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Spatial Effects in Energy-Efficient Residential HVAC Technology Adoption

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Abstract

If your neighborhood adopts greener, energy-efficient residential heating, ventilating, and air conditioning (HVAC) systems, will your pro-environmental behavior become contagious, spilling over into adjacent neighborhoods' HVAC adoptions? Objective data on over 300000 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, our data 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 LEED_ND or Low Impact Development HUD standards.

1 Introduction

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

10 While recent research reveals the benefits of adopting energy-efficient HVACs, research on the
11 adoption behavior is limited. Evidence indicates that adopting energy efficient technologies benefits
12 homeowners, but homeowners frequently forgo cost-effective technologies due to other reasons (Krause,
13 2009; Sovacool, 2009; Stern, 2011). Designing policies to enhance the adoption of energy-efficient HVACs
14 requires improving our understanding of adoption behavior.

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

26 To determine the factors that affect the adoption of energy-efficient HVACs, this study seeks to
27 explain energy-efficient HVAC adoption behaviors with adoption costs, estimated savings, and spatial
28 contagion. This study is especially interested in contagion (i.e., spatial effects) of energy-efficient

1 technology adoption. Learning from neighbors' experiences, suggestions from the same real estate agent,
2 competing for resale value, or simply mimicking the behavior of neighbors can result in the "spillover" of
3 adoptions and thus spatially cluster the adoptions. Diffusion of innovation theory explains how one's
4 technology adoption behavior affects other individuals or groups through either learning from success, peer
5 effects, or copycatting (Rogers, 1995). In this sense, technological change and social change are
6 interrelated, and the social structures involved in technological change are important (Schot & Geels,
7 2008). Innovation, in this sense, is both an individual act and a collective act (Hekkert, Suurs, Negro,
8 Kuhlmann, & Smits, 2007).

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

16 **Literature review**

17 Most studies about HVAC or residential energy efficiency concentrate on either barriers to
18 technology diffusion or the modification of regulations (Jaber, Mamlook, & Awad, 2005; Lawrence,
19 Mullen, Noonan, & Enck, 2005; Menanteau & Lefebvre, 2000; Mills & Schleich, 2010). Several studies
20 directly analyze the adoption behavior of energy-efficient HVACs via case studies or through surveys.
21 Mlecnik (2010), based on a case study of space heating in Belgium, concludes that education,
22 communication via actor networks, economic incentives, and spatial spillover from neighbors may affect
23 the adoption of energy-efficiency improvements. Niemeyer (2010) and Nair, Gustavsson, and Mahapatra
24 (2010) use surveys to determine the factors affecting adoption behavior in Nebraska and Sweden,
25 respectively. The results of these studies are similar: they indicate that both personal factors (such as
26 knowledge and education), economic constraints, obstacles to making changes, demographic variables,
27 attitudinal and belief constraints, and contextual factors (such as the age of the house, thermal discomfort,
28 and perceived energy cost) affect homeowners' adoption behavior. We improve on this past research by

1 relying on house sales records, which provides a more comprehensive sample and avoids the self –
2 presentation biases inherent with survey data.

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

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

25 Spatial econometric approaches can identify spatial contagion effects and are especially well-suited in
26 the presence of social norms, neighborhood effects, or copycatting. Ioannides and Zabel (2003) offer
27 considerable evidence that homeowners' decisions about maintaining their houses are greatly
28 interdependent and that neighbor effects like "keeping up with the Joneses" are powerful phenomenon.

1 However, spatial econometric models have not been used to explain the adoption behaviors of households
2 and neighborhoods for energy-efficiency technologies. Anselin (2000, 2001, 2003) develops several
3 econometric models to determine spatial dependence. Spatial regression models with aggregated data is
4 now common in urban and environmental related areas (e.g., Fragkias & Seto, 2007; Kühn, Bierman,
5 Durka, & Klotz, 2006; Longley & Tobón, 2004).

6

7 **Methods**

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

$$9 \quad y_{ig} = \mathbf{X}'_{ig} \boldsymbol{\beta} + \varepsilon_{ig} \quad (1)$$

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

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

14 where each variable is calculated as a group mean and is represented with a bar, such as

15 $\bar{y}_g \equiv (\sum_{i=1}^{I_g} y_{ig})/I_g$. In this model \bar{y}_g indicates the adoption rate in block-group g , and it is explained by
16 group-level averages of \mathbf{X} .

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

23 There are two basic ways to introduce spatial dependence into standard linear regression model: a
24 spatial lag model or a spatial error model. The spatial lag model directly controls for the influence of the
25 values of the dependent variable in nearby observations – where “nearby” is defined by the analyst's choice
26 of a spatial weights matrix. The spatial error model, in contrast, separates the residual caused by spatial

1 dependence from the white noise error term, essentially allowing for the neighboring observations to share
2 unobservables or unexplained portions of their adoption rates. This model is appropriate when the spatial
3 dependence is more a statistical “nuisance” rather than a spatial effect of direct interest (Anselin, 2001).

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

9 The classical spatial lag model can be written as:

$$\bar{y} = \rho W \bar{y} + \bar{X}' \beta + \bar{\epsilon}$$

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

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

25 Even with detailed house sale records, some variables that belong in equation (1) are unavailable in
26 this dataset. One way to address this, while also isolating owner-occupants' adoption decisions, involves
27 looking at the adoption rate only among houses that appear multiple times in the dataset. Examining the

1 differences (in y and X) controls for potential omitted variable bias that can result when static elements of X
 2 are omitted because they are unobserved. Thus, we estimate the model for the new construction sample and
 3 for the repeat-observation sample to mitigate omitted variable concerns and to isolate and better understand
 4 the adoption behavior by developers and homeowners, respectively.

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

$$9 \quad y_{igt} = X'_{igt} \beta_t + Z'_{ig} \gamma_t + \varepsilon_{igt}$$

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

$$13 \quad y_{igs} - y_{igt} = X'_{igs} \beta_s - X'_{igt} \beta_t + X'_{igt} \beta_s - X'_{igt} \beta_s + Z'_{ig} \gamma_s - Z'_{ig} \gamma_t + \Delta \varepsilon_{ig}$$

$$14 \quad \Delta y_{ig} = \Delta X'_{ig} \beta_s + X'_{igt} \Delta \beta + Z'_{ig} \Delta \gamma + \Delta \varepsilon_{ig} \quad (5)$$

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

$$20 \quad \overline{\Delta y}_g = \rho W \overline{\Delta y}_g + \overline{\Delta X}_g' \beta_t + \overline{X}_{gt}' \Delta \beta + \overline{Z}_g' \Delta \gamma + \overline{\Delta \varepsilon}_g \quad (6)$$

21 where $\overline{\Delta y}_g$ refers to the rate of new installations in block group g in repeat-observation sample (i.e.,
 22 $\overline{\Delta y}_g = (\sum_{i=1}^{I_g^*} \Delta y_{ig}) / I_g^*$ is the count of new adoptions, between sales, divided by I_g^* , the number of
 23 repeat-observations within block group g), $\overline{\Delta X}_g$ represents the average change in X in block group g , \overline{X}_g
 24 represents the average of X in block group g at the time of the initial sale, and \overline{Z}_g represents the average
 25 of Z in block group g . Parameters ρ , β_t , $\Delta \beta$, and $\Delta \gamma$ remain to be estimated. (To be clear, $\overline{\Delta y}_g$ and $\overline{\Delta X}_g$ are
 26 the block-group averages of differences, not the differences in block-group averages between sales.)
 27 Equation (6) models the trends in neighborhood adoption rates and draws flexibly on a micro-level

1 adoption model. It allows for some parameters' influence to vary over time, and also for trends in important
2 factors to influence adoption choices.

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

8 **Data**

9 This study employs a dataset on home sales in over 160 municipalities in the greater Chicago area,
10 containing over 340,000 sale records (of roughly 260,000 unique houses) from January 1, 1992 to June 30,
11 2004. The property data are originally from the Multiple Listing Service (MLS) of Northern Illinois, an
12 information clearinghouse for most residential property sales in that area. All the records are for
13 single-family houses from counties surrounding the city of Chicago (i.e., Cook, DuPage, Kane, Lake,
14 McHenry and Will counties). (The City of Chicago is not included in order to keep the population of
15 suburban areas with single-family homes more comparable.) The estimated effective property tax rate,
16 detailed school quality information, and local impact fees, are derived from multiple sources. The
17 demographic information is from the 2000 Census. Unlike the sales record data which is at the household
18 level, these demographic data are only available at the block-group level using the GeoLytics database.

19 In the dataset, the majority of heating systems is forced air with natural gas. More than 88%
20 households use forced air heating systems, and 90% of households use natural gas as the energy source for
21 heating. The majority of A/C systems is central air, which is used in over 80% of homes. This study uses
22 zoned heating and air conditioning systems to represent more energy-efficient HVACs. Actual energy
23 savings of zoned HVAC systems depends on the size of the house and many other factors. Ardehali and
24 Smith (1996), however, note a 50-53% savings from zoned HVAC systems. The adoption rate of zoned
25 HVACs is relatively low in the dataset. Only 2.2 percent and 3.1 percent of houses have zoned heating
26 systems and zoned A/C systems installed, respectively. The frequency of installation is about six times
27 greater for new construction. The adoption rates by block groups are mapped in Figure 1. Both figures are

1 classified by natural breaks, and darker shades indicate higher adoption rates. Spatial clustering in the
2 adoption rates appears in both figures.

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

- 5 **1. Cost to adopt:** The house vintage, 30-year mortgage interest rate, mean effective property tax rate,
6 median household income, and median house value proxy for the cost of upgrading the HVAC system.
7 This study hypothesizes that block groups with newer houses, where it is easier to adopt new HVAC
8 technology, will have higher adoption rates. Moreover, homeowners may be more willing to invest to
9 keep newer vintages updated. The prevailing mortgage interest rate, as a proxy for the cost of capital
10 investments, should affect the cost to adopt, since the interest rate affects the high up-front costs of
11 renovations. Previous research shows that higher tax rates will lower the rate of return on property
12 investment (Tse & Webb, 1999) and thus lower the adoption rate. Block groups with higher median
13 income and house value should exhibit higher adoption rates, since greater wealth and access to capital
14 makes adoption more affordable.
- 15 **2. Estimated savings:** This study uses the average lot size, average square footage, and share of college
16 graduates in a block group to estimate the perceived savings. Block groups with more large houses
17 should have higher adoption rates, since the estimated energy savings for large houses are usually
18 greater. The education variable, percent of college graduates, might affect adoption if it proxies for the
19 ability of homeowners to understand information related to the energy savings from HVAC adoption.
- 20 **3. Contagion:** The spatial dependence in the spatial lag model will be used to directly measure the
21 contagion effect.
- 22 **4. Control variables:** Block-group means for neighborhood amenities, distance to central business
23 district (CBD), vacancy rate, population density, percent of households that are renters, and county
24 dummies, serve as control variables in these models. We have no prior expectation of the relationships
25 of these variables to the adoption rate. We control for them because they may be correlated with the
26 demand for HVACs. Some variables reflect the quality of a neighborhood and thus might influence the
27 adoption rate of energy-efficient HVACs insofar as the goods are complements or substitutes. The
28 percentage of a population renting also suggests the presence of principal-agent problems, where the

1 incentives of the property owner are not aligned with the incentives of the renter – something
2 frequently claimed to undermine adoption (Lawrence, et al., 2005). Since property owners lack
3 incentives to invest in expensive energy efficiency improvements for rental properties, block groups
4 with higher percentages of renters should have lower adoption rates. Also, the county dummies are
5 used in our models to control for the possible effects of different regulations.

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

14

15 **Results**

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

21 The robust LM diagnostic tests, derived from OLS regressions and reported at the bottom of the
22 tables, show the applicability of spatial lag and spatial error models for each model and sample.
23 (Interested readers can find the OLS regression results using the same data and model specification in the
24 on-line Appendix.) According to Anselin (2000), the Robust LM (Error) statistic tests for spatial error
25 robust to the presence of spatial lag, and the Robust LM (Lag) statistic tests for spatial lag robust to the
26 presence of spatial error. Both Robust LM test statistics are distributed chi-square with one degree of
27 freedom. The p-values for the Robust LM (lag) test in all six models are below conventional values of α ,
28 letting us confidently reject the null hypothesis and employ the spatial lag model. The spatial error model is

1 not appropriate to the zoned A/C model in the repeat-observations sample or to the zoned heat model in
2 new-construction sample. Because a primary purpose of this study is to determine the effects of spatial
3 interdependence on HVAC adoption behavior, it is more useful to adopt the spatial lag model. Moreover,
4 the greater LM test statistic for the lag model than the error model in all instances offers consistent
5 diagnostic evidence to support the spatial lag specification (Anselin, 2000).

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

13 The full sample analysis in Table 3 shows the broad picture of how both spatial and non-spatial
14 factors influence adoption rates. Overall, the model fit is substantial, explaining most of the variation in
15 neighborhood adoption rates. The repeat-observations and new-construction sample models, however, offer
16 more focused results that should also be less susceptible to confounding effects from unobserved
17 characteristics. The results of these models warrant emphasis here. The repeat-observations sample model
18 (Table 4) helps identify the adoption decisions made by the homeowners within the neighborhood. Next,
19 using only the sample of new-construction sales (Table 5) enables a comparison between homeowners and
20 developers.

21 The results in Table 4 resemble the full sample spatial lag results, with a few key modifications. As
22 described in the previous section, the dependent variable in the repeat-observations model represents the
23 adoption rate by existing homeowners as renovations or replacements. *New* and *Rehabilitated* are dropped
24 because they make less sense in a differenced model. Also, the variables showing the average difference
25 between each sales record ($\overline{\Delta X}_g$) are listed near the bottom of the table. All the other independent variables
26 represent the conditions at first sale. As in the full sample, the spatial effects of the repeat-observation
27 sample are also positive and statistically significant. The spillover of the adoption rate is roughly 0.15 for
28 both zoned heating and A/C systems. This statistically significant result is much smaller in magnitude than

1 the ρ in the full sample. This more conservative estimate may also be a more accurate estimation of the
2 contagion effect, since differencing controls for some unobserved home traits that may be spatially
3 clustered. In addition, this estimate more directly measures the behavior of homeowners, which may not be
4 as clustered as developer decisions.

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

19 The energy savings measures exhibit straightforward effects in Table 4. The role of lot size in the
20 repeat-observations sample is simply positive. Larger lots at the time of initial sale and increasing lot sizes
21 predict greater neighborhood adoption rates. Ten percent larger lot sizes at the time of first sale are
22 associated with roughly 0.2 percentage points greater adoption rates of zoned HVAC systems, which is
23 substantial relative to the baseline average adoption rate of two percent. The case of square footage is even
24 stronger. In both models, larger average square footage of the first sale has positive effects on the adoption
25 behavior. For example, block groups with average square footage ten percent larger will tend to have
26 adoption rates 0.5 percentage points greater. Unlike the full sample results, the model in Table 4 shows
27 higher adoption rates in neighborhoods with larger homes *and* with homes that are growing in size.
28 Increasing the average difference in square footage between sales by ten percent is associated with the

1 share of repeat-observation homes adopting increasing by 0.7 percentage points for zoned heating, and 0.9
2 percentage points for zoned A/C. Renovations and expansions clearly play a vital role in the adoption of
3 green HVAC technologies, perhaps because the cost to install is relatively lower when bundled with other
4 home renovations and because the energy savings rise as homes' footprints grow.

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

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

24 Other results in Table 5 differ from those in Table 4, reflect different adoption patterns of
25 homeowners and developers. Home value, not income, has a strong positive effect on adoption rates in the
26 new-construction sample, nearly opposite that of the repeat-observation sample. Apparently developers'
27 installation decisions track with home values more than neighborhood wealth, and vice versa for
28 homeowners. Interestingly, the percent of college graduates positively influences adoption rates in the

1 new-construction sample only; it is insignificant in Table 4. The negative effect of parks in the
2 new-construction sample is interesting to note. It seems that parks and indoor energy efficiency are
3 substitutes. The geographic and temporal controls add little explanatory power to the new-construction
4 model, although zoned heating is more common when more of the newly constructed homes are sold in the
5 fall and winter.

6

7 **Discussion**

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

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

24 Building codes might be another important driver for adopting energy efficiency. This study does not
25 directly control for building codes due to the unavailability of data spanning over 160 municipalities and 12
26 years. Limiting the analysis to only sales records for single-family houses should keep zoning
27 classifications relatively consistent. Though we do have controls for different counties, variation in
28 single-family residential building codes across municipalities and even across time is not observed in this

1 data. We are not aware of differences in building codes in these suburbs that might play a major role in
2 neighborhood adoption. If variation in building codes does help explain the variation in adoption rates, the
3 spatial regression models (tables 3 – 5) will at least partly capture this effect. Interestingly, a spatial error
4 model would treat the omitted regressor of “building codes” as part of a spatially autocorrelated error. Yet
5 the diagnostic tests clearly indicate that a spatial lag model is more appropriate given this data. In short,
6 explicitly incorporating the spatial dependence into these models mitigates the concerns about missing
7 variables like these.

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

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

1 The implications for policy are significant. When designing a policy to promote the adoption of green
2 HVACs, according to our results, the effect of picking several demonstration block groups as the “seeds” of
3 contagion might be significant. For example, suppose a LEED-certified development project occurred in a
4 block group that previously had no green HVAC systems. A seed project that upgraded 90% of the block
5 group homes to zoned A/C and zoned heat systems would have 650 adoptions in an average block
6 containing 726 homes. If that block group had four neighboring block groups (which each had four
7 neighboring block groups), according to our estimates using the repeat-observations sample, holding all
8 else equal, this shift in the adoption rate would bring an increase in the adjacent block groups’ adoption
9 rates of 3.4% (bringing the adoption rate up to 5% from under 2%). (This is computed by multiplying the
10 increase in the weighted average of the four neighbors, $0.9/4=0.225$, by the lag operator, $\rho=0.15$.) Those
11 650 adoptions would translate to an additional 98 adoptions across the four immediate neighboring areas.
12 These adoptions, in turn, affect their adjacent neighbors, and so on. This suggests that small-scale localized
13 efforts to promote energy efficient adoption among homeowners might diffuse outward and have much
14 greater effect than originally anticipated. (In principle, this cuts both ways: the adoption of *inefficient*
15 HVAC systems may have similar contagion effects.) It also suggests that strategic placement of efficiency
16 enhancements (e.g., in areas with many neighbors and other variables predicting adoption rates, such as
17 locating projects farther away from parks) could have particularly large impacts on adoption behavior. This
18 is consistent with theory that suggests that niche markets that nurture new technologies are important for
19 technological diffusion (Schot & Geels, 2008). In fact, the “LEED for Homes” program offers additional
20 points toward certification for homes offering outreach and promoting public awareness (via tours,
21 websites, signage, etc.). Programs like LEED already leverage the power of diffusion of green homes.

22 Beyond “seeding” demonstration projects, other findings presented above point to ways that
23 policymakers can stimulate the adoption rates of energy-efficient HVACs – and how spatial contagion can
24 amplify those impacts. Suppose a policy to boost green HVAC installations lowered tax rates by half a
25 percentage point. Based on Table 4, this policy should increase adoption rates by about one percentage
26 point for zoned HVAC systems. This large impact, relative to the low mean adoption rates, is a direct policy
27 effect. It does not take into account the spatial spillovers identified above. The spatial multiplier of $1/(1 - \rho)$
28 magnifies the marginal impact of the tax break by a factor of 1.18 for zoned heating and 1.16 for zoned A/C

1 (Kim, Phipps, & Anselin, 2003). Neglecting this spatial contagion would substantially underestimate the
2 policy impact on adoption rates. The possibility of a threshold or tipping point in the contagion, also,
3 warrants further investigation, as this analysis assumes a linear spillover effect.

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

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

19

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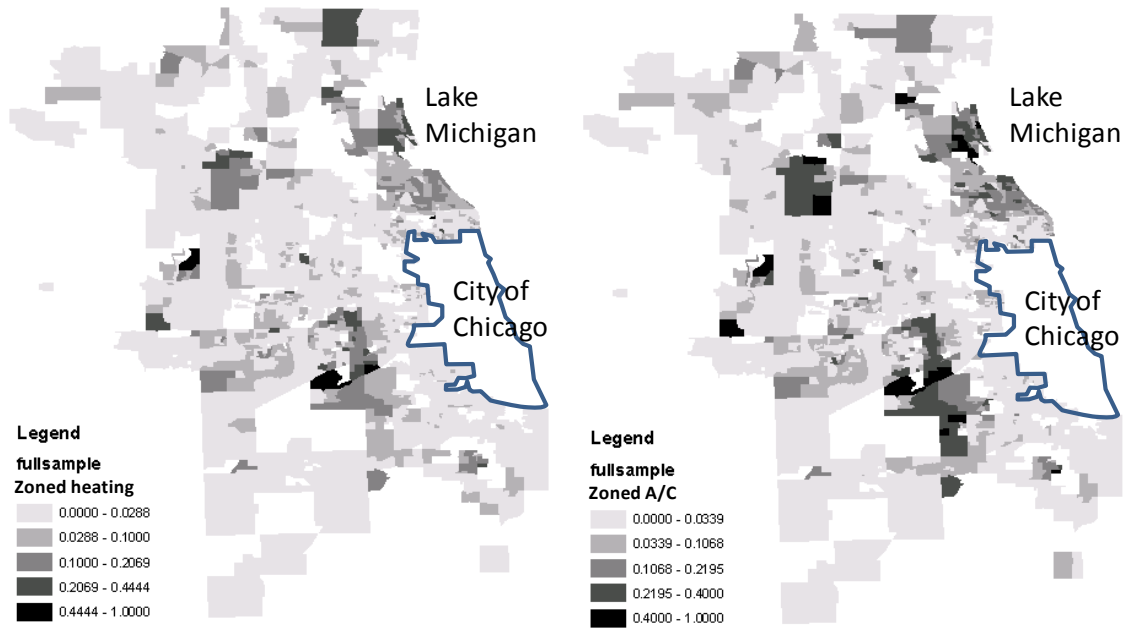
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1 **Appendix**

2 Figure 1. Map of zoned heating and zoned A/C adoption



3

4

1 Table 1. Definitions of variables

Variable	Description
Zoned Heating	Share of zoned heating system in the block group (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 built to suite 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-yr 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
Percent college graduate	Percent of college graduates in the BG, interpolated 1992-2004
Clubhouse	Share of properties listing a clubhouse
Park	Share of properties listing a Park/Playground around
Lake	Share of properties listing a Pond/lake around
Distance to CBD (log)	Distance to Central Business District, 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
Percent 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
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

1

2

1 Table 2. Descriptive statistics

Variables	Full sample		Repeat-observations sample		New-construction sample	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of Obs.	2539		2411		1142	
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-yr 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
Med. household income (log)	10.989	0.363	10.974	0.356	11.115	0.378
Med. 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
Percent college graduate	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
Percent 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	-	-
Diff. in square footage (log)	-	-	0.044	0.109	-	-
Diff. in 30-yr mortgage rate	-	-	-0.586	0.469	-	-
Diff. in year of sale	-	-	3.262	1.235	-	-

1

2

1 Table 3. Spatial lag regression results for the full sample

Variables	Zoned Heating		Zoned A/C	
	Coef.	Std. Err.	Coef.	Std. Err.
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-yr mortgage rate	-0.031	0.008 ***	-0.037	0.009 ***
Effective tax	-0.012	0.004 ***	-0.018	0.004 ***
Med. household income (log)	0.008	0.002 ***	0.014	0.003 ***
Med. 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 ***
Percent college graduate	-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 ***
Percent 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	Prob	Value	Prob
Robust LM (lag)	31.699	0.000	68.238	0.000
Robust LM (error)	19.974	0.000	34.871	0.000
Number of obs. =	2539		2535	
Log likelihood =	4729.98		4253.55	

R² =

0.507

0.605

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

2 Note. The above analyses control for the six counties listed in Table 2 and the proportional sales in each of

3 the 13 years from 1992-2004.

1 Table 4. Spatial lag regression results for the repeat-observations sample

Variables	Zoned Heating		Zoned A/C	
	Coef.	Std. Err.	Coef.	Std. Err.
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-yr mortgage rate	0.015	0.008 *	0.007	0.008
Effective tax	-0.024	0.005 ***	-0.016	0.005 ***
Med. household income (log)	0.019	0.007 ***	0.028	0.007 ***
Med. 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 ***
Percent college graduate	-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
Percent renters	0.000	0.000	0.000	0.000
Difference in lot size (log)	0.005	0.010	0.022	0.010 **
Diff. in square footage (log)	0.077	0.011 ***	0.091	0.011 ***
Diff. in 30-yr mortgage rate	0.013	0.005 **	0.009	0.005
Diff. in year of sale	0.005	0.002 ***	0.000	0.002
	Value	Prob	Value	Prob
Robust LM (lag)	39.105	0.000	9.376	0.002
Robust LM (error)	22.979	0.000	1.698	0.193
Number of obs. =	2411		2411	
Log likelihood =	3721.16		3668.63	
R ² =	0.233		0.271	

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

2 Note. The above analyses control for the six counties listed in Table 2 and the proportional sales in each of
3 the 13 years from 1992-2004.

1 Table 5. Spatial lag regression results for the new-construction sample

Variables	Zoned Heating		Zoned A/C	
	Coef.	Std. Err.	Coef.	Std. Err.
Spatial lag (ρ)	0.115	0.032 ***	0.136	0.031 ***
Constant	-2.189	0.541 ***	-2.631	0.631 ***
30-yr mortgage rate	-0.008	0.015	-0.018	0.018
Effective tax	-0.051	0.032	-0.108	0.037 ***
Med. household income (log)	-0.046	0.043	-0.059	0.050
Med. 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 ***
Percent college graduate	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
Percent 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	Prob	Value	Prob
Robust LM (lag)	4.660	0.031	13.224	0.000
Robust LM (error)	1.084	0.298	4.564	0.033
Number of obs. =	1142		1142	
Log likelihood =	173.057		-2.190	
R ² =	0.338		0.428	

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

3 Note. The above analyses control for the six counties listed in Table 2 and the proportional sales in each of
 4 the 13 years from 1992-2004.

5

1 Online Appendix

2 Table A1. OLS regression results for the full sample

	2539	2539		
Number of obs. =	2539		2539	
Log likelihood =	4588.59		4035.71	
Prob. > χ^2 =	0.0000		0.0000	
R ² =	0.432		0.512	
	Zoned Heating		Zoned A/C	
Variables	Coef.	Std. Err.	Coef.	Std. Err.
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-yr mortgage rate	-0.031	0.008 ***	-0.034	0.010 ***
Effective tax	-0.026	0.004 ***	-0.041	0.005 ***
Med. household income (log)	0.009	0.002 ***	0.018	0.003 ***
Med. 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 ***
Percent college graduate	-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 ***
Percent 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
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

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

2

1 Table A2. OLS regression results for the repeat-observations sample

Number of obs. =	2411		2411	
Log likelihood =	3707.33		3655.71	
Prob. > χ^2 =	0.0000		0.0000	
R ² =	0.221		0.260	
	Zoned Heating		Zoned A/C	
Variables	Coef.	Std. Err.	Coef.	Std. Err.
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-yr mortgage rate	0.016	0.008 *	0.007	0.008
Effective tax	-0.029	0.005 ***	-0.020	0.005 ***
Med. household income (log)	0.021	0.007 ***	0.030	0.007 ***
Med. 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 ***
Percent college graduate	-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
Percent 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 ***
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 **
Diff. in square footage (log)	0.080	0.011 ***	0.092	0.012 ***
Diff. in 30-yr mortgage rate	0.014	0.005 ***	0.009	0.005 *
Diff. in year of sale	0.005	0.002 ***	-0.001	0.002

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

2

1 Table A3. OLS regression results for the new construction sample

Number of obs. =	1142		1142	
Log likelihood =	166.975		-11.4167	
Prob. > χ^2 =	0.0000		0.0000	
R ² =	0.328		0.415	
	Zoned Heating		Zoned A/C	
Variables	Coef.	Std. Err.	Coef.	Std. Err.
Constant	-2.366	0.553 ***	-2.903	0.646 ***
30-yr mortgage rate	-0.009	0.016	-0.017	0.018
Effective tax	-0.061	0.032 *	-0.131	0.038 ***
Med. household income (log)	-0.047	0.044	-0.063	0.051
Med. 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 ***
Percent college graduate	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
Percent 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
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

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

2

3