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Close competition: The contagion effect of neighborhood listings on seller motivation

Nicholas B. Irwin and Mitchell R. Livy

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CALIFORNIA STATE UNIVERSITY, FULLERTON
College of Business and Economics, *Department of Economics*
800 N. State College Blvd., Fullerton, CA 92834-6848 / T 657-278-2228 / F 657-278-3097

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Abstract

In this paper, we examine the contagion effect of contemporaneous neighborhood house listings on homeowners' decision to sell their house. Using a spatially-explicit dataset of all residential parcels in the Baltimore, MD MSA from 2013–2015 and the universe of houses listed for sale, we estimate a series of duration models and find compelling evidence of a neighborhood contagion effect across a multiple dimensions of neighborhood size on the order of a 13 to 19 percent in listing likelihood. These results indicate that a positive multiplier effect exists with nearby listings and adds to an under-studied literature on seller motivation.

JEL Codes: R21, H41, H7

Keywords: housing sales, contagion effect, spillovers, MLS, seller motivation

* Irwin is an assistant professor in the Department of Economics at the University of Nevada-Las Vegas. Contact information: 4505 S. Maryland Pkwy, Las Vegas, NV 89154-6001 nicholas.irwin@unlv.edu.

† Livy is an associate professor in the Department of Economics at California State University, Fullerton. Contact information: 800 N. State College Blvd. Fullerton, CA 92831-3599 mlivy@fullerton.edu.

1. Introduction

The widespread accessibility of housing market information proliferating through websites and applications – Zillow, Redfin, and Realtor.com, among others – have transformed the way the housing market functions. No longer does a real estate agent hold the key knowledge of housing inventory for buyers or information on comparison houses for interested sellers; all parties now have access to a constantly updating inventory of houses and other key information that may impact their economic decision-making. One decision in particular is likely to be influenced by this newfound knowledge of the housing market: the decision of a homeowner to list their house for sale and the extent to which neighboring listings may influence this decision.

Although sellers are heterogenous agents with unique motivations for selling, there has been research on understanding the desire to undertake the arduous process of selling one's house. Much of this literature has focused on the relative "eagerness" of sellers to offload their house to an interested buyer, with motivations such as the need to relocate for a new job, a pending offer on another house, those facing foreclosure, or those undergoing other financial constraints (Springer, 1996; Glower et al., 1998; Anenberg, 2011). An additional vein of research has explored the role of informational asymmetries on seller-decision making, particularly the implications of an unclear anchor point of their house's value, with market experience diminishing these asymmetries while allowing sellers to adjust the listing for current demand (Anenberg, 2016). We expect that this same market knowledge will influence potential sellers as well, particularly through information revealed about their neighborhood competition.

In this paper, we examine the effect of neighborhood housing competition – nearby listings of houses for sale – on a households' decision to list their own for sale, or, more simply, the contagion effect of neighborhood listings. We expect that households who observe their neighbor listing a house will have an increase in the likelihood to list their own houses through a change in their future expectations of housing demand, a desire to capitalize on revealed information related to housing prices, and interest in the neighborhood from observing the marketing efforts of realtors. We assemble a spatially explicit dataset of parcel-level single-family residences from the Baltimore, Maryland Metropolitan Statistical Area (MSA) spanning 2013–2015, a period of housing market recovery and renewed activity, with the Multiple Listing Service (MLS) listing of houses for sale during this time. We focus on a hyper-local definition of neighborhood, employing spatial techniques to identify the nearest neighbors for every single-family residence in our study area. We model the contagion effect as a form social interaction and employ a hazard model to estimate the change in listing likelihood for a house during our study period based on nearby contemporaneous past listings amongst their neighborhood set. In using these lagged values, we control for the reflection problem common in these models (Manski, 2000; Brock and Durlauf, 2001). In addition, we construct an exhaustive set of control variables that may influence the decision to list a house that include house-specific and neighborhood-specific factors, which allows us to isolate the effect of a nearby listing.

This work fits into an emerging body of literature that examines the influence of contagions – social interactions – on households' economic decision making. Towe & Lawley (2013) study the role of contagion in foreclosure likelihood, finding that an additional foreclosure within a household's neighborhood group increases the likelihood of own foreclosure by 18 percent during the housing market crash in Maryland. Irwin (2019) explores the role of contagions within urban housing renovation decisions, finding that an increase in renovation activity within a household's neighborhood increases the likelihood of a future renovation by 1.8 percent. More recently, Bayer et al. (2021) analyze the impact of nearby investors on investment choices during the housing bubble, finding that new investors performed poorly relative to their experienced counterparts. This contagion effect literature is nested within a larger literature on peer effects as they pertain to housing markets, which have been shown to influence housing upkeep (Patacchini & Venanzoni, 2014), purchasing decisions (Bailey et al. 2018), and mortgage selection (McCartney & Shah, 2022). Our work is the first to conclusively link nearby housing market listings to an individual's decision to sell their own house, demonstrating that a positive contagion effect manifests.

We find that a unit-increase in nearby listings within a household's 15 nearest neighbors increases the likelihood of that household listing their house by at least 18 percent, depending on functional form assumptions. We expand our definition of a neighborhood to the 30 nearest neighbors and find smaller but still significant results of at least a 14 percent increase in listing likelihood for the same unit-increase in neighborhood listings. These results provide important evidence of a feedback loop generated through household observation by of neighboring actions that manifests in an economically meaningful way. This work contributes to the literature by uncovering an important new avenue of social contagions that have important implications for understanding the supply-side of the housing market and what impacts seller motivation. We find that the expansion of neighborhood size diminishes but does not eliminate this contagion effect from influencing household decision-making and sales timing. Additional results demonstrate that the contagion effect is driven by the actual act of listing and not a nearby housing sale.

The rest of the paper is structured in the following manner: Section 2 introduces our model and outlines the empirical methodology. Section 3 details the Baltimore, Maryland MSA study area and describe the data we use within this work. Section 4 provides our main results and neighborhood size robustness exercises while Section 5 concludes.

2. A social interactions model framework and methodology

In this section, we develop a modelling framework for estimating our contagion model, which is a variation on a social interactions model. We first provide context for how social interactions can impact economic decision making, with an eye toward our specific empirical question. We then formally develop our model and explain the necessary empirical assumptions for model tractability. In this section, we refer to the model as a social interaction model before reverting to contagion models in the remainder of the paper.

2a. Social interactions framework

Manski (1995) provides a thorough overview of the issues with identifying the effects of social interactions on decision-making by groups of people, pointing out three avenues of concern for how these choices may be intertwined: contextual effects, correlated effects, and endogenous interactions. Contextual effects may manifest from the observable traits of a neighbor influencing one's own behavior. An example of this would be the preference of wealthy households to live in a neighborhood with other wealthy individuals, as measured by housing prices or household wealth. Correlated effects manifest through shared household characteristics amongst neighbors, *i.e.,* in the wealthy neighborhoods, households are likely to have similar education levels. The final effect is endogenous interactions, or how the actual observed actions of neighbors influence another households' actions, which is the effect we seek to estimate within our empirical work. We isolate our endogenous interaction – hereafter social interaction – effect through careful empirical modeling and the selection of appropriate control variables to mitigate the impact of correlated and contextual effects.

Social interactions do not directly cause a new behavioral outcome, but rather increase the likelihood of a change in behavior through a variety of mechanisms. First, observing a neighbor listing their house may alter one's expectations for the future of the neighborhood. One could be worried that the neighborhood is losing its long-term residents or that local school quality could be impacted by the movement of households, increasing the likelihood of listing their own house for sale to avoid this future. Secondly, a neighboring listing may create a potential constraint on one's ability to sell their house in the future if the neighboring house is different (*i.e.* higher perceived quality) by limiting the pool of potential buyers. This could also increase the likelihood of listing now by temporally shifting a future listing.

Finally, observing a neighboring listing may change the preferences of households, particularly once they observe the list or selling price of the neighboring house, its interior photos, or the amount of traffic during any open houses. A household observing this may become convinced that their house could command a higher price and more interest from potential homebuyers, all of which would increase the likelihood of a listing. Sellers may also be motivated by a potential windfall if they believe their house is in high demand, which again may be motivated by the listing actions of their neighbors, particularly if those houses transact quickly. In this paper, we do not try to distinguish between which of these potential mechanisms dominates, as we suspect all play a role in how this particular social interaction manifests.[1] We also expect that households would heterogeneously respond to the same information, *i.e.* a household with children may be driven more by expectations of the future, while a household nearing retirement age may have a response driven more by preferences.

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[1] The existing literature follows the same conventions in assuming multiple mechanisms are at play. Truly isolating the dominance of one would require a substantially different research approach using survey methods that is outside of the scope of this current work but, perhaps, an important avenue of future research.

2b. Empirical model

We model the role of a nearby neighborhood listing as affecting the likelihood of transition from one state to another, *i.e.* a house not being listed for sale to being listed. We follow Sirakaya (2006), Towe & Lawley (2013), and Irwin (2019) and adopt a social interactions framework to causally identify the effect of a nearby neighborhood listing on the probability that household *i* will list their house for sale.

Let *T* be the duration from *t=0* that a household has not listed their house for sale. Each observation is a random process characterized by the following PDF and CDF, respectively:

$$\boldsymbol{f(t) = Pr(t \leq T < t + \delta t)} \tag{1}$$

$$\boldsymbol{F(t) = \int_{o}^{t} f(s)ds = Pr(T \leq t), t \geq 0} \tag{2}$$

The duration to failure – failure defined as the household deciding to sell their house and list it on the MLS – is $T \geq 0$ and *t* is a particular period of *T*. The likelihood of surviving until time *t* is:

$$\boldsymbol{S(t) = 1 - F(t) = Pr(T > t)} \tag{3}$$

The hazard function in (4) measures the instantaneous probability of failure (*i.e.,* listing the house for sale) at any point in time δt, conditional upon survival (*i.e.,* not having listed to that point) until time *t* as shown:

$$\boldsymbol{\lambda(t) = \lim_{\delta t \to \infty} \frac{Pr(t \leq T < t + \delta t | T \geq t)}{\delta t} = \frac{f(t)}{S(t)}} \tag{4}$$

The model thus provides a hazard rate for household *i* and a covariate vector z_i of the form:

$$\boldsymbol{\lambda(t, z_i) = \lambda_0(t) exp(\theta' z_i)} \tag{5}$$

where $\boldsymbol{\lambda_0}$ is the baseline hazard function at time *t* and $\boldsymbol{\theta}$ is a vector of control variables. For expositional ease, we ignore the possibility of time-varying covariates in equation (5), which would contribute spells to the data for each observation over the period where it has time-invariant covariates. This means that each unique observation may contribute multiple spells to the data, depending on the extent to which the covariates change over the study period, which is the case in our data as the number of nearby listings varies with time.

At its heart, our model seeks to understand the role of neighboring actions on each individual household. To do this, we must define a neighborhood for each household at a scale that will allow our estimated social interaction – a neighbor listing their house – to manifest without creating a neighborhood size so large that additional confounders may bias our resulting estimates. Ioannides (2002) and Towe & Lawley (2013) both demonstrate that decisions related to housing maintenance and foreclosure depend on the actions taken along these same dimensions by the immediate neighbors, defined as between the nearest 10 to 25 neighbors. However, Irwin (2019) shows that a larger set of neighbors within either a city-defined or census designated neighborhood can still impact the decision to renovate a house, likely because evidence of work and explicit signage that accompanies renovations is apparent to neighbors; the later trait overlapping with our empirical question. In this paper, we err on the side of caution and conservatively define neighbors as the 15 and 30 nearest neighbors.[2]

We assume the probability of household i listing their house is a function of their individual characteristics, x_i, the characteristics of i's neighborhood, n_i, and the listing behavior of their neighbors, $list_{n(i)}$ in the previous period. We can then replace $\boldsymbol{\theta}$ from (5) with the final hazard model for the empirical specification:

[2] Partially contributing to this decision is the large area of study, which contains a mixture of urban and rural areas. Along the urban-rural gradient, the distance to ones nearest neighbors is expected to grow along with distance from the central business district. In the robustness section, we expand our neighborhood set to the 45 & 60 nearest neighbors, which is geographically close in densely populated areas but can extend several square miles in the more rural areas.

$$\boldsymbol{\lambda}(\boldsymbol{t}, \boldsymbol{z_i}) = \boldsymbol{\lambda_0}(\boldsymbol{t})\ \boldsymbol{exp}\ (\alpha' \boldsymbol{x_i} + \beta' \boldsymbol{n_i} + \gamma' \boldsymbol{list_{n(i)}}) \tag{6}$$

With estimating a hazard model, one must make a choice for the baseline hazard function. We do not have any reason to suspect the hazard function is of a particular shape, so we can either select a Cox proportional hazard model, allowing the hazard function to not be specified, or a semiparametric exponential hazard model, which allows for a non-restrictive flexible hazard function.[3] Within this paper, we estimate models with both assumptions for the baseline hazard function to ensure our results are not driven by a functional form choice.

Brock and Durlauf (2001) note the difficulties in gaining identification in social interactions models, due in large part to the correlation between neighborhood and individual characteristics that could impact the outcome of interest. To overcome these issues, we employ a modeling framework – a hazard model – which helps to confront the reflection problem (Manski, 2000) while our data is collected in a panel. This allows for the identification of the likelihood of a homeowner listing their house as a function of neighboring listings that are non-contemporaneous but still recent. This approach has seen adoption within the literature, with Sirakaya (2006) using it in the context of recidivism amongst criminally-included peers, Towe & Lawley (2013) in the context of foreclosures within neighborhoods, and Irwin (2019) in the context of renovation activity within communities. To address the concerns posed by correlated effects, we include a suite of both household and neighborhood variables, which we discuss in the subsequent section. We also include county-level fixed effects within our model, which provide an additional means of controlling for potential county-specific factors that could motivate the decision to list a house.[4]

[3] There exist additional distributions that can be used such as the Weibull and the Gamma, among others.
[4] We include county-level fixed effects rather than a more standard inclusion of smaller census-level fixed effects (i.e., tract or block groups) to avoid the incidental parameters problem (Lancaster, 2000).

3. Data and Study Setting

We utilize the Baltimore, Maryland MSA for our study area. The Baltimore MSA consists of six counties – Anne Arundel, Baltimore, Carroll, Harford, Howard, and Queen Anne's – in addition to the city of Baltimore, which is an independent political entity as shown in Figure 1. The MSA is the 20th largest in the United States, with a population of 2.8 million people according to the 2020 Census. The MSA is also part of the Washington-Baltimore Combined Statistical area, the fourth largest in the U.S. Within this study, we exclude Queen Anne's County as it is not geographically contiguous with the rest of the MSA, laying across the Chesapeake Bay and connected by a single bridge (see Figure 1). It is also the smallest county in the MSA from both a population and population density standpoint, with the fewest number of houses listed on the MLS during the study period.

We obtain Multiple Listing Service (MLS) data for Baltimore covering our study period from 2013 – 2015[5]. We select this time period for two primary reasons: firstly, 2013 is the first full year of sustained recovery in housing prices from the housing crash within the MSA (see Appendix Figure A1). With this recovery in housing prices, we expect the housing market returned to some amount of normalcy, particularly when it comes to people wishing to sell their house and buyers generating sufficient demand for said houses. Secondly, we use a three-year window for tractability with our model considering the geographic scope of the study and computational intensity of the calculations. We observe 56,216 houses that are listed on the MLS during our study period.[6]

[5] We actually obtain data from Q3 2012 through the end of 2015, but we utilize the pre-2013 data to construct our contagion variable.

[6] In the case that a house is listed multiple times during the study period, we retain only the first listing. We expect that houses that are listed multiple times during such a short period of time are atypical of standard house selling behavior either because the house was bought to be flipped or the sellers have price/liquidity expectations that are unrealistic given their circumstances. A comparison of homes listed and never listed for sale are presented in Appendix Table 2.

We obtain the entire universe of single-family residential houses for our six geographic entities from MDProperty View, a database maintained by the Maryland Department of Planning that contains the complete housing and parcel information for all properties located within the state. We link the houses that were listed on the MLS to the database using GIS software. We clean our sample to remove any houses that are missing key structural variables that may impact the decision to list a house for sale. We also remove any houses that may have been erroneously classified as a single-family residences, such as those with more than eight bathrooms – likely a multifamily or institutional building – or those with a parcel size greater than 10 acres, as those properties may skew toward future development or agricultural use. Next, we append key neighborhood demographic information, drawn at the 2010 Census Tract level from the 2011–2015 American Community Survey 5-year sample. The inclusion of these neighborhood and house-specific variables in our model will minimize the concern of correlated and contextual effects biasing our contagion estimates. Table 1 provides a complete list of the variables and the summary statistics used within the model. All told, our final sample consists of a panel of 649,763 single-family residences that are observed weekly during the study period, with a binary variable appended to the observation in the week if it is ever listed on the MLS.

We create our contagion variable in a two-step process. First, we calculate the nearest neighbors – 15 and 30 – for each house in our sample based on the housing parcel centroid. Secondly, we determine, among this set of nearest neighbors, if a neighboring house was ever listed on the MLS during our study period. We encode this as our variable of interest, which measures the effect of an additional listing on the MLS of a nearby neighborhood house on each households' decision to list their own house. In Table 1, the average house in our sample saw 1.3

neighborhood MLS listings with the 15 nearest neighbor grouping and 2.59 with the 30 nearest neighbor grouping.

4. Results and discussion

We estimate our contagion models and report the results in Table 2. All results are reported as hazard ratios, where a value greater than one indicates an increase in the likelihood of listing, while a value less than one is a decrease in the likelihood of listing. We report only our coefficient of interest in Table 2 with our full results including the control variables reported in Appendix Table 1. As mentioned previously, we estimate the models with two assumptions about the hazard function: a Cox model and a piecewise exponential model.

Within our smallest defined neighborhood set of 15-neighbors, the neighborhood listing variable is both positive and significant, indicating an increase in the likelihood of a listing of 18 percent in the Cox model, and 19 percent in the exponential model from a unit-increase in nearby neighborhood listings. Enlarging each household's neighborhood set to the 30-nearest neighbors, we continue to find a positive and significant effect for our variable of interest. A unit-increase in observed neighborhood listings increases the likelihood of a future listing for a household by 14 to 15 percent, depending on the model specification. This decrease in the economic effect and the size of the estimates are broadly in-line with previous work on social contagion in real estate (notably, Towe & Lawley, 2013) and provide compelling evidence that neighborhood level activity does drive household economic decision making along a previously unexplored facet.

We now turn to the model's control variables, which are provided in Appendix Table 1. Focusing on the housing characteristics, many have small but significant impacts on the probability that a house is listed for sale. For example, the presence of a fireplace leads to an increase in the probability that a house will be listed by 11 percent across all neighborhood size classifications. Higher quality structures, attached garages, exterior siding, the presence of a pool, finished attics and basements, patios, and increasing distance from downtown Baltimore are also consistently associated with a higher likelihood of listing. In contrast, decks, smaller parcel sizes, older houses, increased number of stories, and brick exteriors decrease the listing probability. The coefficients show that these characteristics of a house impact the likelihood that it will be listed for sale.

At the neighborhood level, we find that elevated poverty levels, higher levels of residents with a college degree, increased proportions of minority residents, and heightened vacancy rates are associated with a lower likelihood that a house will be listed for sale. Houses located in areas with a higher proportion of residents with high school diplomas, larger populations of 65 and older individuals, and higher levels of owner-occupied housing leads to an increased likelihood of listing. The significance of the demographic coefficients provides evidence that the makeup of a neighborhood can lead to substantial differences in the probability that a house will be listed for sale. In addition, including the housing and demographic features into the model is essential for modelling the contagion impact of a listing on neighbor behavior because they could confound the relevant estimates of interest.

Adding to the primary results, we estimate multiple robustness specifications. In Table 3, we expand our neighborhood size assumption in the first set of models in columns 1-4. We expect that the role of neighbors likely varies tremendously across space, with urban areas having substantially more neighbors than suburban or rural areas. *A priori*, we expect that increasing the neighborhood set will decrease the magnitude of the effect, echoing the main results. We expand the neighborhood set to the 45 and 60 nearest neighbors and report the results in Table 3. We continue to find strong evidence of a positive contagion effect from neighborhood listings, with the 45-neighbor result of similar size as the previous results, but an order of magnitude decrease for the 60 nearest neighbors. Both results remain positive and significant and provide evidence of a continued contagion effect that diminishes as the size of a household's neighborhood expands in space. We present an additional robustness test as the second set of models in Table 3 in columns 5-6 that limits the maximum distance to 0.5 miles to alleviate the concern about using the 30 nearest neighbors in the exurban and rural areas of the study area where distance between houses may exceed the neighborhood level. Overall, the robustness estimates are similar to the primary model and show the stability of the measured contagion impact.

Finally, we control for the possibility that nearby sales may present an additional contagion that could conflate our estimate of interest. We add in an additional control for the number of neighborhood housing sales that occurred in the previous period, which is a subset of the neighborhood listings as not all listed houses will sell.[7] We re-estimate our main models and report them in the final columns of Table 3 (7-10). The effect of a listing is qualitatively similar as in our initial findings but, interestingly, the effect of a neighborhood sale slightly decreases the likelihood of a listing. While this result seems paradoxical, it comports with one of the possibilities we previously discussed as to what may drive a listing: a seller's concern that a nearby housing sale could limit their own ability to execute a transaction if there are noticeable differences between the houses.

The totality of the results presented here provide evidence that social contagions are an important component of supply-side housing markets. Controlling for housing and neighborhood characteristics that capture differences in areas that may lead to changes in homeowner duration and sales decisions, we show a prominent and highly localized contagion effect associated with

[7] The are a panoply of reasons for why a house may list and not sell ranging from unrealistic price expectations on the seller side to issues revealed during the contingency period on the buyers side.

housing listings. Future research should consider this contagion impact when analyzing housing markets, since listing decisions are determined, in part, by the decisions of one's neighbors.

5. Conclusion

This paper investigates the contagion effect of nearby house listings on a household's decision to list their own house for sale. We control for a variety of housing characteristics and neighborhood demographics that we expect to influence the decision to list a house, finding a unit-increase in previous nearby listings increases the likelihood of a future listing by between 18-19 percent for the smallest neighborhood set and 14-15 percent for a larger neighborhood definition. Additional robustness checks for neighborhood size show that the listing effect decreases with neighborhood size expansion, but it remains significant at an economically significant level while the effect of nearby sales does not increase the likelihood of a listing. This work demonstrates the value of exploring the role social contagions play in economic decision making and future work should continue to expand upon the known list of household level contagions.

These results are significant in the real estate, urban, and housing economics literatures because they show that listing decisions do not arbitrarily occur within a locality. Instead, the listing decisions of households have substantial impacts on the probability that other nearby houses will be listed for sale in the future. The contagion impact of localized listings should be considered in the larger context of the housing market response to any exogenous factor that could motivate an individual to sell their house, such as macroeconomic shocks or changes in the quality of localized public goods such as crime or school quality. These results may also be of interest to policymakers looking to serve existing and new constituents by determining the likelihood of housing turnover.

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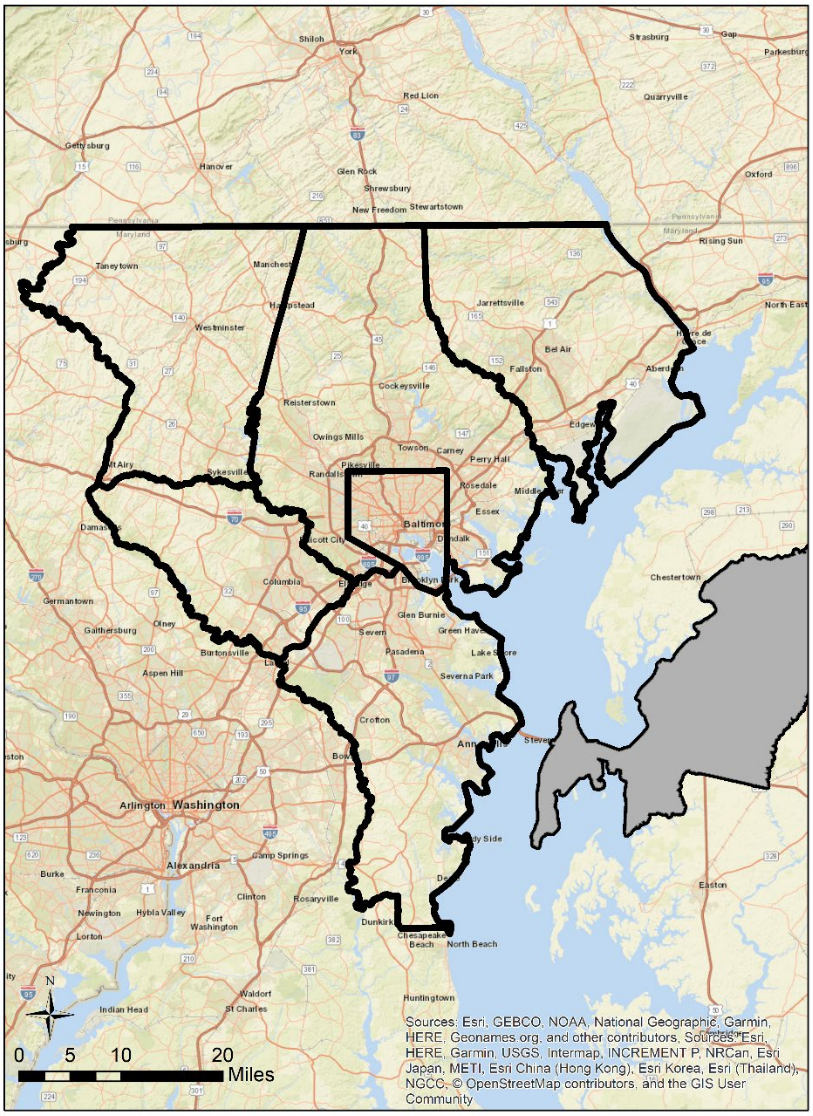
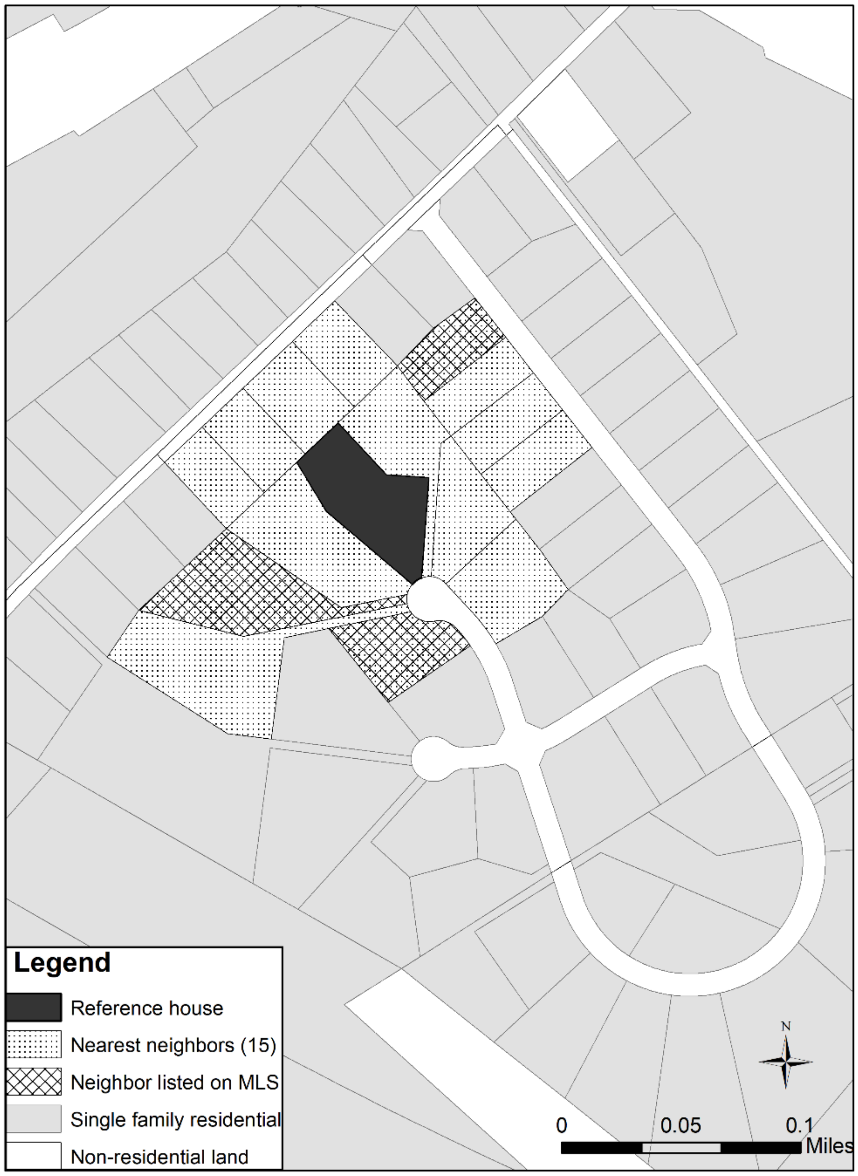
Figures and Tables

Figure 1: Map of Baltimore MSA



Note: Baltimore MSA counties outlined in black. Clockwise from the upper left corner, the counties are as follows: Carroll, Baltimore, Harford, Howard, and Anne Arundel. Baltimore City is nested within Baltimore County. Queen Anne's is the county shaded in gray and is not part of the analysis.

Figure 2: Nearest neighbor explanatory figure



Note: This figure details the process to identify both the nearest neighbors and the social contagion variable for every single-family house within the sample. First, the nearest neighbors are identified from the geographic coordinates for each parcel centroid. Then, amongst those nearest neighbors, the social interaction variable is created as a cumulative count of neighboring listings if said house was listed on the MLS prior to the reference house listing on the MLS.

Table 1: Complete variable list and summary statistics

Variable	Mean	Std. Dev	Min	Max
Social Contagion				
Neighborhood listings (15 nearest neighbors)	1.3	1.33	0	9
Neighborhood listings (30 nearest neighbors)	2.59	2.16	0	15
House Characteristics				
House Size (sqft)	1741.72	851.13	556	11922
Parcel size (acres)	0.48	0.94	0	10
Year built	1963.61	27.82	1880	2013
Stories	1.76	0.52	1	3
Full bathrooms	1.68	0.75	1	8
Attached garage	0.36	0.48	0	1
Quality (1-9)	3.608	0.8	1	9
Brick exterior	0.3	0.46	0	1
Vinyl siding	0.48	0.5	0	1
Central air	0.66	0.48	0	1
Forced air heat	0.57	0.5	0	1
Finished basement	0.37	0.48	0	1
Finished attic	0.02	0.15	0	1
Fireplace	0.44	0.5	0	1
Pool	0.044	0.20	0	1
Deck	0.42	0.49	0	1
Patio	0.16	0.37	0	1
Pier/waterfront access	0.013	0.11	0	1
Distance to downtown Baltimore (mi.)	12.68	8.35	0.4	43.57
Neighborhood Characteristics				
Percent minority	66.38	29.06	0	99.8
HH median income (1000$)	82.09	32.52	12.57	196.31
Monthly housing costs (1000$)	1.78	0.69	0.045	5.15
Percent high school diploma	90.36	7.13	52.1	99.7
Percent college degree	37.43	19.41	1.4	88.5
Owner occupancy rate	73.61	18.78	0	99.6
Vacancy rate	7.9	6.32	0	58.1
Poverty rate	9.5	8.33	0	77
Percentage under 18	22.11	4.77	1.8	45.6
Percentage over 65	14.49	5.84	0	52.6

Table 2: Model results for social contagion of nearby listings

Variable	15 Nearest Neighbors		30 Nearest Neighbors	
	Cox Hazard Model	**PWE Hazard Model**	**Cox Hazard Model**	**PWE Hazard Model**
Neighborhood listings	**1.183*** (0.00347)	**1.192*** (0.00337)	**1.138*** (0.00218)	**1.146*** (0.00210)
Observations	649,763			
Failures (house listed for sale)	56,216			

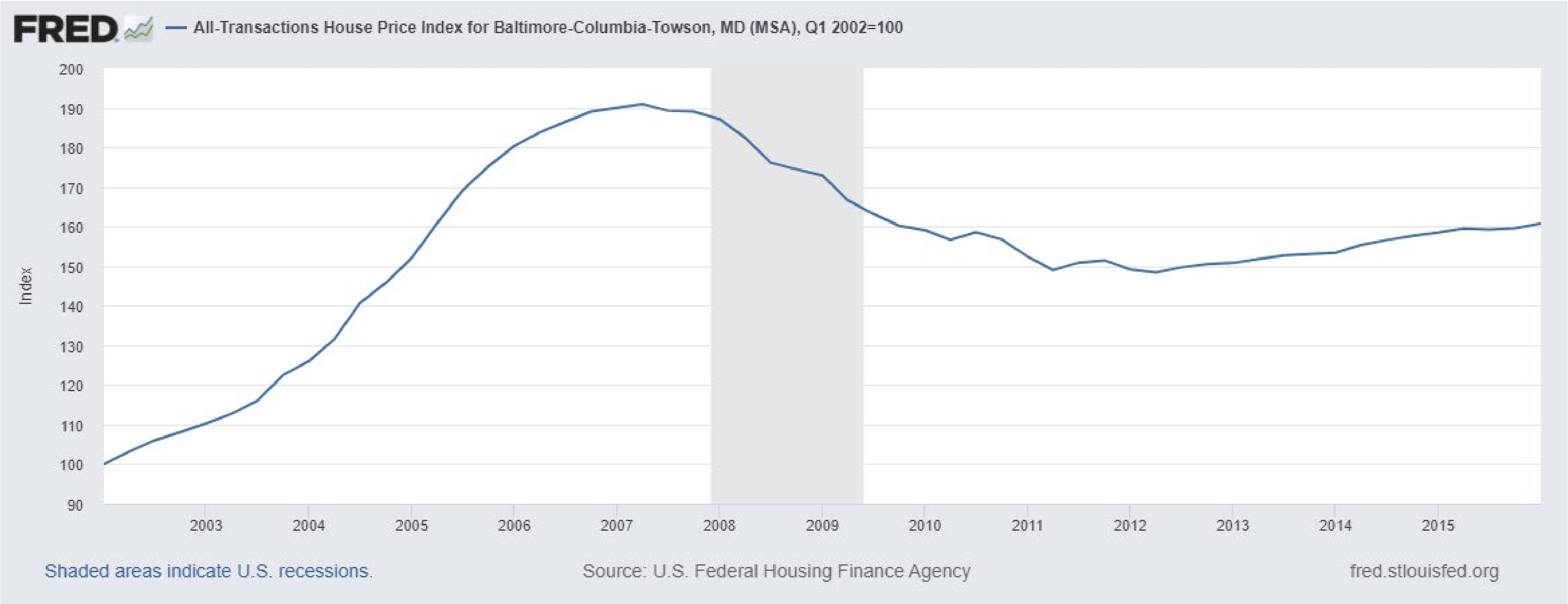
Note: *Hazard ratios reported with robust standard errors clustered at the household level in parentheses. *, **, *** indicates significance at 0.1, 0.05, and 0.01 levels respectively.*

Table 3: Robustness models for contagion effect

Variable	Expanded Neighborhood Size (I) 45 NN		Expanded Neighborhood Size (I) 60 NN		1/2 Mile Neighborhood (II)		Inclusion of Neighborhood Sales (III) 15 NN		Inclusion of Neighborhood Sales (III) 30 NN	
	Cox	**PWE**	**Cox**	**PWE**	**Cox**	**PWE**	**Cox**	**PWE**	**Cox**	**PWE**
Neighborhood listings	**1.113*** **	**1.119*** **	**1.010*** **	**1.007*** **	**1.136*** **	**1.144*** **	**1.187*** **	**1.199*** **	**1.142*** **	**1.151*** **
	-0.00163	-0.00157	-0.00127	-0.000686	-0.00215	-0.00208	(0.00424)	(0.00411)	(0.00269)	(0.00261)
Neighborhood sales	-	-	-	-	-	-	0.988*	0.983***	0.989**	0.987***
							(0.00663)	(0.00635)	(0.00459)	(0.00441)
Observations	649,763									
Failures (house listed for sale)	56,216									

Note: *Hazard ratios reported with robust standard errors clustered at the household level in parentheses. *, **, *** indicates significance at 0.1, 0.05, and 0.01 levels respectively.*

Appendix Figure 1: House Price Index for Baltimore MSA (2002 – 2016)



Appendix Table 1: Complete regression results from social contagion model

Variable	Cox Model (15NN)	PWE Model (15NN)	Cox Model (30NN)	PWE Model (30NN)
Neighborhood listings	**1.183*** **	**1.192*** **	**1.138*** **	**1.146*** **
	(0.00347)	(0.00337)	(0.00218)	(0.00210)
Housing characteristics				
House Size (sqft)	1.000***	1.000***	1.000***	1.000***
	(8.15e-06)	(7.50e-06)	(8.06e-06)	(7.55e-06)
Parcel size (acres)	0.951***	0.944***	0.956***	0.948***
	(0.00503)	(0.00494)	(0.00501)	(0.00495)
Quality (1-9)	1.125***	1.153***	1.119***	1.148***
	(0.00938)	(0.00939)	(0.00937)	(0.00937)
Year built	0.995***	0.994***	0.995***	0.995***
	(0.000257)	(0.000252)	(0.000259)	(0.000253)
Brick exterior	0.669***	0.655***	0.698***	0.686***
	(0.00994)	(0.00970)	(0.0103)	(0.0101)
Vinyl siding	1.081***	1.080***	1.082***	1.081***
	(0.0121)	(0.0118)	(0.0121)	(0.0119)
Full bathrooms	1.017**	1.017**	1.017**	1.017**
	(0.00816)	(0.00792)	(0.00815)	(0.00792)
Central air	0.984	0.998	0.987	1.001
	(0.0122)	(0.0122)	(0.0123)	(0.0122)
Finished basement	1.019**	1.027***	1.023**	1.030***
	(0.00976)	(0.00966)	(0.00979)	(0.00968)
Finished attic	1.109***	1.118***	1.104***	1.110***
	(0.0285)	(0.0279)	(0.0283)	(0.0277)
Attached garage	1.135***	1.136***	1.124***	1.124***
	(0.0133)	(0.0131)	(0.0132)	(0.0129)
Forced air heat	1.000	0.991	0.999	0.990
	(0.00916)	(0.00895)	(0.00917)	(0.00895)
Fireplace	1.112***	1.121***	1.103***	1.111***
	(0.0118)	(0.0117)	(0.0117)	(0.0116)
Pier/waterfront access	0.969	0.963	0.973	0.967
	(0.0338)	(0.0324)	(0.0341)	(0.0325)
Pool	1.050**	1.046**	1.053***	1.047**
	(0.0202)	(0.0193)	(0.0202)	(0.0194)
Deck	0.978**	0.980**	0.980**	0.983*
	(0.00923)	(0.00909)	(0.00926)	(0.00910)
Patio	1.038***	1.051***	1.032***	1.048***

	(0.0119)	(0.0118)	(0.0119)	(0.0117)
Stories	0.771***	0.763***	0.796***	0.789***
	(0.00744)	(0.00727)	(0.00770)	(0.00752)
Distance to downtown Baltimore (mi.)	1.005***	1.006***	1.004***	1.005***
	(0.000944)	(0.000925)	(0.000947)	(0.000925)
Neighborhood characteristics				
HH median income (1000$)	1.000	1.000	1.000	1.000
	(0.000343)	(0.000334)	(0.000342)	(0.000333)
Poverty rate	0.997**	0.997***	0.998**	0.997***
	(0.00111)	(0.00110)	(0.00111)	(0.00109)
Percent high school diploma	1.010***	1.010***	1.009***	1.009***
	(0.00134)	(0.00132)	(0.00135)	(0.00133)
Percent college degree	0.994***	0.993***	0.994***	0.994***
	(0.000531)	(0.000522)	(0.000533)	(0.000523)
Percentage under 18	1.001	1.002	1.001	1.002
	(0.00121)	(0.00120)	(0.00122)	(0.00120)
Percentage over 65	1.003***	1.004***	1.003***	1.003***
	(0.000906)	(0.000887)	(0.000917)	(0.000896)
Percent minority	0.998***	0.998***	0.998***	0.998***
	(0.000249)	(0.000245)	(0.000251)	(0.000247)
Vacancy rate	0.994***	0.994***	0.995***	0.994***
	(0.00110)	(0.00108)	(0.00111)	(0.00108)
Owner occupancy rate	1.002***	1.002***	1.002***	1.002***
	(0.000415)	(0.000409)	(0.000418)	(0.000409)
Monthly housing costs (1000$)	0.999	0.997	0.998	0.995
	(0.00731)	(0.00720)	(0.00730)	(0.00718)
House located in Baltimore County	0.970**	0.943***	0.970**	0.942***
	(0.0147)	(0.0141)	(0.0147)	(0.0141)
House located in Carroll County	1.039*	1.011	1.025	0.996
	(0.0223)	(0.0212)	(0.0220)	(0.0209)
House located in Harford County	1.053***	1.037**	1.052***	1.036**
	(0.0194)	(0.0188)	(0.0195)	(0.0188)
House located in Howard County	1.252***	1.223***	1.201***	1.171***
	(0.0243)	(0.0233)	(0.0234)	(0.0223)

House located in Baltimore City	1.018	1.002	0.999	0.985
	(0.0267)	(0.0260)	(0.0260)	(0.0252)
Hazard function	-	1.889	-	0.833
		(0.937)		(0.415)
Observations	649,763			
Failure events (house listed for sale)	56,216			

Note: *Hazard ratios reported with robust standard errors clustered at the household level in parentheses. *, **, *** indicates significance at 0.1, 0.05, and 0.01 levels, respectively.*

Appendix Table 2: Comparison between listed houses and never listed houses

	Listed on MLS		Never on MLS	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
House Characteristics				
House Size (sqft.)	1907.8	947.2777	1725.99	839.75
Parcel size (acres)	0.57	0.95	0.47	0.94
Year built	1966.09	26.72	1963.37	27.91
Stories	1.67	0.52	1.77	0.52
Full bathrooms	1.79	0.79	1.67	0.74
Attached garage	0.45	0.5	0.35	0.48
Quality (1-9)	3.74	0.87	3.6	0.79
Brick exterior	0.18	0.38	0.31	0.46
Vinyl siding	0.55	0.5	0.47	0.5
Central air	0.68	0.47	0.65	0.48
Forced air heat	0.56	0.5	0.57	0.5
Finished basement	0.36	0.48	0.37	0.48
Finished attic	0.03	0.17	0.02	0.15
Fireplace	0.53	0.5	0.43	0.49
Pool	0.06	0.23	0.04	0.2
Deck	0.45	0.5	0.42	0.49
Patio	0.19	0.39	0.16	0.37
Pier/waterfront access	0.02	0.13	0.01	0.11
Distance to downtown Baltimore (mi.)	14.19	8.17	12.54	8.35
Neighborhood Characteristics				
Percent minority	70.06	26.12	66.03	29.29
HH median income (1000$)	88.62	32.57	81.48	32.45
Monthly housing costs (1000$)	1.82	0.67	1.78	0.7
Percent high school diploma	91.59	5.94	90.24	7.22
Percent college degree	39.44	18.99	37.24	19.44
Owner occupancy rate	77.08	17.35	73.28	18.88
Vacancy rate	6.82	5.22	8.01	6.4
Poverty rate	7.95	6.82	9.65	8.45
Percentage under 18	22.26	4.28	22.1	4.82
Percentage over 65	14.95	5.57	14.44	5.86
Observations	56,216		593,547	