Environment and Behavior
http://eab.sagepub.com/

Spatial Effects in Energy-Efficient Residential HVAC Technology Adoption

Douglas S. Noonan, Lin-Han Chiang Hsieh and Daniel Matisoff
Environment and Behavior published online 20 September 2011
DOI: 10.1177/0013916511421664

The online version of this article can be found at:
http://eab.sagepub.com/content/early/2011/09/16/0013916511421664

Published by:
SAGE
http://www.sagepublications.com

On behalf of:
Environmental Design Research Association

Environment and Behavior
XX(X) 1–28

DOI: 10.1177/0013916511421664
http://eab.sagepub.com

Spatial Effects in Energy-Efficient Residential HVAC Technology Adoption

Douglas S. Noonan[1], Lin-Han Chiang Hsieh[1], and Daniel Matisoff[1]

Abstract

If your neighborhood adopts greener, energy-efficient residential heating, ventilating, and air conditioning (HVAC) systems, will your proenvironmental behavior become contagious, spilling over into adjacent neighborhoods' HVAC adoptions? Objective data on more than 300,000 detailed single-family house sale records in the Greater Chicago area from 1992 to 2004 are aggregated to census block-group neighborhoods to answer that question. Spatial lag regression models show that spatial dependence or "contagion" exists for neighborhood adoption of energy-efficient HVACs. Specifically, if 625 of 726 homes in a demonstration neighborhood upgraded to green HVAC, data of this study predict that at least 98 upgrades would occur in adjacent neighborhoods, more than doubling their baseline adoption rates. This spatial multiplier substantially magnifies the effects of factors affecting adoption rates. These results have important policy implications, especially in the context of new standards for neighborhood development, such as Leadership in Energy and Environmental Design (LEED) or Low-Impact Development standards.

Keywords

HVAC, energy efficiency, adoption behavior, spatial dependence

[1]Georgia Institute of Technology, Atlanta, USA

Corresponding Author:
Douglas S. Noonan, School of Public Policy, Georgia Institute of Technology, Atlanta, GA 30332-0345, USA
Email: Douglas.Noonan@pubpolicy.gatech.edu

Introduction

Due to the growth in energy consumption and the pressures to reduce carbon dioxide emissions, there has been an increased demand for energy efficiency. According to Chandler and Brown (2009), fully deploying current cost-effective energy-efficient technologies could reduce residential electricity consumption 12% by 2020. Moreover, according to the 2009 Building Energy Data Book, heating, ventilating, and air conditioning (HVAC) together consume nearly one third of building energy end-use, which is the largest end-use among all residential energy consumption activities (U.S. Department of Energy, 2009). Thus, if the goal is to reduce the residential energy consumption by improving energy efficiency, the efficiency of HVACs should be a high priority.

Although recent research reveals the benefits of adopting energy-efficient HVACs, research on the adoption behavior is limited. Evidence indicates that adopting energy-efficient technologies benefits homeowners, but homeowners frequently forgo cost-effective technologies due to other reasons (Krause, 2009; Sovacool, 2009; Stern, 2011). Designing policies to enhance the adoption of energy-efficient HVACs requires improving our understanding of adoption behavior.

This study assesses adoption patterns for energy-efficient technologies at the neighborhood level. Considering adoption rates at a neighborhood level makes sense when determining the impact of land-use policies or other geographically targeted policies. Several environmentally minded programs focus on the neighborhood level. The U.S. Green Building Council developed the Leadership in Energy and Environmental Design (LEED) certification system for individual buildings and has recently expended the rating system to include "LEED for Neighborhood Development" (U.S. Green Building Council, 2010). Another example is low-impact development (LID) projects. The U.S. Department of Housing and Urban Development (2003) supports LID projects to mitigate environmental impacts of development activities, especially on water. Addressing urban development means LID often focuses on the neighborhood level. Moreover, traditional zoning regulations (and large-scale planned developments) target rules to specific geographic areas or neighborhoods.

To determine the factors that affect the adoption of energy-efficient HVACs, this study seeks to explain energy-efficient HVAC adoption behaviors with adoption costs, estimated savings, and spatial contagion. This study is especially interested in contagion (i.e., spatial effects) of energy-efficient technology adoption. Learning from neighbors' experiences, suggestions from the same real estate agent, competing for resale value, or simply mimicking the behavior of neighbors can result in the “spillover” of adoptions and thus spatially cluster the adoptions. Diffusion of innovation theory explains how one’s technology adoption behavior affects other individuals or groups through learning from success, peer effects, or copycatting (Rogers, 1995). In this sense, technological change and social change are interrelated, and the social structures involved in technological change are important (Schot & Geels, 2008). Innovation, in this sense, is an individual act and a collective act (Hekkert, Suurs, Negro, Kuhlmann, & Smits, 2007).

This study delves deeper into the mechanisms behind the adoption behavior of energy-efficient HVACs by investigating the spatial interdependence of adoption and interactions across neighborhoods. This is a novel contribution to the literature on household adoption of energy-efficient technologies. Most previous studies are based on survey data with stated preferences, attitudes, or claims of adoption. Rather than the use of survey data that may be prone to biases such as social desirability bias, this study uses data on actual technology adoptions listed in home sales records in the greater Chicago area from 1992 to 2004 to explain neighborhood adoption behavior.

Literature Review

Most studies about HVAC or residential energy efficiency concentrate on either barriers to technology diffusion or the modification of regulations (Jaber, Mamlook, & Awad, 2005; Lawrence, Mullen, Noonan, & Enck, 2005; Menanteau & Lefebvre, 2000; Mills & Schleich, 2010). Several studies directly analyze the adoption behavior of energy-efficient HVACs via case studies or through surveys. Mlecnik (2010), based on a case study of space heating in Belgium, concludes that education, communication via actor networks, economic incentives, and spatial spillover from neighbors may affect the adoption of energy-efficiency improvements. Niemeyer (2010) and Nair, Gustavsson, and Mahapatra (2010) use surveys to determine the factors affecting adoption behavior in Nebraska and Sweden, respectively. The results of these studies are similar: They indicate that both personal factors (such as knowledge and education, economic constraints, obstacles to making changes, demographic variables, attitudinal and belief constraints) and contextual factors (such as the age of the house, thermal discomfort, and perceived energy cost) affect homeowners’ adoption behavior. We improve on this past research by relying on house sales records, which provides a more comprehensive sample and avoids the self-presentation biases inherent with survey data.

This study focuses on groups' adoption of energy-efficient HVAC technologies. Several previous studies examine the determinants of technology adoption and diffusion, in particular, focusing on peer effects. In particular, previous research focuses on the importance of family and social networks on technology adoption (Baerenklau, 2005; Bandiera & Rasul, 2006; Goolsbee & Klenow, 2002; Gowrisankaran & Stavins, 2004; Oster & Thornton, 2009). Much of this research tests the proposition that social networks enhance learning and that technology diffuses through learning by doing (Arrow, 1962). Under this model, productivity can increase through learning and experience and can be enhanced by social institutions, such as education and research (Foster & Rosenzweig, 1995). Several articles also model a neighborhood diffusion model. Baerenklau (2005) identifies the drivers of adoption of agricultural pollution protection practices of farms in the United States, including testing for neighborhood effects by grouping farms into geographic groups. Kok, McGraw, and Quigley (2011) recently estimate the determinants of adoption behavior by geographic groups in modeling the diffusion of energy-efficiency certified buildings at the metropolitan-area level.

On the basis of the determinants identified in these studies, we hypothesize that three sets of variables affect energy-efficient HVAC adoption behavior: cost to adopt, estimated cost savings, and spatial contagion. For example, house vintage has an effect on costs to adopt, as the age or type of a house will affect the feasibility of adoption (Nair et al., 2010). House size will influence the estimated savings, as houses with larger square footage benefit more by adopting energy-efficient HVACs (Niemeyer, 2010). Moreover, peer-group influences (Baerenklau, 2005) and diffusion (Kok et al., 2011) suggest the possibility of spatial contagion. This study emphasizes the effect of contagion because this impact has not been addressed by previous literature on household HVAC technology and because these spatial spillovers are often absent in theoretical models of adoption.

Spatial econometric approaches can identify spatial contagion effects and are especially well suited in the presence of social norms, neighborhood effects, or copycatting. Ioannides and Zabel (2003) offer considerable evidence that homeowners' decisions about maintaining their houses are greatly interdependent and that neighbor effects such as "keeping up with the Joneses" are powerful phenomenon. However, spatial econometric models have not been used to explain the adoption behaviors of households and neighborhoods for energy-efficiency technologies. Anselin (2000, 2001, 2003) develops several econometric models to determine spatial dependence. Spatial regression models with aggregated data are now common in urban- and environmental-related areas (e.g., Fragkias & Seto, 2007; Kühn, Bierman, Durka, & Klotz, 2006; Longley & Tobón, 2004).

Method

First, consider a linear adoption model at the household level:

$$y_{ig} = \mathbf{X}'_{ig}\boldsymbol{\beta} + \varepsilon_{ig}, \tag{1}$$

where y denotes whether the household has adopted the technology, $\mathbf{X}$ is a vector of explanatory variables, ε is a stochastic error term, and β is a vector of corresponding parameters. Household i (where $i = 1, \ldots, I_g$) is observed in block group g (where $g = 1, \ldots, G$). With I_g households in block group g, the aggregated ordinary least squares (OLS) model becomes

$$\bar{y}_g = \bar{\mathbf{X}}'_g\boldsymbol{\beta} + \bar{\varepsilon}_g, \tag{2}$$

where each variable is calculated as a group mean and is represented with a bar, such as $\bar{y}_g \equiv \left(\sum_{i=1}^{I_g} y_{ig}\right) / I_g$. In this model, $\bar{y}_g$ indicates the adoption rate in block group g, and it is explained by group-level averages of $\mathbf{X}$.

An assumption in this basic model is that the adoption rates of neighborhood g are independent of neighborhood hs (for any g, h in G where $g \neq h$). Similarly, the error term ($\bar{\varepsilon}_g$) is assumed to be independent across neighborhoods. OLS is an inconsistent estimator when $\bar{y}_h$ affects $\bar{y}_g$ and is inefficient when $\bar{\varepsilon}_g$ and $\bar{\varepsilon}_h$ are correlated. However, nearby neighborhoods might share some unobservable characteristics or a neighborhood's adoption rate might affect its neighbor's. A model that is robust to these spatial dependence issues is needed.

There are two basic ways to introduce spatial dependence into standard linear regression model: a spatial lag model or a spatial error model. The spatial lag model directly controls for the influence of the values of the dependent variable in nearby observations—where "nearby" is defined by the analyst's choice of a spatial weights matrix. The spatial error model, in contrast, separates the residual caused by spatial dependence from the white noise error term, essentially allowing for the neighboring observations to share unobservable or unexplained portions of their adoption rates. This model is appropriate when the spatial dependence is more a statistical "nuisance" rather than a spatial effect of direct interest (Anselin, 2001).

As the main purpose of this study is to determine the spatial effects of HVAC adoption behavior at the neighborhood level, it is more appropriate to adopt spatial lag model. However, the selection of either the spatial lag or the spatial error model can be evaluated by statistical tests, such as the Lagrange multiplier (LM) test (Anselin, 2000). The GeoDa software is used to estimate the test statistics and the spatial regressions.

The classical spatial lag model can be written as

$$\bar{y} = \rho \mathbf{W} \bar{y} + \bar{\mathbf{X}}'\boldsymbol{\beta} + \bar{\varepsilon} \text{ (with subscripts dropped for parsimony here).} \quad (3)$$

The spatial autoregressive coefficient ρ is a parameter representing the strength of the spatial lag, **W** is a ($G \times G$) spatial weights matrix, and all the other terms are as defined previously. As mentioned previously, the spatial lag model can be viewed as an OLS regression model and a spatial correction term, and this correction term will reflect the strength of spatial effects on the adoption behavior of energy-efficient HVACs. This analysis defines **W** based on first-order queen contiguity, meaning that each block-group adjacent neighbors receive a positive weight (row standardized) and can directly affect it while all others have a zero weight. Of course, each block group can still be affected by more distant block groups indirectly. (Other weights matrices were examined, but the results change negligibly, and this **W** offers a simpler interpretation.)

The energy-efficient HVAC adoption rate in a block-group results from decisions by property developers and homeowners. The adoption rate due to developers can be isolated by looking at the adoption rate of new construction only, as developers usually choose the HVAC systems used in new properties. Looking at this sample has the added advantage of eliminating many unobservable determinants of adoption that vary across older houses but are relatively uniform or unimportant for new homes (e.g., wear and tear on HVAC).

Even with detailed house sale records, some variables that belong in Equation 1 are unavailable in this data set. One way to address this, while also isolating owner–occupants' adoption decisions, involves looking at the adoption rate only among houses that appear multiple times in the data set. Examining the differences (in y and **X**), controls for potential omitted variable bias that can result when static elements of **X** are omitted because they are unobserved. Thus, we estimate the model for the new-construction sample and for the repeat-observation sample to mitigate omitted variable concerns and to isolate and better understand the adoption behavior by developers and homeowners, respectively.

The aggregation process for the repeat-observation sample is somewhat different than that of other samples. It starts with the linear model in Equation 1, modifies it to incorporate a time index t, decomposes the regressors into time-varying (**X**) and time-invariant (**Z**) vectors, and allows for parameters to vary over time:

$$y_{igt} = \mathbf{X}'_{igt}\boldsymbol{\beta}_t + \mathbf{Z}'_{ig}\gamma_t + \varepsilon_{igt} \,. \quad (4)$$

The new **Z** vector includes all the time-invariant explanatory variables (e.g., location). For observations observed multiple times, in period t and again in period s, we can assess the change in y between sales as follows:

$$y_{igs} - y_{igt} = \mathbf{X}'_{igs}\boldsymbol{\beta}_s - \mathbf{X}'_{igt}\boldsymbol{\beta}_t + \mathbf{X}'_{igt}\boldsymbol{\beta}_s - \mathbf{X}'_{igt}\boldsymbol{\beta}_s + \mathbf{Z}'_{ig}\gamma_s - \mathbf{Z}'_{ig}\gamma_t + \Delta\varepsilon_{ig}\,.$$

$$\Delta y_{ig} = \Delta\mathbf{X}'_{ig}\boldsymbol{\beta}_s + \mathbf{X}'_{igt}\Delta\boldsymbol{\beta} + \mathbf{Z}'_{ig}\Delta\gamma + \Delta\varepsilon_{ig}\,. \tag{5}$$

This model in Equation 5 serves as the basis for the repeat-observation sample. Zoned HVAC adoption between sales is explained by trends in **X** and trends in the effects of the determinants (**X** and **Z**). Time-invariant factors that have constant parameters will drop out in the differencing model, effectively controlling for those influences—observed or otherwise. Aggregating the data to the block-group level as above and including the spatial lag model yields

$$\overline{\Delta y}_g = \rho \mathbf{W}\overline{\Delta y}_g + \overline{\Delta \mathbf{X}'_g}\boldsymbol{\beta}_t + \bar{\mathbf{X}}'_{gt}\Delta\boldsymbol{\beta} + \bar{\mathbf{Z}}'_g\Delta\gamma + \overline{\Delta\varepsilon}_g\,, \tag{6}$$

where $\overline{\Delta y}_g$ refers to the rate of new installations in block group g in repeat-observation sample (i.e., $\overline{\Delta y}_g = (\sum_{i=1}^{I_g^*} \Delta y_{ig}) / I_g^*$ is the count of new adoptions, between sales, divided by I_g^*, the number of repeat-observations within block group g), $\overline{\Delta\mathbf{X}}_g$ represents the average change in **X** in block group g, $\bar{\mathbf{X}}_g$ represents the average of **X** in block group g at the time of the initial sale, and $\bar{\mathbf{Z}}_g$ represents the average of **Z** in block group g. Parameters ρ, $\boldsymbol{\beta}_t$, $\Delta\boldsymbol{\beta}$, and $\Delta\gamma$ remain to be estimated. (To be clear, $\overline{\Delta y}_g$ and $\overline{\Delta\mathbf{X}}_g$ are the block-group averages of differences and not the differences in block-group averages between sales.) Equation 6 models the trends in neighborhood adoption rates and draws flexibly on a micro-level adoption model. It allows for influence of some parameters to vary over time and for trends in important factors to influence adoption choices.

According to the discussion in previous section and limited by data availability, the factors (**X**) that affect the adoption rate of zoned HVACs can be divided into four categories: cost to adopt, estimated savings, spatial contagion, and other control variables that influence HVAC demand. To mitigate the possible bias from unobservables, additional factors that might affect the demand of energy-efficiency are controlled for, such as neighborhood characteristics and time trends.

Data

This study uses a data set on home sales in more than 160 municipalities in the greater Chicago area, containing more than 340,000 sale records (of roughly 260,000 unique houses) from January 1, 1992, to June 30, 2004. The property data are originally from the Multiple Listing Service (MLS) of Northern Illinois, an information clearinghouse for most residential property sales in that area. 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 to keep the population of suburban areas with single-family homes more comparable.) The estimated effective property tax rate, detailed school quality information, and local impact fees are derived from multiple sources. The demographic information is from the 2000 census. Unlike the sales record data that are at the household level, these demographic data are only available at the block-group level using the GeoLytics database.

In the data set, the majority of heating systems is forced air with natural gas. More than 88% households use forced air heating systems, and 90% of households use natural gas as the energy source for heating. The majority of air conditioning (A/C) systems are central air, which is used in more than 80% of homes. This study uses zoned heating and A/C systems to represent more energy-efficient HVACs. Actual energy savings of zoned HVAC systems depends on the size of the house and many other factors. Ardehali and Smith (1996), however, note a 50% to 53% savings from zoned HVAC systems. The adoption rate of zoned HVACs is relatively low in the data set. Only 2.2% and 3.1% of houses have zoned heating systems and zoned A/C systems installed, respectively. The frequency of installation is about 6 times greater for new construction. The adoption rates by block groups are mapped in Figure 1. Both figures are classified by natural breaks, and darker shades indicate higher adoption rates. Spatial clustering in the adoption rates appears in both figures.

The variables used in the analysis are defined in Table 1. Table 2 shows their descriptive statistics. They fall into several categories.

Cost to adopt. The house vintage, 30-year mortgage interest rate, mean effective property tax rate, median household income, and median house value proxy for the cost of upgrading the HVAC system. This study hypothesizes that block groups with newer houses, where it is easier to adopt new HVAC technology, will have higher adoption rates. Moreover, homeowners may be more willing to invest to keep newer vintages updated. The prevailing mortgage interest rate, as a proxy for the cost of capital investments, should affect the cost to adopt, as the interest rate affects the high up-front costs of renovations. Previous research shows that higher tax rates will lower the rate of return on property investment (Tse & Webb, 1999) and thus lower the adoption rate. Block groups with higher median income

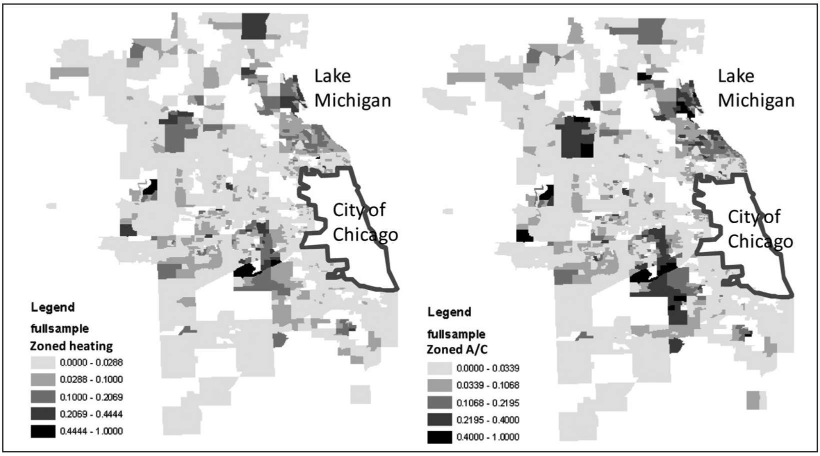

Figure 1. Map of zoned heating and zoned air conditioning adoption

and house value should exhibit higher adoption rates, as greater wealth and access to capital makes adoption more affordable.

Estimated savings. This study uses the average lot size, average square footage, and share of college graduates in a block group to estimate the perceived savings. Block groups with more large houses should have higher adoption rates, as the estimated energy savings for large houses are usually greater. The education variable, percentage of college graduates, might affect adoption if it proxies for the ability of homeowners to understand information related to the energy savings from HVAC adoption.

Contagion. The spatial dependence in the spatial lag model will be used to directly measure the contagion effect.

Control variables. Block-group means for neighborhood amenities, distance to central business district (CBD), vacancy rate, population density, percentage of households that are renters, and county dummies serve as control variables in these models. We have no prior expectation of the relationships of these variables to the adoption rate. We control for them because they may be correlated with the demand for HVACs. Some variables reflect the quality of a neighborhood and thus might influence the adoption rate of energy-efficient HVACs insofar as the goods are complements or substitutes. The percentage of a population renting also suggests the presence of principal-agent problems, where the incentives of the property owner are not aligned with the incentives of the renter—something frequently claimed to undermine adoption (Lawrence et al., 2005). As property owners lack incentives to invest in expensive energy efficiency improvements for rental

Table 1. Definitions of Variables

Variable	Description
Zoned heating	Share of zoned heating system in the BG
Zoned A/C	Share of zoned A/C system in the BG
New	Share of new-ready, new-proposed construction, new-under construction, or new-will build to suit properties in the BG
1-5 years	Share of property age in the BG
6-10 years	Share of property age in the BG
11-25 years	Share of property age in the BG
26-50 years	Share of property age in the BG
51-100 years	Share of property age in the BG
100+ years	Share of property age in the BG
Age unknown	Share of age unknown properties in the BG
Rehabilitated	Share of recent rehabilitated houses in the BG
30-year mortgage rate	Averaged 30-year fixed mortgage rate in the BG, from HSH Associates National Monthly Mortgage Statistics
Effective tax	Mean effective tax rates in the BG
Median household income (log)	Block-group median household income, interpolated 1992-2004
Median house value (log)	Block-group median house value, interpolated 1992-2004
Lot size (log)	Average lot size in the BG
Square footage (log)	Average square footage in the BG
Percentage of college graduates	Percentage of college graduates in the BG, interpolated 1992-2004
Clubhouse	Share of properties listing a clubhouse
Park	Share of properties listing a park or playground around
Lake	Share of properties listing a pond or lake around
Distance to CBD (log)	Distance to CBD, measured from the center of BG
Vacant housing unit rate	Interpolated rate of vacant housing units in the BG
Population density (log)	Block-group population density (people per square mile), interpolated 1992-2004
Percentage of renters	Percentage of housing units occupied by renters in the BG
Cook county	Dummy of BG in Cook county
DuPage county	Dummy of BG in DuPage county
Kane county	Dummy of BG in Kane county
Lake county	Dummy of BG in Lake county
McHenry county	Dummy of BG in McHenry county
Will county	Dummy of BG in Will county
Spring	Share of properties sold in spring (March-May) in the BG
Summer	Share of properties sold in summer (June-August) in the BG
Fall	Share of properties sold in fall (September-November) in the BG

(continued)

Table 1. (Continued)

Variable	Description
Winter	Share of properties sold in winter (December-February) in the BG
Sales in (year)	Thirteen variables represent the share of properties sold in each block group, each year from 1992-2004

Note: BG = block group; A/C = air conditioning; CBD = central business district.

Table 2. Descriptive Statistics

	Full sample		Repeat-Observation Sample		New-construction sample	
Number of observations	2,539		2,411		1,142	
Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*
Zoned heating	0.021	0.053	0.018	0.059	0.120	0.255
Zoned A/C	0.031	0.071	0.022	0.062	0.184	0.320
New	0.021	0.059	—	—	—	—
1-5 years	0.061	0.133	0.059	0.141	—	—
6-10 years	0.053	0.096	0.055	0.120	—	—
11-25 years	0.162	0.218	0.165	0.242	—	—
26-50 years	0.437	0.302	0.435	0.332	—	—
50-100 years	0.195	0.243	0.191	0.266	—	—
100+ years	0.021	0.065	0.018	0.069	—	—
Age unknown	0.049	0.065	0.058	0.115	—	—
Rehabilitated	0.010	0.018	0.008	0.031	—	—
30-year mortgage rate	7.377	0.226	7.628	0.327	7.273	0.732
Effective tax	1.664	0.316	1.664	0.315	1.645	0.335
Median household income (log)	10.989	0.363	10.974	0.356	11.115	0.378
Median house value (log)	12.101	0.487	12.111	0.479	12.232	0.491
Lot size (log)	9.046	0.323	9.032	0.303	9.138	0.332
Square footage (log)	7.192	0.255	7.157	0.278	7.443	0.333
Percentage of college graduates	0.330	0.198	0.328	0.195	0.379	0.213
Clubhouse	0.018	0.050	0.022	0.058	0.013	0.091
Park	0.034	0.077	0.029	0.077	0.037	0.140
Lake	0.013	0.050	0.011	0.050	0.018	0.099
Distance to CBD (log)	–0.993	0.453	–0.990	0.453	–0.902	0.433
Vacant housing unit rate	3.072	3.270	3.016	3.169	3.138	3.162
Population density (log)	8.268	0.938	8.272	0.914	7.970	0.950

(continued)

Table 2. (Continued)

Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*
Percentage of renters	20.284	19.543	19.712	18.928	16.083	15.812
Cook county	0.549	0.498	0.541	0.498	0.421	0.494
DuPage county	0.192	0.394	0.201	0.401	0.243	0.429
Kane county	0.082	0.274	0.084	0.278	0.078	0.268
Lake county	0.061	0.240	0.060	0.238	0.102	0.302
McHenry county	0.041	0.199	0.042	0.200	0.070	0.255
Will county	0.074	0.263	0.072	0.258	0.087	0.282
Spring	0.218	0.132	—	—	0.216	0.313
Summer	0.256	0.150	—	—	0.206	0.297
Fall	0.193	0.124	—	—	0.182	0.294
Winter	0.140	0.096	—	—	0.154	0.265
Sales in 1992	0.026	0.043	0.035	0.075	0.022	0.111
Sales in 1993	0.029	0.062	0.041	0.083	0.020	0.101
Sales in 1994	0.035	0.057	0.055	0.093	0.033	0.142
Sales in 1995	0.058	0.058	0.095	0.125	0.055	0.171
Sales in 1996	0.066	0.069	0.098	0.124	0.055	0.169
Sales in 1997	0.066	0.060	0.084	0.105	0.068	0.186
Sales in 1998	0.077	0.062	0.088	0.117	0.073	0.192
Sales in 1999	0.079	0.065	0.082	0.114	0.077	0.200
Sales in 2000	0.081	0.070	0.082	0.121	0.074	0.194
Sales in 2001	0.079	0.067	0.061	0.110	0.069	0.190
Sales in 2002	0.081	0.066	0.046	0.103	0.067	0.188
Sales in 2003	0.088	0.076	0.025	0.082	0.092	0.237
Sales in 2004	0.042	0.041	0.004	0.029	0.055	0.187
Difference in lot size (log)	—	—	–0.010	0.117	—	—
Difference in square footage (log)	—	—	0.044	0.109	—	—
Difference in 30-year mortgage rate	—	—	–0.586	0.469	—	—
Difference in year of sale	—	—	3.262	1.235	—	—

Note: A/C = air conditioning; CBD = central business district.

properties, block groups with higher percentages of renters should have lower adoption rates. Moreover, the county dummies are used in our models to control for the possible effects of different regulations.

As the sales data span 12 years, it is important to control for the effect of time on the change in adoption rates. More recent sales in a block group might increase the adoption rate as technology improves, public awareness of sustainability issues grows, incomes rise, or prices fall over time. To control for the effect of time in the models, the share of sales that occur within each year in each block group is included in the model. Moreover, for the purpose of controlling for the effect of sales occurring in different seasons, the shares of sales in the four seasons are included. Although perhaps unlikely to matter at the aggregate level, this allows for a block group with, for example, a disproportionate share of fall sales to have higher zoned heating adoption rates.

Results

Tables 3, 4, and 5 show the results of spatial lag regressions and the robust LM test statistics for the full sample, repeat-observation sample, and the new-construction sample, respectively. For each sample, two regression models are estimated to determine the effects of independent variables on two dependent variables: the share of zoned heating systems in the block group and the share of zoned A/C in the block group.

The robust LM diagnostic tests, derived from OLS regressions and reported at the bottom of Tables 3 to 5, show the applicability of spatial lag and spatial error models for each model and sample. (Interested readers can find the OLS regression results using the same data and model specification in the online appendix.) According to Anselin (2000), the Robust LM (Error) statistic tests for spatial error robust to the presence of spatial lag, and the Robust LM (Lag) statistic tests for spatial lag robust to the presence of spatial error. Both Robust LM test statistics are distributed chi-square with one degree of freedom. The *p* values for the Robust LM (lag) test in all six models are below conventional values of α, letting us confidently reject the null hypothesis and use the spatial lag model. The spatial error model is not appropriate to the zoned A/C model in the repeat-observation sample or to the zoned heat model in new-construction sample. Because a primary purpose of this study is to determine the effects of spatial interdependence on HVAC adoption behavior, it is more useful to adopt the spatial lag model. Moreover, the greater LM test statistic for the lag model than the error model in all instances offers consistent diagnostic evidence to support the spatial lag specification (Anselin, 2000).

Table 3 shows the spatial lag regression results of the full sample, for zoned heating and zoned A/C systems. The spatial dependence in both cases is explicit and statistically significant. Holding all the other variables constant, if the weighted average of the adoption rate of zone heating systems for the neighboring block groups increased by one percentage point (or if every neighbor's rate increased uniformly), then we expect an increase in the adoption rate in this block group of 0.39 percentage points. In a rough sense, nearly two fifths of changes in a neighborhood's adoption behavior spill over to its neighbor. For A/C systems, the effect is even higher: $\rho = 0.44$.

Table 3. Spatial Lag Regression Results for the Full Sample

	Zoned heating		Zoned A/C	
Variables	Coefficient	SE	Coefficient	SE
Spatial lag (ρ)	0.384	0.023***	0.445	0.021***
Constant	–0.393	0.084***	–0.699	0.100***
New	0.136	0.014***	0.134	0.017***
1-5 years	0.019	0.008**	0.011	0.010
6-10 years	0.011	0.012	0.036	0.014**
26-50 years	0.018	0.005***	0.024	0.006***
50-100 years	0.025	0.006***	0.040	0.007***
100+ years	–0.018	0.014	0.019	0.017
Age unknown	0.073	0.016***	0.097	0.020***
Rehabilitated	0.154	0.047***	0.258	0.056***
30-year mortgage rate	–0.031	0.008***	–0.037	0.009***
Effective tax	–0.012	0.004***	–0.018	0.004***
Median household income (log)	0.008	0.002***	0.014	0.003***
Median house value (log)	–0.002	0.001*	–0.003	0.002**
Lot size (log)	–0.018	0.004***	–0.011	0.004***
Square footage (log)	0.104	0.005***	0.139	0.007***
Percentage of college graduates	–0.027	0.007***	–0.034	0.008***
Clubhouse	0.041	0.017**	0.066	0.020***
Park	–0.045	0.012***	–0.056	0.015***
Lake	–0.036	0.017**	0.011	0.021
Distance to CBD (log)	–0.001	0.004	0.002	0.004
Vacant housing unit rate	0.001	0.000**	0.001	0.000*
Population density (log)	–0.004	0.001***	–0.005	0.001***
Percentage of renters	0.000	0.000	0.000	0.000
Summer	0.033	0.012***	0.018	0.014
Fall	0.019	0.012	0.031	0.014**
Winter	–0.008	0.014	0.007	0.017
	Value	*p*	Value	*p*
Robust LM (lag)	31.699	.000	68.238	.000
Robust LM (error)	19.974	.000	34.871	.000
Number of observations	2,539		2,535	
Log likelihood	4729.98		4253.55	
R^2	.507		.605	

Note: A/C = air conditioning; CBD = central business district; LM = Lagrange multiplier. The above analyses control for the six counties listed in Table 2 and the proportional sales in each of the 13 years from 1992 to 2004.
*$p < .10$. **$p < .05$. ***$p < .01$.

The full sample analysis in Table 3 shows the broad picture of how spatial and nonspatial factors influence adoption rates. Overall, the model fit is substantial, explaining most of the variation in neighborhood adoption rates. The repeat-observations and new-construction sample models, however, offer more focused results that should also be less susceptible to confounding effects from unobserved characteristics. The results of these models warrant emphasis in this study. The repeat-observation sample model (Table 4) helps identify the adoption decisions made by the homeowners within the

Table 4. Spatial Lag Regression Results for the Repeat-Observation Sample

	Zoned heating		Zoned A/C	
Variables	Coefficient	*SE*	Coefficient	*SE*
Spatial lag (ρ)	0.151	0.029***	0.142	0.029***
Constant	−0.782	0.116***	−1.007	0.119***
1-5 years	0.022	0.010**	0.041	0.010***
6-10 years	−0.011	0.011	0.007	0.012
26-50 years	0.007	0.006	0.020	0.006***
50-100 years	0.013	0.007*	0.023	0.007***
100+ years	0.033	0.017**	0.075	0.017***
Age unknown	0.039	0.012***	0.058	0.012***
30-year mortgage rate	0.015	0.008*	0.007	0.008
Effective tax	−0.024	0.005***	−0.016	0.005***
Median household income (log)	0.019	0.007***	0.028	0.007***
Median house value (log)	0.002	0.002	0.003	0.002
Lot size (log)	0.017	0.006***	0.024	0.006***
Square footage (log)	0.050	0.007***	0.051	0.007***
Percentage of college graduates	−0.014	0.011	−0.007	0.011
Clubhouse	0.010	0.019	0.009	0.020
Park	−0.026	0.016	−0.023	0.017
Lake	−0.018	0.038	−0.009	0.039
Distance to CBD (log)	−0.010	0.005**	−0.019	0.005***
Vacant housing unit rate	0.001	0.000***	0.001	0.000**
Population density (log)	0.000	0.002	0.000	0.002
Percentage of renters	0.000	0.000	0.000	0.000
Difference in lot size (log)	0.005	0.010	0.022	0.010**
Difference in square footage (log)	0.077	0.011***	0.091	0.011***
Difference in 30-year mortgage rate	0.013	0.005**	0.009	0.005
Difference in year of sale	0.005	0.002***	0.000	0.002
	Value	*p*	Value	*p*
Robust LM (lag)	39.105	.000	9.376	.002
Robust LM (error)	22.979	.000	1.698	.193
Number of observations	2,411		2,411	
Log likelihood	3721.16		3668.63	
R^2	.233		.271	

Note. A/C = air conditioning; CBD = central business district; LM = Lagrange multiplier. The above analyses control for the six counties listed in Table 2 and the proportional sales in each of the 13 years from 1992 to 2004.
*$p < .10$. **$p < .05$. ***$p < .01$.

neighborhood. Next, using only the sample of new-construction sales (Table 5) enables a comparison between homeowners and developers.

The results in Table 4 resemble the full sample spatial lag results, with a few key modifications. As described in the previous section, the dependent variable in the repeat-observations model represents the adoption rate by existing homeowners as renovations or replacements. *New* and *Rehabilitated* are dropped because they make less sense in a differenced model. Moreover,

Table 5. Spatial Lag Regression Results for the New-Construction Sample

	Zoned heating		Zoned A/C	
Variables	Coefficient	*SE*	Coefficient	*SE*
Spatial lag (ρ)	0.115	0.032***	0.136	0.031***
Constant	–2.189	0.541***	–2.631	0.631***
30-year mortgage rate	–0.008	0.015	–0.018	0.018
Effective tax	–0.051	0.032	–0.108	0.037***
Median household income (log)	–0.046	0.043	–0.059	0.050
Median house value (log)	0.100	0.034***	0.113	0.040***
Lot size (log)	0.030	0.023	0.026	0.027
Square footage (log)	0.160	0.030***	0.251	0.035***
Percentage of college graduates	0.144	0.066**	0.205	0.077***
Clubhouse	0.042	0.082	0.075	0.095
Park	–0.077	0.046*	–0.121	0.053**
Lake	–0.116	0.086	0.003	0.101
Distance to CBD (log)	–0.004	0.029	–0.015	0.034
Vacant housing unit rate	0.006	0.002***	0.002	0.002
Population density (log)	0.017	0.009*	0.014	0.010
Percentage of renters	0.000	0.001	0.000	0.001
Summer	0.041	0.027	0.020	0.031
Fall	0.052	0.028*	0.019	0.032
Winter	0.061	0.029**	0.052	0.034
	Value	*p*	Value	*p*
Robust LM (lag)	4.660	.031	13.224	.000
Robust LM (error)	1.084	.298	4.564	.033
Number of observations	1,142		1,142	
Log likelihood	173.057		–2.190	
R^2	.338		.428	

Note: A/C = air conditioning; CBD = central business district; LM = Lagrange multiplier. The above analyses control for the six counties listed in Table 2 and the proportional sales in each of the 13 years from 1992 to 2004.
*p < .10. **p < .05. ***p < .01.

the variables showing the average difference between each sales record ($\overline{\Delta \mathbf{X}_g}$) are listed at the bottom of Table 4. All the other independent variables represent the conditions at first sale. As in the full sample, the spatial effects of the repeat-observation sample are also positive and statistically significant. The spillover of the adoption rate is roughly 0.15 for zoned heating and A/C systems. This statistically significant result is much smaller in magnitude than the ρ in the full sample. This more conservative estimate may also be a more accurate estimation of the contagion effect, as differencing controls for some unobserved home traits that may be spatially clustered. In addition, this estimate more directly measures the behavior of homeowners, which may not be as clustered as developer decisions.

Table 4 illustrates how cost variables determine neighborhood adoption rates. The house vintage variables are not as easily interpreted in this study as in the full sample because they only measure the average house age at the time of first sale and the date of adoption is unknown. Still, the results suggest that newer homes and much older homes are significantly more likely to upgrade to zoned HVAC systems. Adoptions are more common in wealthier neighborhoods, although the average home prices do not explain adoptions. Unsurprisingly, average interest rates at the time of the initial sale have only a marginal impact on adoption rates, likely because that interest rate poorly proxies for the rates facing current owners making the investment decisions. However, the change in (average) interest rates between sales exhibits unexpected effects. The change in interest rates does not matter for zoned A/C adoption, and it has a positive effect on the adoption of zoned heating system. This is inconsistent with the theory that predicts that rising interest rates will discourage adoption of high up-front cost investments. We attribute this unexpected result to a poor proxy for actual interest rates faced by homeowners, although the lack of evidence that lower interest rates drive adoption certainly merits further research with better data, ideally at the household level.

The energy savings measures exhibit straightforward effects in Table 4. The role of lot size in the repeat-observation sample is simply positive. Larger lots at the time of initial sale and increasing lot sizes predict greater neighborhood adoption rates. Ten percent larger lot sizes at the time of first sale are associated with roughly 0.2 percentage points greater adoption rates of zoned HVAC systems, which is substantially relative to the baseline average adoption rate of 2%. The case of square footage is even stronger. In both models, larger average square footage of the first sale has positive effects on the adoption behavior. For example, block groups with average square footage 10% larger will tend to have adoption rates 0.5 percentage points greater. Unlike the full sample results, the model in Table 4 shows higher adoption rates in neighborhoods with larger homes *and* with homes that are growing in size. Increasing the average difference in square footage between sales by 10% is associated with the share of repeat-observation homes adopting increasing by 0.7 percentage points for zoned heating and 0.9 percentage points for zoned A/C. Renovations and expansions clearly play a vital role in the adoption of green HVAC technologies, perhaps because the cost to install is relatively lower when bundled with other home renovations and because the energy savings rise as homes' footprints grow.

Some of the demand-shifting control variables in the repeat-observation sample have significant effects on the adoption rate. Neighborhoods with higher vacancy rates have higher adoption rates, perhaps because vacancy facilitates the installation of HVAC and thus lowers the cost to adopt. Park and lake access, population density, the percentage of renters, and the host county do not appear to influence adoption rates.

Finally, Table 5 illustrates the results of spatial lag models for the sample of new constructions. Note that all the house vintage variables are dropped in the new sample models because the age of all houses in this sample is zero. The most striking result in Table 5 is the spatial dependence. The spatial contagion ρ parameter in the new-construction sample is not larger than that of the repeat-observation sample. This might be due to a limitation of the data. The full sample data set contains 2,539 block groups, but only 1,142 of them have new-construction home sales records during this time frame. Aside from leaving a possibly biased subsample of block groups, this means that many block groups lose some adjacent block groups, and leaving some of them more isolated. This could bias the true spatial contagion effect. Still, it is remarkable that the lag effect ρ for new-construction adoption—presumably driven by developers who certainly produce suburban housing in highly positively spatially correlated ways—is similar in magnitude to the ρ for existing homeowners in Table 4. This might be a result of spatial competition among developers, where the expected clustering is at least partially offset by developer's efforts to differentiate their products from nearby substitutes. This negative spatial lag process might explain the weaker net spillover effect in the new-construction sample.

Other results in Table 5 differ from those in Table 4, reflecting different adoption patterns of homeowners and developers. Home value, not income, has a strong positive effect on adoption rates in the new-construction sample, nearly opposite that of the repeat-observation sample. Apparently developers' installation decisions track with home values more than neighborhood wealth and vice versa for homeowners. Interestingly, the percentage of college graduates positively influences adoption rates in the new-construction sample only; it is insignificant in Table 4. The negative effect of parks in the new-construction sample is interesting to note. It seems that parks and indoor energy efficiency are substitutes. The geographic and temporal controls add little explanatory power to the new-construction model, although zoned heating is more common when more of the newly constructed homes are sold in the fall and winter.

Discussion

In this study, the spatial effect is a strong factor affecting neighborhood adoption behavior for energy-efficient residential HVACs. The estimated spillover parameter, ρ, ranged from 0.11 to 0.44 across different models and samples, indicating roughly that 11% to 44% of neighboring block groups' adoptions spill over or are reflected in each block group. We illustrate this mechanism further in the following. As the repeat-observation models focus on owners making changes to their own properties, this more conservative estimate of ρ (roughly 0.14) might also be more reliable and meaningful.

The mechanisms behind this contagion effect remain to be explored empirically. However, several socially oriented mechanisms (e.g., shared information, spatial competition, mimicking) have been explored in recent research. Abrahamse, Steg, Vlek, and Rothengatter (2005) review 38 studies that examine decision making behind household-level energy consumption and emphasize the role that social pressure and feedback play in relationship to information or learning. Osbaldiston and Schott (2011) provide an overview of 253 experimental treatments across 87 published articles, noting that social modeling—which includes the diffusion of technology and norms—plays a role in individual-level environmental behavior. Stern (2011) suggests that social motives and learning play a major role in influences of energy efficiency equipment adoptions. Although these studies do not speak directly to spatial diffusion, they explore social mechanisms that could be drivers of spatial diffusion.

Building codes might be another important driver for adopting energy efficiency. This study does not directly control for building codes due to the unavailability of data spanning over 160 municipalities and 12 years. Limiting the analysis to only sales records for single-family houses should keep zoning classifications relatively consistent. Though we do have controls for different counties, variation in single-family residential building codes across municipalities and even across time is not observed in these data. We are not aware of differences in building codes in these suburbs that might play a major role in neighborhood adoption. If variation in building codes does help explain the variation in adoption rates, the spatial regression models (Tables 3-5) will at least partly capture this effect. Interestingly, a spatial error model would treat the omitted regressor of "building codes" as part of a spatially autocorrelated error. However, the diagnostic tests clearly indicate that a spatial lag model is more appropriate given these data. In short, explicitly incorporating the spatial dependence into these models mitigates the concerns about missing variables such as these.

Market-based data might have their own limitations. For example, the data set lacks micro-level data regarding the attitudes and demographics of individual homeowners, and the sample of sales might not be representative of the housing stock. Houses with higher turnover might have different determinants (i.e., $\boldsymbol{\beta}$ is different) of adoptions than the population as a whole. Moreover, weaker local connections for more transitory homeowners might affect the strength of spatial spillovers, which is consistent with the lower lag effects ($\boldsymbol{\rho}$) observed in the repeat-observation and new-construction samples than the full sample. A more direct test of this hypothesis, however, finds little support. Including the block group's share of population living in the same home over the past 10 years, as a proxy for social networks, adds little to the models reported in this study, and a comparison of maps of this variable and maps of local measures of spatial autocorrelation shows no clear relationship. Less neighborhood turnover neither promotes nor detracts from localized spillovers. Further tests of mechanisms for this spatial diffusion are needed.

According to the results from the full sample models, neighborhoods with more newly constructed or recently rehabilitated houses, with larger square footage, and with higher median income and lower population density areas tend to adopt energy-efficient HVACs. These factors reflect the adoption behaviors of developers and owners. Using the results from the repeat-observations models, neighborhoods with homes experiencing larger remodels and expansions tend to have greater adoption rates for energy-efficient HVACs. Moreover, neighborhoods with houses with larger lot sizes and square footage, with greater wealth, and with lower tax rates are more likely to adopt energy-efficient HVACs. Importantly, across all the models, it is lower property tax rates that tell a consistent story in promoting energy-efficient HVAC adoption (rather than lower interest rates).

The implications for policy are significant. When designing a policy to promote the adoption of green HVACs, according to our results, the effect of picking several demonstration block groups as the “seeds” of contagion might be significant. For example, suppose a LEED-certified development project occurred in a block group that previously had no green HVAC systems. A seed project that upgraded 90% of the block-group homes to zoned A/C and zoned heat systems would have 650 adoptions in an average block containing 726 homes. If that block group had four neighboring block groups (which each had four neighboring block groups), according to our estimates using the repeat-observation sample, holding all else equal, this shift in the adoption rate would bring an increase in the adjacent block groups’ adoption rates of 3.4% (bringing the adoption rate up to 5% from less than 2%; this is computed by multiplying the increase in the weighted average of the four neighbors, 0.9 / 4 = 0.225, by the lag operator, $\rho = 0.15$.) Those 650 adoptions would translate to an additional 98 adoptions across the four immediate neighboring areas. These adoptions, in turn, affect their adjacent neighbors, and so on. This suggests that small-scale localized efforts to promote energy-efficient adoption among homeowners might diffuse outward and have much greater effect than originally anticipated. (In principle, this cuts both ways: The adoption of *in*efficient HVAC systems may have similar contagion effects.) It also suggests that strategic placement of efficiency enhancements (e.g., in areas with many neighbors and other variables predicting adoption rates, such as locating projects farther away from parks) could have particularly large impacts on adoption behavior. This is consistent with theory that suggests that niche markets that nurture new technologies are important for technological diffusion (Schot & Geels, 2008). In fact, the "LEED for Homes" program offers additional points toward certification for homes offering outreach and promoting public awareness (via tours, websites, signage, etc.). Programs such as LEED already leverage the power of diffusion of green homes.

Beyond "seeding" demonstration projects, other findings presented previously point to ways that policy makers can stimulate the adoption rates of energy-efficient HVACs—and how spatial contagion can amplify those impacts. Suppose a policy to boost green HVAC installations lowered tax rates by half a percentage point. On the basis of Table 4, this policy should increase adoption rates by about one percentage point for zoned HVAC systems. This large impact, relative to the low mean adoption rates, is a direct policy effect. It does not take into account the spatial spillovers identified previously. The spatial multiplier of $1 / (1 - \rho)$ magnifies the marginal impact of the tax break by a factor of 1.18 for zoned heating and 1.16 for zoned A/C (Kim, Phipps, & Anselin, 2003). Neglecting this spatial contagion would substantially underestimate the policy impact on adoption rates. Moreover, the possibility of a threshold or tipping point in the contagion warrants further investigation, as this analysis assumes a linear spillover effect.

All the results in this study are based on the aggregation of individual-level transactions into the block-group level. Though we still have a large data set of more than 2,500 observations after the aggregation, and those data exhibit considerable geographic variation, the aggregation process will obscure some information. Exploring the mechanisms for individual level, rather than neighborhood level, spatial interdependence in adoption behaviors for energy efficiency requires applying a spatial econometric approach to data at the household level. In light of these results showing strong spatial dependence at the neighborhood level, future work that seeks to inform policies promoting energy efficiency adoption at the household level would do well to investigate these interactions.

It remains to be seen whether these results generalize to other contexts or green technologies. We expect similar results for similar models of other major appliances, but this study offers no direct evidence on this. As our findings are consistent with previous research that shows social factors matter and that simple economics plays a modest role, this consistency suggests some generalizability to other residential technology adoptions. The limited success of energy-efficient technologies in penetrating markets generally is consistent with our findings. Although we look at just one type of technology, admittedly a major one, there are obviously other residential technologies that merit studies of their own.

Appendix

Table A1. OLS Regression Results for the Full Sample

Number of observations	2,539		2,539	
Log likelihood	4588.59		4035.71	
$p > \chi^2$	.0000		.0000	
R^2	.432		.512	

	Zoned heating		Zoned air conditioning	
Variables	Coefficient	SE	Coefficient	SE
Constant	–0.510	0.090***	–0.960	0.112***
New	0.141	0.015***	0.143	0.019***
1-5 years	0.026	0.009***	0.020	0.011*
6-10 years	0.009	0.013	0.031	0.016**
26-50 years	0.019	0.005***	0.024	0.006***
50-100 years	0.024	0.006***	0.041	0.008***
100+ years	–0.026	0.015*	0.011	0.019
Age unknown	0.099	0.018***	0.141	0.022***
Rehabilitated	0.212	0.051***	0.404	0.063***
30-year mortgage rate	–0.031	0.008***	–0.034	0.010***
Effective tax	–0.026	0.004***	–0.041	0.005***
Median household income (log)	0.009	0.002***	0.018	0.003***
Median house value (log)	–0.002	0.001*	–0.004	0.002**
Lot size (log)	–0.018	0.004***	–0.009	0.005*
Square footage (log)	0.120	0.006***	0.167	0.007***
Percentage of college graduates	–0.015	0.007**	–0.015	0.009*
Clubhouse	0.050	0.018***	0.082	0.022***
Park	–0.055	0.013***	–0.070	0.017***
Lake	–0.031	0.019*	0.017	0.023
Distance to CBD (log)	–0.005	0.004	–0.003	0.005
Vacant housing unit rate	0.001	0.000***	0.001	0.000***
Population density (log)	–0.006	0.001***	–0.008	0.001***
Percentage of renters	0.000	0.000	0.000	0.000
DuPage county	0.056	0.026**	0.075	0.032**
Kane county	0.012	0.005**	0.009	0.006
Lake county	0.027	0.004***	0.023	0.005***
McHenry county	0.003	0.005	0.000	0.007
Will county	0.011	0.004***	0.008	0.005
Summer	0.035	0.013***	0.021	0.016
Fall	0.023	0.013*	0.035	0.016**
Winter	–0.005	0.015	0.013	0.019
Sales in 1993	0.072	0.032**	0.114	0.040***
Sales in 1994	0.138	0.031***	0.122	0.038***
Sales in 1995	0.091	0.028***	0.129	0.035***
Sales in 1996	0.052	0.027*	0.084	0.033**
Sales in 1997	0.010	0.028	0.036	0.035
Sales in 1998	0.001	0.030	–0.009	0.038
Sales in 1999	0.039	0.028	0.015	0.035
Sales in 2000	0.055	0.027**	0.136	0.033***
Sales in 2001	0.017	0.029	0.039	0.036

(continued)

Table A1. (Continued)

	Zoned heating		Zoned air conditioning	
Variables	Coefficient	*SE*	Coefficient	*SE*
Sales in 2002	0.005	0.031	0.028	0.039
Sales in 2003	–0.041	0.032	–0.017	0.040
Sales in 2004	0.025	0.038	0.076	0.047

Note: OLS = ordinary least squares; CBD = central business district.
$^{*}p < .10$. $^{**}p < .05$. $^{***}p < .01$.

Table A2. OLS Regression Results for the Repeat-Observation Sample

	Zoned heating		Zoned air conditioning	
Number of observations	2,411		2,411	
Log likelihood	3707.33		3655.71	
$p > \chi^2$	.0000		.0000	
R^2	.221		.260	
Variables	Coefficient	*SE*	Coefficient	*SE*
Constant	–0.850	0.118***	–1.055	0.121***
1-5 years	0.021	0.010**	0.041	0.010***
6-10 years	–0.012	0.012	0.007	0.012
26-50 years	0.008	0.006	0.021	0.006***
50-100 years	0.014	0.007**	0.025	0.007***
100+ years	0.033	0.017*	0.079	0.018***
Age unknown	0.042	0.012***	0.060	0.012***
30-year mortgage rate	0.016	0.008*	0.007	0.008
Effective tax	–0.029	0.005***	–0.020	0.005***
Median household income (log)	0.021	0.007***	0.030	0.007***
Median house value (log)	0.002	0.002	0.004	0.002
Lot size (log)	0.019	0.006***	0.025	0.006***
Square footage (log)	0.053	0.007***	0.054	0.007***
Percentage of college graduates	–0.010	0.011	–0.002	0.011
Clubhouse	0.010	0.019	0.014	0.020
Park	–0.028	0.017*	–0.025	0.017
Lake	–0.015	0.038	–0.007	0.039
Distance to CBD (log)	–0.012	0.005**	–0.022	0.005***
Vacant housing unit rate	0.002	0.000***	0.001	0.000***
Population density (log)	–0.001	0.002	0.000	0.002
Percentage of renters	0.000	0.000	0.000	0.000
DuPage county	–0.021	0.020	0.029	0.020
Kane county	0.008	0.007	0.011	0.007*
Lake county	0.005	0.006	0.000	0.006
McHenry county	0.001	0.008	0.013	0.008
Will county	0.006	0.005	0.005	0.006
Sales in 1993	–0.075	0.025***	0.041	0.026
Sales in 1994	–0.055	0.022**	0.018	0.022
Sales in 1995	–0.064	0.019***	0.032	0.019*
Sales in 1996	–0.050	0.019***	0.018	0.019
Sales in 1997	–0.068	0.020***	0.012	0.021
Sales in 1998	–0.025	0.021	0.042	0.022*
Sales in 1999	–0.006	0.020	0.065	0.021***

(continued)

Table A2. (Continued)

	Zoned heating		Zoned air conditioning	
Variables	Coefficient	*SE*	Coefficient	*SE*
Sales in 2000	–0.009	0.020	0.031	0.021
Sales in 2001	–0.037	0.023	0.027	0.023
Sales in 2002	–0.020	0.025	0.025	0.026
Sales in 2003	–0.016	0.029	0.027	0.029
Sales in 2004	0.036	0.046	0.049	0.047
Difference in lot size (log)	0.004	0.010	0.021	0.010**
Difference in square footage (log)	0.080	0.011***	0.092	0.012***
Difference in 30-year mortgage rate	0.014	0.005***	0.009	0.005*
Difference in year of sale	0.005	0.002***	–0.001	0.002

Note: OLS = ordinary least squares; CBD = central business district.
**p* < .10. ***p* < .05. ****p* < .01.

Table A3. OLS Regression Results for the New-Construction Sample

Number of observations	1,142	1,142
Log likelihood	166.975	–11.4167
$p > \chi^2$	0.0000	0.0000
R^2	.328	.415

	Zoned heating		Zoned air conditioning	
Variables	Coefficient	*SE*	Coefficient	*SE*
Constant	–2.366	0.553***	–2.903	0.646***
30-year mortgage rate	–0.009	0.016	–0.017	0.018
Effective tax	–0.061	.032 0*	–0.131	0.038***
Median household income (log)	–0.047	0.044	–0.063	0.051
Median house value (log)	0.113	0.035***	0.134	0.041***
Lot size (log)	0.031	0.024	0.027	0.028
Square footage (log)	0.163	0.031***	0.259	0.036***
Percentage of college graduates	0.164	0.067**	0.236	0.079***
Clubhouse	0.043	0.084	0.065	0.098
Park	–0.078	0.047*	–0.122	0.055**
Lake	–0.114	0.088	0.005	0.103
Distance to CBD (log)	–0.008	0.030	–0.022	0.035
Vacant housing unit rate	0.006	0.002***	0.002	0.003
Population density (log)	0.018	0.009**	0.015	0.011
Percentage of renters	0.000	0.001	0.000	0.001
DuPage county	0.025	0.068	0.027	0.080
Kane county	0.004	0.035	0.029	0.041
Lake county	–0.012	0.030	0.023	0.035
McHenry county	0.016	0.039	0.033	0.046
Will county	0.026	0.031	0.047	0.036
Summer	0.044	0.028	0.020	0.032
Fall	0.057	0.028**	0.025	0.033
Winter	0.063	0.030**	0.057	0.035

(continued)

Table A3. (Continued)

Variables	Zoned heating Coefficient	Zoned heating *SE*	Zoned air conditioning Coefficient	Zoned air conditioning *SE*
Sales in 1993	0.007	0.091	0.139	0.107
Sales in 1994	–0.057	0.074	–0.056	0.087
Sales in 1995	–0.038	0.070	0.057	0.082
Sales in 1996	0.052	0.070	0.035	0.082
Sales in 1997	–0.009	0.069	0.026	0.081
Sales in 1998	–0.040	0.071	–0.053	0.083
Sales in 1999	0.056	0.068	0.116	0.080
Sales in 2000	0.025	0.068	0.045	0.079
Sales in 2001	0.073	0.071	0.122	0.083
Sales in 2002	0.054	0.075	0.074	0.087
Sales in 2003	0.087	0.076	0.078	0.089
Sales in 2004	0.123	0.079	0.073	0.093

Note: OLS = ordinary least squares; CBD = central business district.
**p* < .10. ***p* < .05. ****p* < .01.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors declared that the funding for this research was provided by the U.S. NSF grant 0836046: EFRI-RESIN Project: Sustainable Infrastructures for Energy and Water Supply (SINEWS). Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the view of the supporting organizations.

References

Abrahamse, W., Steg, L., Vlek, C., & Rothengatter, T. (2005). A review of intervention studies aimed at household energy conservation. *Journal of Environmental Psychology, 25*, 273-291.

Anselin, L. (2000). *Spatial econometrics*. Oxford, UK: Basil Blackwell.

Anselin, L. (2001). Spatial effects in econometric practice in environmental and resource economics. *American Journal of Agricultural Economics, 83*, 705-710.

Anselin, L. (2003). Spatial externalities. *International Regional Science Review, 26*, 147-152.

Ardehali, M. M., & Smith, T. F. (1996). Evaluation of variable volume and temperature HVAC system for commercial and residential buildings. *Energy Conversion and Management, 37*, 1469-1479.

Arrow, K. (1962). The economic implications of learning by doing. *Review of Economic Studies, 29*, 155-173.

Baerenklau, K. A. (2005). Toward an understanding of technology adoption: Risk, learning, and neighborhood effects. *Land Economics, 81*, 1-19.

Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in Northern Mozambique. *Economic Journal, 116*, 869-902.

Chandler, S., & Brown, M. (2009). *Meta-review of efficiency potential studies and their implications for the south* (Working Paper No. 51). Atlanta: Georgia Institute of Technology, School of Public Policy.

Foster, A., & Rosenzweig, M. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy, 103*, 1176-1209.

Fragkias, M., & Seto, K. C. (2007). Modeling urban growth in data-sparse environments: A new approach. *Environment and Planning B: Planning and Design, 34*, 858-883.

Goolsbee, A., & Klenow, P. J. (2002). Evidence on learning and network externalities in the diffusion of home computers. *Journal of Law & Economics, 45*, 317-343.

Gowrisankaran, G., & Stavins, J. (2004). Network externalities and technology adoption: Lessons from electronic payments. *RAND Journal of Economics, 35*, 260-276.

Hekkert, M. P., Suurs, R. A. A., Negro, S. O., Kuhlmann, S., & Smits, R. E. H. M. (2007). Functions of innovation systems: A new approach for analysing technological change. *Technological Forecasting & Social Change, 74*, 413-432.

Ioannides, Y. M., & Zabel, J. E. (2003). Neighbourhood effects and housing demand. *Journal of Applied Econometrics, 18*, 563-584.

Jaber, J. O., Mamlook, R., & Awad, W. (2005). Evaluation of energy conservation programs in residential sector using fuzzy logic methodology. *Energy Policy, 33*, 1329-1338.

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: A spatial hedonic approach. *Journal of Environmental Economics and Management, 45*, 24-39.

Kok, N., McGraw, M., & Quigley, J. M. (2011). The diffusion of energy efficiency in building. *American Economic Review, 101*, 77-82.

Krause, R. (2009). *Energy efficiency and conservation*. Paper presented at The Search for Wise Energy Policy Conference, Washington, DC.

Kühn, I., Bierman, S. M., Durka, W., & Klotz, S. (2006). Relating geographical variation in pollination types to environmental and spatial factors using novel statistical methods. *New Phytologist, 172*, 127-139.

Lawrence, T. M., Mullen, J. D., Noonan, D. S., & Enck, J. (2005). Overcoming barriers to efficiency. *ASHRAE Journal, 47*, S40-S47.

Longley, P. A., & Tobón, C. (2004). Spatial dependence and heterogeneity in patterns of hardship: An intra-urban analysis. *Annals of the Association of American Geographers, 94*, 503-519.

Menanteau, P., & Lefebvre, H. (2000). Competing technologies and the diffusion of innovations: The emergence of energy-efficient lamps in the residential sector. *Research Policy, 29*, 375-389.

Mills, B. F., & Schleich, J. (2010). Why don't households see the light? Explaining the diffusion of compact fluorescent lamps. *Resource and Energy Economics, 32*, 363-378.
Mlecnik, E. (2010). Adoption of highly energy-efficient renovation concepts. *Open House International, 35*, 39-48.
Nair, G., Gustavsson, L., & Mahapatra, K. (2010). Factors influencing energy efficiency investments in existing Swedish residential buildings. *Energy Policy, 38*, 2956-2963.
Niemeyer, S. (2010). Consumer voices: Adoption of residential energy-efficient practices. *International Journal of Consumer Studies, 34*, 140-145.
Osbaldiston, R., & Schott, J. P. (2011). Environmental sustainability and behavioral science: Meta-analysis of proenvironmental behavior experiments. *Environment & Behavior*. Advance online publication. doi:10.1177/0013916511402673
Oster, E., & Thornton, R. (2009). *Determinants of technology adoption: Private value and peer effects in menstrual cup take-up* (NBER Working Paper No. 14828). Cambridge, MA: National Bureau of Economic Research.
Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). New York, NY: Free Press.
Schot, J., & Geels, F. W. (2008). Strategic niche management and sustainable innovation journeys: Theory, findings, research agenda, and policy. *Technology Analysis & Strategic Management, 20*, 537-554.
Sovacool, B. K. (2009). The cultural barriers to renewable energy and energy efficiency in the United States. *Technology in Society, 31*, 365-373.
Stern, P. C. (2011). Contributions of psychology to limiting climate change. *American Psychologist, 66*, 303-314.
Tse, R. Y. C., & Webb, J. R. (1999). Property tax and housing returns. *Review of Urban & Regional Development Studies, 11*, 114-126.
U.S. Department of Housing and Urban Development. (2003). *The Practice of Low Impact Development*. Washington, DC: Author. Retrieved from http://www.huduser.org/publications/pdf/practlowimpctdevel.pdf
U.S. Department of Energy. (2009). *2009 Buildings Energy Data Book.* Washington, DC: Author. Retrieved from http://buildingsdatabook.eren.doe.gov/docs%5CDataBooks%5C2009_BEDB_Updated.pdf
U.S. Green Building Council. (2010). *Leadership in Energy and Environmental Design (LEED)*. Available from http://www.usgbc.org/

Bios

Douglas S. Noonan is an environmental policy professor in the School of Public Policy at the Georgia Institute of Technology. His research applies microeconomic and policy analytic approaches to urban environmental topics (e.g., brownfield remediation, greenspace provision, and behavioral responses to air pollution).

Lin-Han Chiang Hsieh is pursuing a doctoral degree in public policy at the Georgia Institute of Technology. His research interests involve environmentally friendly technologies, environmental economics, and spatial econometrics.

Daniel Matisoff is an environmental policy professor in the School of Public Policy at the Georgia Institute of Technology. His research emphasizes the role of voluntary compliance, information-based policies, and institutional design on environmental outcomes.