Economic, Sociological, and Neighbor Effects in Energy-Efficient Residential Heating and Air Conditioning System Installations: Evidence from the U.S.

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Abstract

This study identifies factors that affect the adoption behavior for residential Heating, Ventilating, and Air Conditioning (HVAC) systems, including a spatial and temporal contagion effect, house characteristics, and other economic and contextual factors. The study draws on a dataset of house sale records in the greater Chicago area, spanning 1992 to 2004. First-differenced models and restricting the sample to new construction allow separate identification of adoption determinants for homeowners and for developers, respectively. We show that attributes of the building stock and demographics influence adoption decisions of both homeowners and developers. This includes a strong influence of square footage, a modest spatial clustering effect for existing homes, a consistent deterrent effect of higher property tax rates, and a positive influence of neighborhood education levels. Adoption decisions for existing homeowners appear to be driven by different factors than sellers of newly constructed homes. Adoption coincided with multi-story homes for developers, and neighbor adoption rates predicted adoption by existing homeowners but not developers. The results highlight the need for more research into the social context of energy efficiency investment.

keywords: energy efficiency, green buildings, technology adoption, housing

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1. Introduction

Demand for energy and pressures to reduce carbon dioxide emissions continue to grow. Instead of increasing energy supply to meet demand, many recommend improving energy efficiency. Gillingham et al. (2004) review a cost-effective collection of energy efficiency programs that could reduce energy consumption in buildings by 12 percent. In this sense, energy efficiency can be viewed as a source of supply of energy resources (Paul et al. 2011). Moreover, Heating, Ventilation, and Air Conditioning (HVAC) consume nearly one-third of building energy end-use, making this the largest end-use among all residential energy consumption activities (Kelso 2009). Thus, if the goal is to reduce residential energy consumption by improving energy efficiency, HVACs should be a top priority. As residential use accounts for 20-30% of total energy demand globally (Estiri 2015) and rapidly increasing electricity consumption around the world follows higher economic status (D'Oca et al. 2014), better understanding the human and social aspects of residential energy efficiency poses a challenge to energy-intensive economies and those rapidly intensifying.

A growing volume of research demonstrates the benefits of adopting energy-efficient or zoned HVACs, with engineers concluding that substantial energy savings can be achieved through zoned systems (Burgett et al. 2013, Mathews et al. 2001, Pérez-Lombard et al. 2011, Meyers et al. 2010, Ardehali and Smith 1996). Zoned HVAC systems allow the consumer to set different temperatures for different parts of the house and reduce energy consumption when a room is unoccupied, similar to turning off lights when leaving a room. It is generally accepted that zoned HVAC systems can substantially reduce the 39 percent of HVAC energy costs that do not add to increased comfort (Meyers et al. 2010). Ardehali and Smith (1996) report reductions in energy consumption exceeding 50 percent for zoned HVAC systems and simulate a 65 percent energy cost savings for a typical residential building in Des Moines, Iowa. Mathews et al. (2001) find similar simulated savings. While our data do not measure energy consumption or savings in individual houses, understanding the factors that drive technological adoption and choices about housing characteristics can inform our understanding of the energy efficiency gap and households' indirect effects on energy consumption (Estiri 2015).

Research focusing on the adoption behavior for these systems, however, is relatively limited. Evidence indicates that adopting energy efficient technologies benefits homeowners, but homeowners frequently forgo the adoption of cost-effective technologies, creating an energy efficiency "paradox" or "gap" (Hassett and Metcalf 1994, Jaffe and Stavins 1994, Allcott and Greenstone 2012). Factors affecting homeowners' decision-making – either the possible motivations or barriers to the adoption of energy efficient HVACs – merit additional research (Allcott and Mullainathan 2010). From a policy perspective, an improved understanding of adoption behavior enables better policies to enhance the diffusion of energy-efficient HVACs or lower the barriers to adoption. Higher energy prices, for example, should result in more energy-efficient HVAC adoption. Yet prices are not consumers' sole consideration, and they cannot explain the variation in adoption behavior among homeowners in the same market, facing identical energy prices and building codes. Identifying the determinants of adoption can guide the design of appropriate policies to stimulate the diffusion of energy-efficient HVACs.

This study offers several contributions to the literature regarding energy efficiency technology adoption behavior. First, we use market data on major investments at the house level. This represents an improvement over many existing studies, which typically rely on potentially biased survey (Wilson et al. 2015) or aggregated data. Second, this study allows for spatio-temporal spillovers in household behavior, which measures the diffusion of technology change. Third, this study adds new empirical tests of the relationships between the factors expected to impact HVAC adoptions and observed adoptions. This study also contributes to Estiri's (2015) new approach to understanding residential energy use by providing more evidence about housing choice behaviors that impact energy consumption.

In addition to identifying the relationships between HVAC adoption and microeconomic determinants that ought to affect HVAC adoption (e.g., tax rates, age of the house, size of the house), suggestive evidence about a "spatial contagion" is offered. That is, our model construction allows us to test for peer effects and the impact that energy efficient technology adoption behavior at the house level has on nearby house adoption behavior. Policymakers and economists appear increasingly interested in the diffusion of energy-efficient technologies among houses. Early adopters can influence later adopters through sharing knowledge, "keeping up with the Joneses" copycatting, "green signaling," "competitive altruism," or "conspicuous conservation" (Bollinger and Gillingham 2011, Sexton and Sexton 2014). We examine a spatial contagion effect for HVAC technology adoption in a large panel dataset of home sales that reveal housing choices across the Chicago suburbs.

The empirical analysis here directly addresses the shortcomings of the "physical-technical-economic model" (PTEM) of energy efficiency adoption, with its "very little consideration of social systems, consumers as social actors, or other non-engineering/non-economic social considerations" (Lutzenhiser 2014, 143). We explicitly introduce neighborhood effects and allowing for more heterogeneity by decision-makers, all while controlling for many PTEM concerns either by explicit controls (e.g., structural characteristics) or by holding those conditions fixed within the data (e.g., climate, regional policies). Broadening the adoption model to include factors beyond financial attributes like technology costs and energy prices lends insight into the contextual factors as well as more rarely analyzed personal influences (Wilson et al. 2015) and peer effects (McCoy and Lyons 2014).

2. Background

2.1 Related Work

An “energy efficiency gap,” where decision-makers forgo seemingly cost-effective energy efficiency technologies, has recently attracted renewed interest by economists (Gillingham et al. 2009). Economists have raised concerns that engineering estimates of energy efficiency overstate real-world gains, in part, by overlooking behavioral components (e.g., Jacobsen and Kotchen 2013, Brounen et al. 2012, Allcott and Greenstone 2012, Metcalf and Hassett 1999, Greening et al. 2000, Jaffe and Stavins 1994). The question of who adopts efficiency technologies remains critical. A handful of recent studies have explored these questions with respect to household technologies, both large (Kahn and Vaughn 2009, Metcalf and Hassett 1999, Jaffe and Stavins 1995) and small (Mills and Schleich 2010). Nevertheless, investigations of single-family household-level adoption behavior for energy efficient large appliances like HVAC systems remain rare.

To date, studies that focus on homeowners’ adoption of zoned HVAC systems are limited. The handful of studies addressing homeowners’ adoption of energy-efficient heating and cooling systems tend to use case studies (e.g., Mlecnik 2010) or surveys (e.g., Nair et al. 2010, Niemeyer 2010). Niemeyer’s (2010) survey of 800 households in Nebraska finds variables that impact adoption choices such as knowledge of existing technologies, budget constraints, obstacles to making changes, demographics, and attitudes. Nair et al. (2010) survey 3,000 Swedish homeowners to discover that personal attributes, such as income and education, and contextual factors, such as age of the house and perceived energy cost, influence homeowners' choices regarding energy efficiency improvements (which could include major investments like new heating systems). Of course, increases in resale price (Dinan and Miranowski 1989, Fuerst and McAllister 2011) might also motivate adoption. Wilson et al.'s (2015) lengthier review of the literature modeling renovation decisions highlights the dominance of choice experiments and surveys. Our analysis of actual market data complements this previous household-level adoption literature.

In a broader context, our work stems from Griliches' (1957) work on technology diffusion theory, which has received recent attention in green building and other energy efficiency technology adoption studies. Ioannides and Zabel (2003) show considerable evidence of a powerful "keeping up with the Joneses" effect in home maintenance decisions. More recently, Helms (2012) finds evidence of neighborhood effects in residential renovations. Kahn and Vaughn (2009) discuss the idea of contagion among neighbors' hybrid vehicle purchases, and work by Costa and Kahn (2010) and others (see, e.g., Allcott and Mullainathan 2010, Sexton and Sexton 2014, Bollinger and Gillingham 2011) frequently point to social pressure involved in energy consumption decisions. The influence of neighbor characteristics is also evident in Dastrup et al. (2012), who identify larger price premiums for homes with solar panels in communities with high education levels. Keeping up with the Joneses may include major decisions like upgrading HVAC systems, although these interior investments are not as visible as the distinctive Prius or exterior solar paneling. Network effects, via personal communication among neighbors or shared real estate agents or contractors, may promote information sharing, increased demand, and diffusion of new technologies (Galster 2008, Axsen et al. 2009, Axsen and Kurani 2011).[1] Social interaction can promote energy efficiency improvements as recently shown with survey data (Southwell and Murphy 2014) and simulations (McCoy and Lyons 2014).

The emerging literature on green building diffusion demonstrates similar trends. Kok et al. (2011) analyze the metropolitan-level diffusion of green building certifications. Professional networks predict more adoptions (Kok et al. 2011), and local policies that require green building certification promote networks that generate positive spillovers to neighboring cities (Simcoe and Toffel 2011, Cidell 2009). Brounen and Kok (2011) find significant effects of neighborhood-level characteristics rather than buildings' thermal characteristics (e.g., insulation) in predicting household participation in an energy efficiency certification program. Dastrup et al. (2012) also find an important role for neighborhood demographics in their study of residential solar panel installations.

2.2 Determinants of Technology Adoption

Our analysis builds on the previous literature by exploring the house characteristics and contextual factors that might influence the adoption of energy efficient "zoned" HVACs by homeowners. A cost-benefit calculus for homeowners and developers to predict adoption includes a variety of costs and expected benefits. While we cannot precisely estimate a net-present value calculation for each house, zoned system design elements and prior literature, what Wilson et al. (2015) term as applied behavioral research, lead us to expect several house

[1] In addition, economic circumstances of some neighbors that lead to adoption may also attract localized efforts to market the technology to others in the neighborhood. This economic development spillover, in Galster's terms, functions equivalently to a social network effect although it does not require direct ties between neighbors but rather a more indirect spillover of merely attracting businesses to the area.

characteristics to predict people's decisions to undertake energy efficiency upgrades. On the cost side, the vintage, stories, and rooms of the house are expected to reflect the cost of adoption. The ultimate impact of HVAC energy efficiency improvements depends on a well-sealed thermal envelope for the building and its overall footprint, whereas the ease of installation depends on details like attic access and preexisting systems. For zoned systems, home designs that lend themselves to partitioning into zones (e.g., many rooms, multiple stories) make for good candidates for zoned systems. High tax and interest rates are also expected to deter the adoption decisions of purchases involving high capital costs (Parente and Prescott 1994, Lawrence et al. 2005). The square footage and lot size of the house are employed to predict the expected benefits of zoned systems, due to larger houses.

The diffusion and efficiency gap literatures indicate that more than structural characteristics influence adoption decisions. Contextual or neighborhood-level socioeconomic characteristics, such as distance to a central business district (CBD), median household income, median house value, population density, housing vacancy rate, percent renters, and percent of the population that are college graduates might affect adoption decisions (Baerenklau 2005, Noonan et al. 2013). These neighborhood attributes might affect the benefits of adoption (Dastrup et al. 2012), either by increasing the expected returns to investment, or by spatial clustering households with higher demand for energy efficiency. Neighborhood attributes might also affect costs, perhaps because low-cost installers market to that area or because knowledge is shared locally and thus search costs or providing inspiration (McCoy and Lyons 2014, Schelly 2014). Neighborhood demographic variables (e.g., median household income level, median house value, population density, percent vacant units, and percent who graduated college) might affect the adoption of energy efficiency improvements.

3. Data and Methodology

We measure a dichotomous dependent variable for energy-efficient HVAC adoption, based on the sales records of Chicago-area homes. This study uses *zoned heating* and *zoned air conditioning systems* to understand the technological adoption of more energy-efficient HVACs. Actual energy savings of zoned HVAC systems depend on the size and design of the house, the efficiency of the individual systems, and many other factors. House sales data contain systematic measures, collected independently of this research, of house attributes and thus implicitly reflect human behavior that constructed, selected, and sometimes renovated the housing.

This study employs a dataset on home sales in over 160 municipalities in the greater Chicago area, originally containing over 340,000 sale records (of roughly 260,000 unique houses) from January 1, 1992 to June 30, 2004. The property data, including address, vintage, stories, number of rooms, type of HVAC, architectural style, etc., are from the Multiple Listing Service (MLS) of Northern Illinois, an information clearinghouse for most residential property sales in that area. Realtors and others in the residential real estate market routinely create and search MLS records for homes listed for sale. All the records are for single-family houses from counties surrounding the city of Chicago (i.e., Cook, DuPage, Kane, Lake, McHenry, and Will counties). (The City of Chicago is not included in order to keep the population of suburban areas with single-family homes more comparable.) The demographic information is from the 1990 and 2000 Censuses. Unlike the sales record data, which are household level, these demographic data are available at the block-group level using the GeoLytics database.[2] Using GIS tools, the

[2] Using the demographic data from GeoLytics, Inc. (East Brunswick, NJ) provides the 1990 Census data in geographic boundaries consistent with 2000 boundaries. Demographic values are linearly interpolated based on 1990 and 2000 values for years other than 2000.

corresponding demographic data is assigned to each sales record based on the block group in which each house is located.

In our dataset, more than 88 percent of households use forced-air heating systems, and 90 percent of households use natural gas as the energy source for heating. The majority of A/C systems is central air, which is used in over 80 percent of homes. Only 2 percent of sales records indicate zoned HVACs.

The empirical model considered here takes the form:

$$y_{igt} = \ln\left[\frac{\mathrm{P}_{igt}}{1-\mathrm{P}_{igt}}\right] = \boldsymbol{\alpha_{igt}} + \boldsymbol{X}'_{igt}\boldsymbol{\beta}_t + \boldsymbol{Z}'_{ig}\boldsymbol{\gamma}_t + \theta_{igt} \qquad (1)$$

where y = 1 to indicate a zoned system is installed and a 0 otherwise, $P_{igt} / (1-P_{igt})$ is defined as the probability of a house i in block group g and sold in year t adopting an energy efficient HVAC system; $\boldsymbol{X}$ and $\boldsymbol{Z}$ are time-varying and time-invariant vectors of control variables, $\boldsymbol{\alpha_{igt}}$ is an intercept and θ is an error term. Random-effects logit models are estimated, where local neighborhoods (i.e., block groups) are given individual error terms (i.e., $\theta_{igt} = \mu_g + \varepsilon_{igt}$), due to concern that might result from uneven sampling or measurement consistency across these areas, as well as to alleviate concerns regarding block level heterogeneity. (The results from ordinary logit analyses are substantively similar, differing largely in the size of standard errors.

Not all of the 340,000 sales records are appropriate for this study. Because the data do not include timing of adoption or installation for HVAC systems, and because building maintenance and other important attributes may be unobserved in the data, care is taken to construct final datasets that mitigate these problems and offer the cleanest interpretation of results. Accordingly, we create three samples from the data: a new construction sample, a renovation sample, and a new-installation sample. The first concerns developers' (i.e., those who sell new construction) adoption decisions, while the second two concern adoption decisions of homeowners (i.e., those who resell houses). We use equation (1) to estimate developers' adoption decisions; equation (2), discussed below, is used to estimate homeowners' decisions.

First, the **new-construction sample** focuses the analysis on adoption decisions by housing developers. The new-construction sample includes only sales records that are labeled in the MLS sales record as new construction (approximately 7,000), thus minimizing the problem of unobservable equipment age and maintenance. Decisions by housing developers have not yet been examined in prior literature related to residential energy efficiency adoption in the U.S., yet developers and new construction clearly play major roles in the prospects for altering the carbon footprint and energy efficiency the U.S. residential building sector (Costa and Kahn 2011, Chong 2012). Deng and Wu's (2014) analysis of price premiums reveals that energy efficiency investments may be treated very differently for new and resold homes. We estimate adoptions with the new construction sample using equation (1).

Second, we examine only homes that sold multiple times in the dataset in order to observe homeowner decisions, mitigate problems related to static but unobservable characteristics of houses, and control for unobserved timing in adoption. We use the multiple sales to isolate the impact of changes of house and neighborhood characteristics on changes in HVAC decisions and avoid the bias of omitting many housing characteristics that do not change over time. Looking at homes' HVAC systems at two points in time amounts to predicting renovations between sales. The **renovations sample** consists of houses that had a non-zoned heating (or A/C) system at their initial sale (approximately 18,000 observations), and may potentially renovate to install a zoned system.[3] The other type of households that might adopt are homes that had no heating (or A/C) system at their initial sale. This **new-installation sample** (2,700 observations) includes

[3] Houses with multiple heating (or A/C) systems at the time of initial sale are also dropped, as they might be seen to already operate a de facto zoned system.

houses not coded in the MLS data as "new" homes but still lacking an HVAC system. This smaller sample of predominantly very young houses, possibly not yet owner-occupied, lacks a technological lock-in and may involve different adoption behavior than in the renovations sample. Comparing the results from the renovation and new-installation samples with the new-construction sample will highlight the differences in decision criteria for homeowners reselling houses and house developers selling new construction.[4]

These constructions essentially function like first-differenced models, where *changes* in house HVAC technology are predicted by changes in key factors (e.g., square footage, tax rates) as well as initial home attributes, while differencing out unobserved static heterogeneity.[5] Predicting changes in installed technology between the first and last sales in the dataset reduces the sample size to roughly 18,000 observations.[6] The resulting model is a modification of equation (1):

$$\Delta y_{igt} = \ln\left[\frac{P_{igt}}{1-P_{igt}}\right] = \Delta \boldsymbol{X}'_{ig}\boldsymbol{\beta}_s + \boldsymbol{X}'_{igt}\Delta\boldsymbol{\beta} + \boldsymbol{Z}'_{ig}\Delta\boldsymbol{\gamma}_t + \Delta\theta_{igt} \qquad (2)$$

Zoned HVAC adoption between sales in period *t* and *s* is explained by changes in ***X*** and changes in the effects of the determinants. Time-invariant factors ***Z***, observed or unobserved, will difference out if their parameters are constant. A logistic regression is estimated for equation (2) to identify the determinants of adoption by individual homeowners using the renovation and new-installation samples.

The three samples identify different determinants of adoption of energy efficient HVAC

[4] The distinction between the new-construction and the new-installation samples is that the former is listed as "new construction" in the MLS and only gets sold once in our data, while the latter is not listed as "new construction," gets sold multiple times, and apparently has no system in place initially.
[5] Including the initial attribute levels or time-invariant attributes (e.g., location) in what is essentially a first-differenced model implies an interaction of these variables and the time variable. Thus, our interpretation of these variables is that they identify a time trend in their effect on adoption.
[6] The much smaller new-installation sample has only 2,700 observations with no initial A/C and 1,300 observations with no initial heating system.

systems. For the renovations sample, the coefficients indicate the effect of the regressor on the likelihood of switching from a non-zoned system to a zoned system between sales. For the new-installation and new-construction samples, the coefficients indicate the effect of the regressor on the likelihood of initially installing a zoned system relative not installing such a system. While zoned systems can be expected to be more energy efficient than conventional systems, houses with zoned systems are likely to consume more energy than a house with no system.

We estimate separate models for adoption of zoned heating systems and of zoned A/C systems (for each of the three samples). This is done to detect different determinants for the two systems, although clearly adoption decisions may be very interdependent. Brounen et al.'s (2012) sample of Dutch homes suggest structural and behavioral factors play different roles in explaining consumption dependent on whether it is gas or electricity use. Given that ninety percent of heating is fueled by gas in our sample, we estimate adoptions for heating and cooling systems separately to account for different sources of fuel cost savings. In addition to these structural and contextual factors, neighborhood factors may influence adoption differently for heating and A/C for other social reasons (e.g., residents sort into neighborhoods based partly on differential demand for better A/C).

The definitions and descriptive statistics of all the variables introduced in this study are listed in Tables 1 and 2, respectively. Estimating similar models improves the comparability across the three samples. The vector $\boldsymbol{X}$ includes a host of structural, neighborhood, and other contextual variables. We include in $\Delta\boldsymbol{X}$ the differences in square footage, lot size, interest rates, sale date, and rehab status for the renovation and new-installation samples. Included in $\boldsymbol{X}$, as measured at the time of first sale, are structural characteristics (e.g., vintage, rooms, size), neighborhood factors (e.g., income, education, vacancies), and tax and interest rates. Following equation (2), these variables capture the changes in parameter values between sales. Year of (first) sale dummies to allow for time trends (in "green" tastes, in energy prices, in installation prices, etc.). Seasonal dummies allow tests for whether houses adopting zoned HVAC systems tend to sell disproportionately in certain seasons, something that might occur if owners upgrade before selling their home in certain seasons or salience of HVAC systems varies seasonally. Busse et al. (2012) observe a similar sort of seasonality for hedonic values of central air conditioning. Differences between renovating and new installation suggest that some factors are irrelevant to one choice (e.g., vintage for new installations) and others may operate differently between samples. For instance, the offsetting effects of multi-story houses on renovation adoptions become largely positive for multi-story new construction, due to fewer structural barriers to zoned HVAC installation.at the time of construction.

The *neighborhood adoption* variable is a (spatially and temporally) lagged adoption rate defined as the share of homes in the block group that have installed zoned HVACs and are sold within a 5-year window before the sale date of each sales record.[7] In other words, it is the density of homes sold with zoned HVACs in the block group during the moving 5-year window. We hypothesize that higher zoned HVAC density will lead to a greater probability of adoption. We remain agnostic about the mechanism for this interdependence, although certainly social pressure and norms, social networks, competition, learning, a lowering of transaction and search costs, and other mechanisms may all be at work (Allcott and Mullainathan 2010, Galster 2008). Insofar as higher neighborhood adoption rates reduce search costs for homeowners considering installing

[7] This contagion concept aims to capture the share among neighbors of recent sales that have already adopted the technology. As a practical matter, five years is used to define "recent," although other windows could readily be selected. A sensitivity check of using one and three years shows that different definition of "recent" generally does not affect other estimators. The contagion effect is stronger as "recent" is defined as a shorter time period. Similarly, different definitions of neighbors (other than being in the same block group) could be used.

a zoned HVAC system, renovators can learn from (Southwell and Murphy 2014) and experience neighbors' prior installations (Wallenborn and Wilhite 2014), and new home developers have already conducted basic marketing research (Dastrup et al. 2012), we expect neighborhood adoption to have a stronger effect on renovation decisions than on new construction decisions.

<<<insert table 1 about here>>>

<<<insert table 2 about here>>>

4. Results

4.1 New-Construction Sample

Table 3 provides the results for the random-effects logistic regressions for both zoned heating systems and zoned air-conditioning systems in the new-construction sample. In the new-construction sample, multistory and square footage have positive effects on adoption. Unlike those in the two repeat-observations (i.e., renovations and new-installation) samples, *multistory* has a positive effect in the new sample, perhaps due to the ease of installing zoned HVAC systems during new construction, and the logic of designating zones in multistory homes. Like those in the renovation sample, the property tax rate has a negative effect on the inclusion of zoned HVAC systems in new construction.

The prevailing mortgage interest rates do not appear to predict zoned HVAC adoption by homeowners or developers. Interest rates are inconsistent and only weakly significant for zoned air conditioning in Table 3, zoned heating in Table 4 and Table 5. Inconsistent findings may result from similar fixed costs among substitutes or an incentive to construct homes that shift costs to operating costs as interest rates rise to offset homebuyers' expected higher mortgage payments.

For developers rather than existing homeowners, the effect of neighborhood adoptions is not significant in either zoned heating or air conditioning systems. This insignificant effect indicates that social pressure and knowledge sharing may be less likely to occur between developers and existing owners than among owners of existing stock.[8] It is likely that social pressure and knowledge sharing have not occurred if new homes are built by new entrants to a neighborhood.

<<<insert table 3 about here>>>

Neighborhood variables are generally insignificant, except for distance to CBD for the adoption of zoned air-conditioning, and median house value and population density for zoned heating. The percent of college graduates in the neighborhood has positive and significant effects for both heating and air conditioning. The median house value has a positive effect on the installation of zoned heating system in the new-construction sample, likely reflecting localized demand and clustering of higher-value homes. Numerous hedonic studies have demonstrated that energy efficiency brings a sales premium to a property (Dinan and Miranowski 1989, Eichholtz et al. 2010b, Fuerst and McAllister 2011) and this premium is even greater in highly educated communities (Dastrup et al. 2012). Even though neighborhood variables are generally individually insignificant for new-construction sample, they are jointly significant for both zoned air-conditioning (χ^2 = 15.48) and heating system (χ^2 = 23.88) models.

4.2 Renovation Sample

Table 4 lists the results of random-effects logistic regressions for the renovation sample. Two models are reported to show the determinants for two dependent variables: the adoption of zoned heating systems and the adoption of zoned air conditioning systems. For house

[8] Instead of defining the lagged adoption as “share of all sales with zoned HVAC in the block group,” if we change the definition to the “share of new construction sales with zoned HVAC,” the results are similar.

characteristics, the effect of property vintage is significant for both technologies. The likelihood of installing a zoned system between sales falls with age until houses are over 50 years old, beyond which the odds of adoption begin to rise with age. Compared with newer properties (age under five years), older houses are less likely to adopt zoned HVACs. This may be because installing zoned HVACs in newer houses is easier due to home design characteristics or greater rewards to keeping modern homes updated.

The effect of square footage is positive and significant. Houses with larger indoor space have greater benefits from adopting zoned HVAC systems due to greater potential energy savings. Interestingly, *multistory* and *rooms* do not have significant effects on adoption, conditional on house size. Gross size (square footage) appears to drive adoption decisions more than the ease of separating zones in the home (stories, rooms). However, house characteristic is jointly significant for both heating (χ^2=165.47) and air conditioning (χ^2=42.68).

Context matters as well. Effective property tax rates have significant negative effects on the adoption of energy efficiency. Consistent with the expectation that property taxes reduce the returns on property investments (Tse and Webb 1999), higher tax rates indeed reduce the odds of adopting zoned HVAC systems. The weak effect of interest rates likely follows from its poor measurement. It is a market average rate (rather investor-specific) at the time of sale (rather than time of installation). The effects of neighborhood adoption are only positive and statistically significant for zoned heating. In other words, higher adoption rates in the previous five years at the block group level only affects the adoption of heating, not air conditioning. The effects of neighborhood quality (i.e., neighborhood attributes listed after *neighborhood adoption* and above sales year in the table) are inconsistent between two technologies. For air conditioning, a location closer to the central business district, a higher housing vacancy rate, and a higher proportion of rental units have positive effects on adoption. For heating systems, median household income is negatively related, while median house value and the percent of college graduates in the neighborhood are positively related with adoption. These neighborhood quality variables are jointly significant at the 0.01 level for both heating and air conditioning. Their different roles for different technologies are expected as demographic correlates of demand and the ways people experience the systems differ for heating versus cooling.

<<<*insert table 4 about here*>>>

The change in square footage between each sales record has a significant positive effect on the adoption of both zoned air conditioning and heating systems. The effect is even stronger than the effect of square footage for the first sale. This is as expected. Homes that add square footage are much more likely to adopt zoned HVAC systems because the estimated savings from adoption also increases. In addition, the cost to adopt will also likely be lower since a major renovation is already taking place or the addition to the house may require an additional HVAC system. As Judson and Maller (2014) observe for efficiency upgrades generally, it is the expansion of square footage (not any Δ*rehabilitation*) that drives adoption. The changes in lot size and interest rate also do not influence the probability of adoption. While those results confirm expectations, the weak effect of *time elapsed* in Table 4 is somewhat surprising in light of the expectation that more time between sales offers more time for HVAC upgrades to occur. Apparently the incentive and opportunity to renovate HVACs in homes with rapid turnover (i.e., shorter time elapsed) roughly offset the effect having more time to renovate.

4.3 New-Installations Sample

Table 5 lists results for the random-effects logistic regressions for both zoned air-conditioning systems and zoned heating systems in the new-installations sample. Observations in this smaller sample have no HVAC systems before resale and are virtually all very young houses. Thus, vintage variables are dropped. Since observations having no air-conditioning system at previous sale do not necessarily overlap with observations with no heating system, the two columns of Table 4 are discussed separately.

For the new-installation of air-conditioning sample, neighborhood adoptions (block group zoned HVAC adoption density), square footage, difference in square footage, lot size, and population density all have positive effects on the adoption. The density and neighborhood adoption effects might capture more social activity and a greater probability of information exchange. Except as a possible proxy for owner income, it is unclear why the lot-size effect remains significant even after controlling for indoor square footage. (The income explanation is consistent with the insignificant lot-size effect for zoned heating, in any sample, as Brounen et al. (2012) suggest that A/C use – and hence cost-savings from efficiency upgrades – depends more on income.)

<<<insert table 5 about here>>>

Zoned heating systems have different drivers than zoned air-conditioning systems. For homebuyers installing new heating systems in existing houses, the effects of neighborhood adoption, lot-size, population density and rental proportions are no longer significant. Instead, effective tax rates and mortgage rates have weakly negative effects on adoption. Increases of square footage and difference in square footage remain positively correlated with zoned heating system adoption, as expected.

5. Discussion

5.1 Comparisons Across Adopter Types

The results for homeowners (both renovations and new-installations) and developers are generally quite consistent, although some interesting differences exist. Out of 14 house and neighborhood variables shared in Tables 3, 4, and 5, all but a handful of variables exhibit the same sign or are insignificant in all tables. Only one parameter estimate is statistically significant with opposite valences for homeowners and developers. The split-incentives (Davis 2010, Gillingham et al. 2010, Levinson and Niemann 2003) problem facing new construction does not appear to lead to very different adoption criteria. Moreover, the much higher adoption rates for new construction noted in Table 2 indicate that the split incentives problem, to the extent it exists here, may be a bigger problem between current and future homeowners than between developers and future owners.

Both homeowners and developers are responsive to economic characteristics such as tax rates, physical attributes such as house size, and neighborhood characteristics such as the percentage of the population that has a college degree. In contrast to homeowners, developers appear more responsive to structural characteristics, such as whether the house is multi-story. The effect of neighborhood adoption rates is positive and statistically significant for the renovations sample (heating), new installations (cooling). For the other homeowner samples, the effect is positive, though not statistically significant. For new construction, there does not appear to be a contagion effect. These results confirm the hypothesis that adoption density in the neighborhood has a positive effect on adoption decisions for homeowners (and less so for builders, who may not be situated in that neighborhood).

Both house characteristics and contextual factors like neighborhood demographic characteristics influence adoption behavior. Factors beyond financial attributes and those commonly found in engineering cost models certainly influence adoption. For homeowners (renovations and new-installations samples), neighborhood adoption and house size have positive effects on the adoption of energy efficiency; the tax rate and house age have negative effects. For developers (new-construction sample), neighborhood adoption fails to impact adoption decisions, but having multiple stories, the size of houses, and the percent of college educated residents in a neighborhood have positive effects on adoption. Similar to the effect on homeowners, tax rates have a negative effect on the adoption of energy efficiency. Nonetheless, the overall statistical insignificance of many variables highlights the heterogeneity of individual actors with regards to energy efficiency investment decisions.

5.2 Robustness checks and extensions

Fixed-effect logit models (available upon request) yield somewhat comparable results but are not reported here primarily because the tract-level fixed effects soak up much variation in local neighborhood characteristics. Other specifications (available upon request) take advantage of the many other covariates in the MLS dataset. This includes indicators for six age categories, 25 architectural styles, 11 structural types, seven exterior materials, and three roof materials. The new-installation sample is not included in this analysis due to its small sample size. These joint F-test statistics are reported in Table 6.[9] The significance of the age and roofing categories is expected, although the collectively weak predictive power of structural styles is somewhat surprising. Interestingly, architectural styles appear independent of developers' decisions to install zoned HVAC systems, while exterior materials are closely related.

<<<insert table 6 about here>>>

5.3 Comparisons to Prior Work

[9] The lengthy results of unrestricted logit models that include these dummy variables are available from the authors upon request.

Comparing results of these models to survey-based studies provides an opportunity to see how revealed and stated preferences might differ. These differences appear small. Nair et al. (2010) report similar findings for energy costs and income. They find a positive effect of building age that differs from our results, where age exhibits a negative and convex relationship with adoption propensity among homeowners. Our results are less consistent with Niemeyer (2010), who identifies the most common barriers to energy efficiency as "need financial assistance or discount on costs," "need added information," and "need professional or additional assistance." Our findings suggest price effects would need to overcome more powerful income effects that deterred adoption. Information and professional assistance may be partly supported by our research in the positive spillover and diffusion impacts observed among existing homeowners and from block-group education levels.

One large advantage of this study is its use of detailed microdata, while many previous studies use aggregate data on adoption. Noonan et al. (2013) use the same data, aggregated to the block group level for analysis, and obtain different results. (Helms' (2012) analysis of renovation clustering in Chicago also aggregates across time and space, although more modestly.) Serious problems arise when applying results from aggregated data to individual-level relationships (Anselin 2002), and this comparison is a prime example of those challenges. The spatial lag operator is very large and positive in all samples in Noonan et al. (2013), whereas its magnitude is much smaller here, especially for new construction. The more plausible results here likely reflect both the modeling at the appropriate scale (the theoretical interdependency is at the household level, where households are influenced by their neighbors, rather than at the neighborhood level as if neighborhoods were a decision-maker influenced by nearby neighborhoods) and the inclusion of the temporal dimension of the spillover. Noonan et al.

(2013) aggregate to the block-group level and compress 12 years of data into a single cross-section. This allows observations from later years to affect preceding years and could inflate the spatial lag operator. Nonetheless, many results remain consistent, despite the aggregation. For the repeat-observation sample, both studies indicate that neighborhood adoption rates have positive effects on adoption. The effects of square footage, lot size, effective property tax rates, and vacancy rates share the same signs in both studies. It is interesting to note that median household income has positive effects on adoptions at the block-group level but typically negative effects at the house level.

Our data's advantage over survey data (a large sample reflecting actual behavior) comes with limitations for the analysis. While our metric of zoned HVAC systems provides insight into household level energy efficiency technology decisions, we do not directly observe the potential for zoned HVAC systems to reduce energy consumption in individual households. We assume that, ceteris paribus, zoned HVAC systems are more efficient than non-zoned systems, but we cannot observe this directly. Second, these sales data have houses, rather than households, as the unit of observation and shed no light on the specific demographics and attitudes of buyers and sellers. Moreover, the timing of home sales may correspond poorly with timing of adoption decisions, bringing noise and possible bias in the analysis. Even the rich MLS sales data lack detailed information about the quality of installed HVAC technologies, such as their vintage or efficiency ratings, and actual energy consumption data are unavailable. Our data also exclude the major rental (apartment, condo) market. Finally, like many case studies and qualitative analyses, establishing causality of many of the factors here remains a challenge and subject to several crucial assumptions. Future research would do well to better address these limitations in explaining adoption behavior.

A major advantage of this study's research design, which controls for many unobserved economic and regulatory factors by differencing them out and by restricting attention to suburbs of a single large city, also prevents us from explicitly identifying those factors' effects on adoption. Richer data would let us place these more social and contextual factors alongside the economic and regulatory ones, as small-N studies like Schelly (2014) and Walker et al. (2014) have done. Future research with data exhibiting substantial exogenous variation in economic (e.g., installation costs, heating degree days, energy prices) and policy (e.g., subsidies, building codes) factors would complement these results. Although the more inductive, reduced-form quantitative approach here has the advantage of making fewer assumptions about the particular roles of different technical and economic factors in adoption choices, it consequentially is constrained in shedding light on specific mechanisms through which these factors influence behavior. A more structural approach or tool based on financial attributes could be developed to estimate potential gains from adoption, but our findings are not promising for that explaining much of the variation in adoption within this market (although such an approach might fare better in explaining variation across markets).

6. Conclusion

Adoption of a particular type of technology – one offering substantial gains to energy efficiency – may be a matter of public interest because homeowners systematically undervalue energy efficiency upgrades (Gillingham et al. 2009), because energy consumption includes unpriced negative externalities, because split incentives undermine investment incentives, and because of other "barriers" to adoption. Promoting adoption of green technology remains a priority, yet models based on cost-effectiveness criteria or engineering-based approaches predict more adoption than empirically observed. Nevertheless, adoption does not imply less energy consumption (Estiri 2015). Frequently, these installations accompany renovations, expansions, or possibly altered behavior that leads to a "rebound effect" (Gillingham et al. 2009). The results presented here highlight the importance of other *social* factors related to technology adoption, those not typically included in simple cost-effectiveness or engineering approaches to assessing the likelihood of energy efficiency adoption. The evidence here supports a broader sense of cost-effectiveness criteria in analyzing adoption because clearly social context plays a role at least in these data.

We find a weak relationship between adoption and some architectural characteristics of the house (see table 6). While larger houses are more likely to include zoned systems (perhaps due to greater energy efficiency savings potential), the number of rooms and the architectural style do not affect adoption as expected. A house that is a standard deviation larger has a greater probability of adopting of 1.0% to 4.4%. However, because larger houses are likely to consume more energy, these findings highlight tradeoffs related to economic development and sustainability.

Some results may be unexpected to some, especially those using a narrower physical-technical-economic model of adoption (Lutzenhiser 2014). Having multiple stories mattered to developers, but not to homeowners. The age of the house and house systems, such as the roof mattered, but this relationship was not straightforward. These findings highlight the importance of the lifecycles of HVAC systems as well as timing of home renovations. Socioeconomic characteristics at the neighborhood level matter, such as education levels. But perhaps most interestingly, the importance of the effects of neighbors is consistently one of the strongest drivers of zoned HVAC adoption on homeowners, while having no effect on developers. This points to social processes like sorting and search costs as significant factors in homeowner adoption of this greener technology. More generally, different adoption determinants between decision-makers suggests targeting policies by owner type (e.g., building codes for developers, "early retirement" programs for homeowners' existing systems, lowering search costs for owner-occupants).

Corresponding policies to promote adoption might leverage education, incentives, rule changes, or even behavioral tendencies. The results here offer mixed implications for policy. The results suggest that education (proxied by neighborhood education) may be a lever to improving energy efficiency. Home suitability, as measured by house size and whether a house is multi-story, suggests that certain homes might be better candidates for zoned HVAC adoption, but that developers (i.e., those who sell new construction) may be more responsive than homeowners (i.e., those who resell homes) to design issues. Finally, that higher taxes deter energy efficiency adoption across all three models suggests prominent disincentives to home investment in areas with higher tax rates.

Nevertheless, these direct paths may not be as effective as indirectly seeding adoption via pilot programs or targeted adoption subsidies. For home renovations, neighbors may provide more opportunity for learning (information sharing, copycatting) and more incentives to adopt (keeping up with the Joneses) than conventional policy tools. The neighborhood adoption rate was one of the few house-specific characteristics – other than house size – that was positive in all four models (renovations and new installation; heating and A/C) and statistically significant in two (heating for renovations and A/C for new installations) of the four models. If a policy could induce adoption of zoned heating systems in five additional homes out of the 40 sales in the previous five years in a particular block group, the probability of the next sale having adopted a zoned heating system between sales would rise from a baseline of almost 2% to around 30%.

This is a dramatic increase in the likelihood of future adoption.

Beyond the particular technology and region studied here, the results point to lessons for other contexts and for the broader literature on energy efficiency behavior. Recent studies in Africa (Haselip et al. 2015, Eder et al. 2015) share a similar theme with the present study: social context complements narrow economic and financial factors. Better understanding the social context of adoption decisions is as important as it is challenging, whether those decisions occur in Belgium (Mlecnik 2010), Wisconsin (Schelly 2014), or Sunderland (Walker et al. 2014). Our results offer quantitative evidence of neighbors' previous adoption influencing households' decisions, addressing an important question in this literature. Our findings also advance our understanding of other important and unresolved questions, such as how the identity of the decision maker matters (Wilson et al. 2015, Ellsworth-Krebs et al. 2015), how retrofitting decisions differ from de novo installations (Mlecnik 2010), and how well simple economic "payback" models explain behavior (Schelly 2014, Wilson et al. 2015).

Overall, this research highlights how energy efficiency adoption rates are influenced by numerous factors beyond a narrow set of financial attributes (Wilson et al. 2015) and simple cost-benefit analysis. We find that house and neighborhood characteristics play an important role in energy efficiency investment. Neighbor behavior also matters, even if the investments in HVAC upgrades are not particularly visible to neighbors. Prior research on technological diffusion has focused primarily on the diffusion associated with highly visible conspicuous investments and consumption, such as solar panels and Prius cars, which consumers adopt to signal their conservation-related values (Bollinger and Gillingham 2011, Sexton and Sexton 2014). Zoned HVAC systems, similar to window caulking or attic insulation inconspicuously confer energy efficiency. Yet neighbor effects persist in this context as well, suggesting that mechanisms other than “keeping up with the Joneses,” “competitive altruism,” “conspicuous conservation,” or “green signaling” may be at work. These findings reinforce the call for research on the mechanisms that shape interpersonal influence in social networks, as well more research into the social context in which decision-makers choose to invest in energy efficiency.

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Table 1: Variable Descriptions

Variable	**Description**
Zoned Heating	Dummy for zoned heating system
Zoned A/C	Dummy for zoned A/C system
Δ Zoned Heating	Dummy for zoned heating system (installed between sales)
Δ Zoned A/C	Dummy for zoned A/C system (installed between sales)
Neighborhood adoption: heating	Share of houses sold with zoned heating within the previous 5-year window in the block group
Neighborhood adoption: A/C	Share of houses sold with zoned A/C within the previous 5-year window in the block group
1 - 5 years	Dummy for house age at the time of sale
6 - 10 years	Dummy for house age at the time of sale
11 - 25 years	Dummy for house age at the time of sale
25 - 50 years	Dummy for house age at the time of sale
51 - 100 years	Dummy for house age at the time of sale
100+ years	Dummy for house age at the time of sale
Multistory	Dummy for house with multiple stories
Rooms	Number of rooms
Square footage (log)	log(square footage)
Lot size (log)	log(lot size in square feet)
Tax rate	Effective property tax rate
Interest rate	Averaged 30-year fixed mortgage interest rate, from HSH Associates National Monthly Mortgage Statistics
Distance to CBD (log)	log(distance to Central Business District)
Median household income (log)	Block-group median household income, interpolated 1992-2004
Median house value (log)	Block-group median house value, interpolated 1992-2004
Population density (log)	Block-group population density (people per square mile), interpolated 1992-2004
Percent vacant	Percent of housing units vacant in the block group, interpolated 1992-2004
Percent renters	Percent of housing units occupied by renters in the block group, interpolated 1992-2004
Percent college graduate	Percent of college graduates in the block group, interpolated 1992-2004
Sale in YEAR	Dummy for property's sale in YEAR
Spring	Dummy for property's sale in spring (March – May)
Summer	Dummy for property's sale in summer (June – August)
Fall	Dummy for property's sale in fall (September – November)
Winter	Dummy for property's sale in winter (December – February)
Δsquare footage (log)	Difference in *square footage (log)* between sales
Δlotsize (log)	Difference in *lot size (log)* between sales
Δinterest rate	Difference in *interest rate* between sales
Time elapsed	Time elapsed between sales (years)
Rehab	Dummy for houses rehabilitated after initial sale

Table 2: Descriptive Statistics

Variables	Full sample	New-construction	Renovations	New-installation (A/C)	New-installation (heat)
	Mean (standard deviation)				
Zoned Heating	0.022 (0.15)	0.088 (0.28)	0.007 (0.09)	- -	- -
Zoned A/C	0.032 (0.18)	0.128 (0.33)	0.001 (0.04)	- -	- -
Δ Zoned Heating	- -	- -	0.010 (0.10)	0.011 (0.10)	0.013 (0.12)
Δ Zoned A/C	- -	- -	0.016 (0.13)	0.016 (0.13)	0.018 (0.13)
1 - 5 years	0.09 (0.29)	- -	0.07 (0.26)	0.04 (0.20)	0.06 (0.24)
6 - 10 years	0.09 (0.28)	- -	0.11 (0.32)	0.04 (0.19)	0.08 (0.28)
11 - 25 years	0.19 (0.39)	- -	0.20 (0.40)	0.07 (0.25)	0.15 (0.35)
26 - 50 years	0.39 (0.49)	- -	0.40 (0.49)	0.32 (0.47)	0.41 (0.49)
51 - 100 years	0.15 (0.36)	- -	0.17 (0.38)	0.39 (0.49)	0.24 (0.43)
100+ years	0.01 (0.12)	- -	0.01 (0.11)	0.06 (0.23)	0.02 (0.13)
Age unknown	0.04 (0.20)	- -	0.03 (0.17)	0.08 (0.28)	0.03 (0.18)
Multistory	0.61 (0.49)	0.92 (0.27)	0.60 (0.49)	0.46 (0.50)	0.49 (0.50)
Rooms	7.51 (1.73)	8.86 (1.69)	7.34 (1.60)	6.66 (1.64)	7.04 (1.69)
Square footage (log)	7.22 (0.38)	7.42 (0.32)	7.18 (0.35)	6.97 (0.42)	7.10 (0.38)
Lot size (log)	9.07 (0.37)	9.19 (0.29)	9.05 (0.34)	8.94 (0.40)	9.00 (0.38)
Tax rate	1.70 (0.33)	1.75 (0.33)	1.71 (0.35)	1.80 (0.36)	1.71 (0.35)
Interest rate	7.40 (0.87)	7.46 (0.80)	7.74 (0.66)	7.77 (0.71)	7.61 (0.72)
Distance to CBD (log)	-0.88 (0.44)	-0.65 (0.37)	-0.85 (0.48)	-0.86 (0.57)	-0.92 (0.49)
Neighborhood adoption: heating	0.020 (0.05)	0.041 (0.07)	0.018 (0.04)	0.012 (0.03)	0.017 (0.04)
Neighborhood adoption: A/C	0.028 (0.06)	0.06 (0.09)	0.02 (0.05)	0.02 (0.04)	0.02 (0.05)
Median household income (log)	11.10 (0.35)	11.25 (0.31)	11.07 (0.33)	10.89 (0.37)	11.07 (0.35)
Median house value (log)	12.17 (0.46)	12.32 (0.41)	12.19 (0.45)	12.02 (0.54)	12.14 (0.50)
Population density (log)	8.18 (0.83)	7.40 (0.96)	8.13 (0.86)	8.37 (0.91)	8.28 (0.84)
Vacant housing unit rate	2.74 (2.89)	4.10 (3.95)	2.65 (2.53)	3.39 (2.91)	2.80 (2.90)
Percent renters	14.77 (15.34)	9.81 (11.82)	13.98 (14.54)	21.80 (16.71)	14.57 (14.23)
Percent college graduate	37.25 (20.28)	42.89 (18.37)	36.37 (19.40)	29.83 (22.67)	35.66 (20.79)
Sales in 1992	0.04 (0.19)	0.02 (0.14)	- -	0.00 (0.05)	- -
Sales in 1993	0.04 (0.19)	0.02 (0.15)	0.01 (0.08)	0.01 (0.09)	0.01 (0.09)
Sales in 1994	0.05 (0.21)	0.05 (0.21)	0.00 (0.05)	0.00 (0.06)	0.00 (0.06)
Sales in 1995	0.07 (0.26)	0.06 (0.24)	0.01 (0.09)	0.01 (0.11)	0.01 (0.09)
Sales in 1996	0.08 (0.27)	0.09 (0.28)	0.03 (0.16)	0.04 (0.20)	0.02 (0.13)
Sales in 1997	0.08 (0.28)	0.11 (0.31)	0.04 (0.21)	0.06 (0.23)	0.04 (0.19)
Sales in 1998	0.10 (0.30)	0.13 (0.33)	0.07 (0.26)	0.08 (0.26)	0.07 (0.26)
Sales in 1999	0.10 (0.30)	0.14 (0.35)	0.10 (0.29)	0.10 (0.31)	0.07 (0.26)

Sales in 2000	0.10 (0.30)	0.13 (0.33)	0.12 (0.33)	0.13 (0.34)	0.10 (0.29)
Sales in 2001	0.09 (0.29)	0.10 (0.30)	0.14 (0.35)	0.14 (0.35)	0.13 (0.33)
Sales in 2002	0.10 (0.30)	0.07 (0.26)	0.17 (0.38)	0.16 (0.37)	0.18 (0.38)
Sales in 2003	0.10 (0.30)	0.06 (0.24)	0.20 (0.40)	0.18 (0.38)	0.24 (0.42)
Sales in 2004	0.05 (0.21)	0.03 (0.17)	0.10 (0.30)	0.09 (0.28)	0.14 (0.35)
Spring	0.21 (0.41)	0.21 (0.41)	0.29 (0.45)	0.28 (0.45)	0.31 (0.46)
Summer	0.26 (0.44)	0.23 (0.42)	0.33 (0.47)	0.32 (0.47)	0.29 (0.46)
Fall	0.18 (0.39)	0.18 (0.38)	0.22 (0.41)	0.21 (0.41)	0.23 (0.42)
Winter	0.13 (0.34)	0.17 (0.38)	0.16 (0.37)	0.19 (0.39)	0.17 (0.37)
Δ square footage (log)	- -	- -	0.05 (0.19)	0.07 (0.30)	0.06 (0.21)
Δ lotsize (log)	- -	- -	-0.01 (0.21)	-0.02 (0.21)	-0.02 (0.23)
Δ interest rate	- -	- -	-0.79 (0.97)	-0.73 (0.94)	-0.82 (0.93)
Time elapsed	- -	- -	3.73 (2.31)	4.01 (2.73)	3.22 (2.39)
Rehab	- -	- -	0.01 (0.12)	0.03 (0.20)	0.01 (0.14)

[a] Renovations and new-installations samples are combined as **repeat** sample for simplification. The descriptive statistics of these two samples are generally similar. Variables measured at time of first sale.

Table 3: Logit Results for New-Construction Sample

	A/C		Heating	
Number of obs. =	6770		6770	
Log likelihood =	-1373.031		-1276.951	
McFadden’s pseudo-R^2 =	0.480		0.434	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Multistory	0.612	(0.324) *	0.924	(0.402) **
Rooms	0.051	(0.049)	0.007	(0.048)
Square footage (log)	4.042	(0.307) ***	3.502	(0.298) ***
Lot size (log)	0.524	(0.192) ***	0.081	(0.186)
Tax rate	-1.609	(0.484) ***	-1.430	(0.457) ***
Interest rate	0.124	(0.174)	0.391	(0.183) **
Neighborhood adoption	1.960	(4.524)	-0.489	(5.044)
Distance to CBD (log)	-0.649	(0.388) *	-0.212	(0.371)
Median household income (log)	-0.321	(0.520)	-0.807	(0.506)
Median house value (log)	0.449	(0.387)	0.629	(0.374) *
Population density (log)	0.035	(0.109)	0.198	(0.114) *
Percent vacant	-0.004	(0.018)	0.020	(0.018)
Percent renters	0.002	(0.009)	0.003	(0.009)
Percent college graduate	1.501	(0.770) *	1.901	(0.760) **
Sales in 1998	0.187	(0.237)	0.359	(0.249)
Sales in 1999	0.079	(0.204)	-0.059	(0.212)
Sales in 2000	0.146	(0.209)	-0.126	(0.217)
Sales in 2001	0.149	(0.245)	0.183	(0.252)
Sales in 2002	0.767	(0.307) **	0.637	(0.319) **
Sales in 2003	0.390	(0.411)	0.480	(0.423)
Sales in 2004	0.821	(0.435) *	0.794	(0.452) *
Summer	0.353	(0.133) ***	0.263	(0.140) *
Fall	0.156	(0.153)	0.228	(0.159)
Winter	-0.013	(0.155)	0.219	(0.160)
Constant	-41.043	(6.083) ***	-33.269	(5.822) ***

*p < .10. **p < .05. ***p < .01.

1 Table 4: Logit Results for Renovations Sample

	A/C		Heating	
Number of obs. =	18163		18163	
Log likelihood =	-987.268		-632.206	
McFadden's pseudo-R^2 =	0.462		0.468	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
6 - 10 years	-1.212	(0.277) ***	-1.352	(0.389) ***
11 - 25 years	-1.367	(0.245) ***	-1.499	(0.332) ***
26 - 50 years	-1.937	(0.240) ***	-1.890	(0.305) ***
51 - 100 years	-1.443	(0.254) ***	-1.446	(0.317) ***
100+ years	-1.003	(0.452) **	-1.859	(0.792) **
Age unknown	-0.637	(0.407)	-0.270	(0.470)
Multistory	-0.180	(0.184)	-0.236	(0.237)
Rooms	0.028	(0.058)	0.082	(0.078)
Square footage (log)	3.277	(0.336) ***	1.744	(0.436) ***
Lot size (log)	-0.042	(0.230)	0.220	(0.289)
Tax rate	-1.289	(0.399) ***	-1.564	(0.501) ***
Interest rate	0.457	(0.268) *	0.147	(0.341)
Neighborhood adoption	7.853	(5.051)	25.252	(7.251) ***
Distance to CBD (log)	-0.590	(0.333) *	-0.198	(0.412)
Median household income (log)	0.449	(0.553)	-1.808	(0.635) ***
Median house value (log)	-0.028	(0.399)	0.904	(0.485) *
Population density (log)	0.078	(0.128)	0.099	(0.167)
Percent vacant	0.050	(0.025) **	0.048	(0.032)
Percent renters	0.016	(0.008) *	-0.002	(0.010)
Percent college graduate	1.381	(0.872)	2.377	(1.062) **
Sale in 1998	2.025	(1.078) *	-0.581	(0.830)
Sale in 1999	1.844	(1.058) *	0.258	(0.691)
Sale in 2000	1.771	(1.060) *	0.006	(0.704)
Sale in 2001	2.007	(1.058) *	0.233	(0.698)
Sale in 2002	1.946	(1.083) *	0.165	(0.760)
Sale in 2003	2.241	(1.131) **	0.357	(0.871)
Sale in 2004	2.294	(1.141) **	0.686	(0.888)
Summer	-0.186	(0.170)	-0.023	(0.223)
Fall	-0.148	(0.200)	-0.106	(0.266)
Winter	-0.275	(0.219)	-0.268	(0.287)
Δ square footage (log)	3.535	(0.333) ***	2.909	(0.405) ***
Δ lotsize (log)	-0.222	(0.354)	-0.267	(0.443)

Δ interest rate	0.253	(0.231)	0.080	(0.296)
Time elapsed	0.094	(0.051) *	0.018	(0.066)
Rehab	0.416	(0.348)	0.488	(0.427)
Constant	-37.780	(6.629) ***	-11.536	(7.848)

*p < .10. **p < .05. ***p < .01.

Note: Both models include dummy variables for the year of the (second) sale.

Table 5: Logit Results for New-Installations Sample

	A/C		Heating	
Number of obs. =	2682		1337	
Log likelihood =	-132.453		-56.234	
McFadden's pseudo-R^2 =	0.615		0.544	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Multistory	0.497	(0.509)	0.061	(0.823)
Rooms	-0.210	(0.151)	0.141	(0.224)
Square footage (log)	2.593	(0.972) ***	2.636	(1.446) *
Lot size (log)	1.509	(0.630) **	1.116	(0.793)
Tax rate	0.544	(0.809)	-2.344	(1.303) *
Interest rate	-0.528	(0.694)	-1.714	(0.964) *
Neighborhood adoption	37.287	(16.799) **	10.871	(25.485)
Distance to CBD (log)	-0.202	(0.628)	-1.019	(0.993)
Median household income (log)	-1.252	(1.196)	-0.827	(2.235)
Median house value (log)	0.676	(1.003)	-1.407	(1.514)
Population density (log)	1.666	(0.546) ***	-0.427	(0.573)
Percent vacant	0.029	(0.074)	0.060	(0.083)
Percent renters	-0.037	(0.021) *	-0.001	(0.035)
Percent college graduate	2.854	(1.864)	2.706	(3.087)
Sale in 1998/1999[a]	-0.639	(1.248)	-4.536	(1.482) ***
Sale in 2000	-0.042	(1.225)	-2.424	(1.387) *
Sale in 2001	-0.405	(1.291)	-3.965	(1.389) ***
Sale in 2002	-1.307	(1.450)	-	-
Sale in 2003	-0.535	(1.673)	-	-
Sale in 2004	-1.576	(1.713)	-	-
Sale in 2002/2003/2004[a]	-	-	-6.197	(2.068) ***
Summer	-0.409	(0.473)	0.450	(0.704)
Fall	-0.411	(0.578)	-1.084	(1.013)
Winter	-0.472	(0.538)	-0.337	(0.964)
Δ square footage (log)	3.995	(0.654) ***	5.343	(1.295) ***
Δ lotsize (log)	1.371	(1.320)	1.158	(1.734)
Δ interest rate	-0.311	(0.594)	-1.040	(0.874)
Time elapsed	-0.058	(0.144)	0.106	(0.254)
Rehab	1.060	(0.540) *	-0.785	(1.736)
Constant	-41.903	(15.920) ***	12.079	(23.323)

*p < .10. **p < .05. ***p < .01.

[a] Due to small sample for some years, the *Sale in YEAR* dummies combine some categories here.

Table 6: Joint Hypothesis Tests for Unrestricted Models[a]

Group of variables	Renovations				New-Constructions			
	A/C		Heat		A/C		Heat	
	χ^2	p	χ^2	p	χ^2	p	χ^2	p
architectural styles	37.21	0.06	14.56	0.95	24.85	0.41	18.50	0.78
structural styles	8.17	0.70	7.82	0.73	6.34	0.85	9.14	0.61
exterior types	6.13	0.41	6.84	0.33	101.76	<0.001	81.40	<0.001
roofing types	7.28	0.06	12.63	0.01	13.86	0.03	8.2	0.04
age categories	58.04	<0.001	45.14	<0.001	n/a	n/a	n/a	n/a

[a] Model specifications follow those in Tables 3 and 4, except for inclusion of vectors of dummy variables for the groups: architectural styles (American 4-Square, Bi-Level, Brownstone, Bungalow, Cape Cod, Colonial, Contemporary, Cottage, English, Farmhouse, French Provincial, Georgian, Greystone, Long, Mediterranean/Spanish, Prairie, Quad Level, Queen Anne, Ranch, Rowhouse, Step Ranch, Traditional, Tri-Level, Tudor, Victorian, Other), structural types (1 story, 1.5 story, 2 stories, 3 stories, 4 stories, coach house, hillside, Raised ranch, split level, split level w/sub, other), exterior materials (Aluminum/Vinyl/Steel, brick, cedar, frame, stucco, stone, clad trim), and roof materials (Asphalt/Glass(Rolled), Asphalt/Glass(Shingles), Wood Shakes/Shingles).