concerned households may prefer to own a residence, rather than rent it, because ownership would give them more flexibility for retrofits and changes that they may want to make to the home. An endowment effect may also encourage households to invest more in residences that they own. In any case, those unobservable factors could cause the error term (ε_i) from Eqs. (1) and (2), from previous sections, to be correlated with y_i and $[rented]_i$. Linear or probit estimates of those equations could therefore be biased.

As an attempt to attenuate those potential biases, bivariate probit models were estimated. Biprobits were introduced by Heckman (1978) and are now commonly used in applied economics (e.g. Bhattacharya et al., 2006; Evans and Schwab, 1995; Goldman et al., 2001; Neal, 1997) for estimation of simultaneous equation models for latent variables. For the context of this research, the following model is proposed:

$$y_i^* = \delta_1 [rented]_i + \boldsymbol{\gamma}_1 \mathbf{X}_{1i} + u_{1i} \tag{4}$$

$$[rented]_i^* = \boldsymbol{\gamma}_2 \mathbf{X}_{2i} + u_{2i} \tag{5}$$

where y_i^* is a latent variable that determines if residence i has an Energy Star or a standard appliance; $[rented]_i^*$ is a latent variable that determines tenure mode; $\mathbf{Z} = (\mathbf{X}_1, \mathbf{X}_2)$ are vectors of exogenous control variables (which could include the full set of controls described in the previous sections); $\mathbf{u} = (u_1, u_2)$ are error terms with a bivariate normal distribution, assumed to be independent of $\mathbf{Z}$. The latent variables y_i^* and $[rented]_i^*$ can be proxied by indicators, as described in the previous subsections.

Parameters from Eqs. (4) and (5) can be estimated simultaneously through maximum likelihood, which requires the construction of a log-likelihood function. To obtain the likelihood function, the following joint is derived:

$$f(y|[rented], \mathbf{Z}) f([rented]|\mathbf{Z}).$$

Note that the joint density is unchanged regardless of whether $[rented]$ is included as a control in Eq. (4), because construction of $f(y|[rented], \mathbf{Z})$ already requires conditioning on $[rented]$. That particular feature implies that biprobits can be used to identify the parameters in Eqs. (4) and (5), even if Eq. (4) includes $[rented]$ as an endogenous explanatory variable (Wooldridge, 2010).

Han and Vytlacil (2017) demonstrate that the nonlinear nature of the probits allows for identification in systems of the above form. They show that if control vectors are the same for both equations (i.e. $\mathbf{X}_1 = \mathbf{X}_2$), then exclusion restrictions are not necessary for identification. Through maximum likelihood, the parameters from Eqs. (4) and (5) above were estimated, for 6 types electric appliances and 2 types of heating equipment.[16] Using the biprobit estimates of marginal probabilities of adoption, it was possible to construct Table 8 below, which reports average marginal effects analogous to $\beta_1 = \frac{\partial P(y=1 \mid \mathbf{Z})}{\partial [rented]}$ and $\beta_2 = \frac{\partial P(y=1 \mid \mathbf{Z})}{\partial [lpu]}$ from the previous sections. The regression specifications include the full set of controls from Tables 1–3.

The endogeneity-corrected estimates of the effect of renting are negative and statistically significant for most appliances (with the exception of Room ACs, and Clothes Dryers), again indicating that rented units are less likely to have the ES appliances. For some of those, the biprobits produced weaker effects than linear models (Room ACs, Dishwashers, and Refrigerators). If the distributional assumptions of the biprobits are a good fit for the true relationship between variables, then the linear models were overestimating the effects of renting in adoption of those ES appliances. On the other hand, linear models were underestimating the effects for Central ACs, Clothes Washers, and Gas

[13] Note that some census divisions are combined, since that is how they are reported within the 2011 American Housing Survey.

[14] Electricity prices were obtained from EIA, (2011a), and population estimates were obtained from US Census Bureau (2011).

[15] Natural gas prices were obtained from EIA, (2011b).

[16] Results for ES Oil Heating are omitted, because convergence was not achieved for that appliance.

Heating. Those results attest the non-trivial direction of linear model biases in this context. Nevertheless, the effects remain substantial after correcting for endogeneity biases.

Biprobit estimates also indicate that utility payment regimes have a significant effect on the adoption of some ES appliances. Average marginal effects are positive and statistically significant for Dishwahsers, Refrigerators, and Electric Heating. Landlord-pay units are therefore more likely, compared to tenant-pay units, to have those appliances. The difference in saturation between those two groups could range from 6.36 percentage points, for the case of ES clothes washers, to 3.54 percentage points, for ES electric heating. Results are therefore consistent with hypotheses about the landlord-tenant problem, presented in Gillingham et al. (2012), and Myers (2015).

4. Conclusions

This paper has assessed the effects of tenure mode and utility payment regimes on energy efficiency outcomes in US residences. Estimates indicate that rented residences, compared to owner-occupied residences, are less likely to have Energy Star rated central air conditioners, dishwashers, clothes washers, refrigerators, and heating equipment. When compared to Davis (2012), updated estimates form this study suggest that the gap between owner-occupied and rented units has become wider. For example, the preferred specification from Davis (2012) (for refrigerators) produced a point estimate of − 6.7%, while estimates from this study are closer to − 15%. Those effects are significantly attenuated when housing attributes, not considered in Davis (2012), are controlled for. Nevertheless, the effects remain strong (e.g. − 12.9% for ES refrigerators, and − 14.8% for ES dishwashers). There is also evidence of attenuation of those effects (for dishwashers, refrigerators, and electric heating) when landlords pay the utility bills of rented dwellings. That is consistent with hypotheses from Myers (2015), Gillingham et al., (2012), about split incentives in residential rental markets.

Heterogeneity by energy prices is assessed, by looking at how effects vary across US census divisions. That analysis reveals an inverse relationship between energy prices and adoption of Energy Star appliances. Residents from regions with higher energy prices are more likely to adopt efficient appliances. Finally, this paper is also the first to investigate if energy efficiency outcomes are heterogeneous by tenancy duration. Results indicate that homeowners are more likely to invest in efficiency around the time of purchase of the residence, rather than at later time periods. On the other hand, investments in rented homes occur in later periods of tenancy, when the relations between landlords and tenants are already well established. Those results are consistent with hypotheses derived from the urban economics literature: information asymmetries with respect to tenancy duration cause underinvestments in rented units, but not in owner-occupied units.

Collectively, results from this study reinforce the importance of policies that can encourage more adoption of efficient appliances in rented dwellings. It seems that rented units are falling behind in terms of investments in energy efficiency. This can be a problem especially for low-income renter families, which might face heavier burdens in terms of utility costs. It can be argued that those families are also in a position of low bargaining power (compared to their landlords), due to less access to information (about possibilities of efficiency investments) and lower education levels. With more complex contract structures (which imply adjustments to rents, for example), it may be possible to make arrangements that are beneficial both to landlords and tenants, such that both can share the benefits of efficiency investments. However, the short-duration nature of some rental contracts may be a barrier, given that some efficiency investments have relatively long payback periods.

It may be more cost-effective to target educational campaigns, appliance rebate programs or retrofit subsidies to rental markets, given that rental dwellings tend to contain older and less efficient appliances. However, those programs also need to take into account the well-being of renters, rather than landlords. Energy audit and disclosure requirement policies can potentially attenuate information asymmetries that exist in residential markets, empowering tenants to demand better upkeep from their landlords. For example, Austin's Energy Conservation Audit and Disclosure Ordinance (ECAD) establishes clear regulation in terms of mandatory energy audits, as well as mandatory disclosure of results. Nevertheless, the debate about gentrification is relevant in this context, since intensive quality and efficiency improvements to certain areas may drastically increase rental prices, which may become prohibitive for lower-income families.

Acknowledgements

I would like to thank CAPES (Coordination for the Improvement of Higher Education Personnel - Brazil) for their support. I am also grateful for helpful comments from Erica Myers, and attendees at ISEFI 2017, AERE 2017, and LCM 2017 conferences.

Appendix A

.

Table A1
Regression results for clothes washer and dryer combined.

Regression Specification:	LPM	LPM	Probit	Biprobit
Owner-Occupied Mean Adoption	[0.2508]	[0.2529]	[0.2529]	[0.2529]
Rented (β_1)	− 0.0249	− 0.0211	− 0.0189	− 0.0203
	(0.0197)	(0.0268)	(0.0251)	(0.0326)
Landlord Pays Utilities (β_2)	.0266	0.0241	0.0291	0.0394
	(0.0268)	(0.0303)	(0.0274)	(0.0292)
Sample Size	67,840	60,895	60,895	60,895
Housing Controls	No	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Geographic and Climate Controls	Yes	Yes	Yes	Yes

Notes: This table reports estimates of effects of tenure mode and utility payment regimes on the likelihood of having Energy Star clothes washers and dryers combined (sample restricted to homes that have both). Regressions include all the control variables described in Tables 1, 2, and 3. Standard errors are presented in parentheses, and are clustered by census division. Means of the dependent variable for the omitted comparison group (owner-occupied residences) are presented in brackets. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively. Samples are restricted to dwellings that have the appliance in question (either standard or rated Energy Star).

Table A2
Average upfront costs of appliances (compiled by Chini et al., 2016).

Appliance	Purchase Cost		Installation Cost		Total Upfront Cost		Upfront Cost Premium
	Standard	Energy Star	Standard	Energy Star	Standard	Energy Star	(Energy Star - Standard)
Dishwasher	$ 244.00	$ 539.00	$ 362.00	$ 362.00	$ 606.00	$ 901.00	$ 295.00
Clothes Washer	$ 599.00	$ 1199.00			$ 599.00	$ 1199.00	$ 600.00
Clothes Dryer	$ 749.00	$ 799.00			$ 749.00	$ 799.00	$ 50.00
Refrigerator	$ 468.00	$ 599.00			$ 468.00	$ 599.00	$ 131.00
Central Air Conditioning	$ 1025.00	$ 3370.00	$ 506.00	$ 506.00	$ 1531.00	$ 3876.00	$ 2345.00
Furnace (Central Gas Heating)	$ 1094.00	$ 1599.00	$ 714.00	$ 1454.00	$ 1808.00	$ 3053.00	$ 1245.00

Notes: The table presents average upfront costs for standard versus Energy Star appliances in th US, compiled by Chini et al. (2016) from various sources.

References

Allcott, H., Greenstone, M., 2012. "Is There an Energy Efficiency Gap?". In:. Journal of Economic Perspectives 26 (1), 3–28.

Bhattacharya, J., Goldman, D., McCaffrey, D., 2006. "Estimating probit models with self-selected treatments". In:. Statistics in Medicine 25, 389–413.

Chandler, S. and M. Brown (2009). "Meta-review of efficiency potential studies and their implications for the South." In: Georgia Tech Ivan College of Public Policy Working Paper (51), pp. 1–41.

Chini, Christopher M., et al., 2016. "Quantifying Energy and Water Savings in the U.S. Residential Sector". In:. Environmental Science & Technology 50 (17), 9003–9012.

Davis, L. (2012). "Evaluating the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances?" In: The design and implementation of U. S. climate policy. NBER Conference Report, pp. 301–316.

Electric Power Research Institute (2009). "Assessment of achievable potential from energy efficiency and demand response programs in the US 2010 to 2030." In: Technical Report, EPRI, pp. 1–342.

Evans, W.N., Schwab, R.M., 1995. "Finishing high school and starting college: Do catholic schools make a difference?". In:. The Quarterly Journal of Economics 110, 941–974.

Gillingham, Kenneth, Harding, Matthew, Rapson, David, 2012. "Split incentives in residential energy consumption". In:. Energy Journal 33 (2), 37–62.

Gillingham, Kenneth, Palmer, Karen, 2014. "Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence". In:. Review of Environmental Economics and Policy 8 (1), 18–38.

Goldman, D., et al., 2001. "Effect of Insurance on Mortality in an HIV-Positive Population in Care". In:. Journal of the American Statistical Association 96, 883–894.

Halket, J., di Custoza, M., 2015. "Homeownership and the scarcity of rentals". In:. Journal of Monetary Economics 76, 107–123.

Han, S., Vytlacil, E., 2017. "Identification in a generalization of bivariate probit models with dummy endogenous regressors". In:. Journal of Econometrics 63–73.

Haurin, D.R., Gill, H.L., 2001. "The Impact of Transaction Costs and the Expected Length of Stay on Homeownership". In:. Journal of Urban Economics 51, 563–584.

Heckman, J., 1978. "Dummy Endogenous Variables in a Simultaneous Equation System". In:. Econometrica 46, 931–959.

Jaffe, A., Stavins, R., 1994. "The energy-efficiency Gap: what does it mean?". In:. Energy Policy 22, 804–810.

Levinson, Arik, Niemann, Scott, 2004. "Energy use by apartment tenants when landlords pay for utilities". In:. Resource and Energy Economics 26 (1), 51–75.

McKinsey & Co (2009). "Pathways to a low-carbon economy: Version 2 of the global greenhouse gas abatement cost curve". In: Technical Report, McKinsey & Company, pp. 1–165.

Montgomery, C., 1992. "Explaining Home Improvement in the Context of Household Investment in Residential Housing". In:. Journal of Urban Economics 32, 326–350.

Myers, E., 2015. "Asymmetric Information in Residential Rental Markets: Implications for the Energy Efficiency Gap". In:. Energy Institute at Haas Working Paper Series 246R, 1–56.

Neal, D.A., 1997. "The effects of catholic secondary schooling on educational achievement.". In:. Journal of Labor Economics 15, 98–123.

Potepan, M.J., 1989. "Interest Rates, Income, and Home Improvement Decisions". In:. Journal of Urban Economics 25, 282–294.

Sweeney, J., 1974. "Housing Unit Maintenance and the Mode of Tenure". In:. Journal of Economic Theory 8, 111–138.

US Census Bureau (2011). Population and Housing Unit Estimates. [Online; accessed in 2017]. url: 〈https://www.census.gov/programs-surveys/popest.html〉.

US Energy Information Administration (2009). Residential Energy Consumption Survey. [Online; accessed in 2017]. url: 〈https://www.eia.gov/consumption/residential/〉.

US Energy Information Administration (2011a). Electricity Sales (consumption), revenue, prices & customers. [Online; accessed in 2017]. url: 〈https://www.eia.gov/electricity/data.php#sales〉.

US Energy Information Administration (2011b). Natural Gas Prices. [Online; accessed in 2017]. url: 〈https://www.eia.gov/naturalgas/data.php#prices〉.

US Energy Information Administration (2015). Energy-Related Carbon Dioxide Emissions. [Online; accessed in 2017]. url: https://www.eia.gov/environment/emissions/carbon/.

US Environmental Protection Agency (2016). About ENERGY STAR. [Online; accessed in 2017]. url: 〈https://www.energystar.gov/about〉.

Wooldridge, J.M., 2010. "Binary Response Models". Econometric Analysis of Cross Section and Panel Data., 2nd ed. The MIT Press, pp. 561–642.