The Impact of Foreclosures on Neighboring Housing Sales

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Abstract

Housing foreclosures likely have little neighborhood impact if there are few foreclosures in a neighborhood and the foreclosed housing can resell quickly. However, when there are many foreclosures along with a sluggish housing market, foreclosures can lead to neighborhood destabilization, which should cause house prices to further fall. This paper measures the impact of foreclosures on housing sales using a unique dataset from St. Louis County, Missouri. Results show an expected decline in the sales price of neighboring sales but the marginal impact of foreclosures seems to decline with an increase in the number of foreclosures. These results are robust to a variety of neighborhood control variables and spatial econometric techniques.

A rising tide of residential foreclosures has pushed the issue on the political agenda of leaders at every level of American government. Nationally, the number of homes in foreclosure in 2007 was 79% higher than the previous year (Veiga, 2008); experts forecast a continuing increase in foreclosures under a perfect storm of subprime lending, interest rate resets, and declining or stagnant home prices (Edmiston and Zalneraitis, 2007). In St. Louis County, Missouri, the focus of this study, recorded foreclosure deeds increased 46% in the same period. These trends have renewed fears that foreclosures could further weaken local housing markets and some local leaders have argued for an aggressive federal response (U.S. Conference of Mayors, 2007).

In doing so, advocates of policy action point to how foreclosures are adversely affecting local housing markets, increasing the number of houses on the market and corresponding vacancies as housing inventories increase. Scholars have also detailed the costs to local governments as they respond to housing vacancy issues, with estimates ranging from $27,000 to $30,000 for each foreclosure (Moreno, 1995; Apgar and Duda, 2005). More broadly, however, scholars have used econometric models to quantify the impact of foreclosures upon local sales prices. Among the most fruitful of recent research uses data on foreclosures in the city of Chicago in 1997 and 1998 to explore their impact on single-family property sales in 2000 (Immergluck and Smith, 2006a). The authors found that foreclosures had a statistically significant impact on property values within an eighth of mile of the foreclosed property, a 0.9% decline for each foreclosure. Similar results were replicated using a national pool of both foreclosed and non-foreclosed properties (Lin, Rosenblatt, and Yao, 2009). The study found that foreclosures have a significant negative impact of up to 8.7% on neighborhood property values up to 10 blocks from the foreclosure and from five years of the foreclosure.

In their focus on individual single-family property sales as the dependent variable and inclusion of a range of housing and locational characteristics as predictors, these more recent analyses have significantly improved the modeling of foreclosure impacts and generally resulted in more precise estimates of impact. In doing so, they link to a broader literature in the field of urban econometrics that has explored the impact of various types of housing investments on residential property prices. For example, scholars have found strong evidence that investments in new housing positively impact sales values (Simons, Quercia, and Maric, 1998; Lee, Culhane, and Wachter, 1999; Ding, Simons, and Baku, 2000; Ellen, Schill, Susin, and Schwartz, 2001; Ding and Knapp, 2003); additionally, some studies have shown a similar impact with the rehabilitation of existing housing (Lee, Culhane, and Wachter, 1999; Ding, Simons, and Baku, 2000), with some variation based on the type and scale of the project.

At the same time, problems remain with the current research agenda, particularly with model specification. Most significant is the use of the relatively limited dataset of both foreclosures and sales—restricted to just two years in the former case and one year in the latter for Immergluck and Smith (2006a). Because of this fact, the authors restrict their temporal and geographic modeling to just two years and two predetermined distance dimensions. Secondly, Immergluck and Smith's use of the median block group of self-reported single-family house values from the 2000 Census—in effect, a 1999 measurement—introduces some endogeneity problems.

This paper adds to the literature by estimating the foreclosure effect but allowing the foreclosure effect to change over time and space, thus allowing for a more flexible estimate. In contrast to past estimates, this analysis utilizes a dataset of foreclosures from 1998 through 2007 and sales from a similar time period. Also, unobserved neighborhood characteristics are controlled for in a manner more consistent with the spatial econometric literature. Results show an expected decline in the sales price of neighboring sales but the effect is quite local in both temporal and spatial dimensions. Furthermore, and unexpectedly, the foreclosure impact shows no point in the number of foreclosures where neighborhood sales decline rapidly. By contrast, while the impact of foreclosures is both statistically significant and, aggregated across communities, significant in real terms, the marginal impact of foreclosures seems to decline as foreclosures increase. These results are robust to a variety of neighborhood control variables and spatial econometric techniques; although though we were unable to control for the quality of foreclosure events (i.e., the foreclosed property's physical condition or vacancy status).

Method

Foreclosure is first and foremost a characteristic describing the seller of the property not necessarily the condition of the property. Therefore, when one speaks of a foreclosure as being a distressed property, it is really the distress of the seller that is being described not necessarily the property. The negative correlation between foreclosure locations may exist because foreclosed properties tend to produce negative spillover effects including vacancies, reduced maintenance of the foreclosure property (Harding, Miceli, and Sirmans, 2000), and possibly increased crime (Immergluck and Smith, 2000b).[1]

A hedonic model was chosen to estimate the effect of foreclosures on neighboring housing prices. The model's dependent variable was the natural log of sales price followed by two variables sets:

$$lnP = \Sigma\alpha A + \Sigma\beta B + \varepsilon, \tag{1a}$$

where the first term included yearly dummies denoting the time of sale, the house structural characteristics, and spatial characteristics. The second term included foreclosure variables that were meant to account for the potential marginal impact of neighboring foreclosure by counting the number of foreclosures within a spatio-temporal ring:

$$\Sigma\beta_{t,s}B_{t,s}, \tag{1b}$$

where t and s denote the linear temporal and spatial distance from each sale respectively. Specification 1b allows the marginal price impact of foreclosures to vary such that foreclosures closer in time and space were allowed to have a different impact than foreclosures farther away. Temporal distance was measured in months between foreclosure and sale, and spatial distance was measured by Euclidean calculation in yards between foreclosure and sale. Each ring maintained mutually exclusivity, for example, $B_{6,100}$ counts foreclosures within six months before the sale and within 100 yards of the sale, and $B_{12,200}$ counts foreclosures between six and 12 months before the sale and between 100 and 200 yards of the sale.

Equation 1a was extended by allowing for non-linear effects in quadratic form:

$$\Sigma\beta_{t,s}B_{t,s} + \beta_{t,s}B_{t,s}^{2}. \tag{1c}$$

This specification allows the marginal price impact to vary by the number of existing foreclosures in the area. It was expected that neighborhoods with few foreclosures will have a small marginal impact but as foreclosures begin to accumulate, the marginal impact of foreclosure will rise as residents become concerned about rapid neighborhood decline. Thus, we expected all beta coefficients in Equation 1c to be negative.

Spatial Dependence

The hedonic model received an adjustment to account for spatial autocorrelation due to spatial heterogeneity. Spatial autocorrelation exists whenever the errors are correlated across space (Anselin, 1988), which is likely with housing data but is especially important given the potential for a missing neighborhood variable bias. Spatial autocorrelation may be a particularly corrosive error when measuring the impact of foreclosures because foreclosures tend to be spatially clustered. We employed an adjustment to our model following Anselin (1988) and Kelejian and Prucha (1999), where the error term becomes:

$$\varepsilon^* = \lambda W\varepsilon + u, \tag{2}$$

where W is the predetermined spatial weight representing the spatial relationship between residuals, λ is a coefficient to be estimated that acts as a scalar "weighting" the spatial structure, and a small λ (close to zero) signifies as weak spatial relationship. Because the spatial weight W is not estimated but chosen, consequently there is an unlimited variety of spatial weights that could be constructed. Choosing a proper spatial weight is akin to choosing an econometric functional form: the researcher must use economic theory, formal tests, and expert experience. Currently, it is common practice among real estate researchers to use a nearest-neighbor weighting structure, where each k nearest neighboring sales, not including the sale in question, are assigned a one in the matrix and all other sales are assigned a zero. Sales dates are not considered in the construction of our W, and thus k observed OLS errors of past and/or future sales are included for each observation. As a consequence, this spatial correction controls for temporally fixed but spatially variable unobserved characteristics of the housing market.

A nearest-neighbor spatial weight was chosen using the 10 nearest neighbors.[2] Given the large sample size and the asymmetric spatial weight, a maximum likelihood procedure could not be used (Anselin, 1988), so a method of moments estimator (GMM) was employed following Kelejian and Prucha (1999) and Bell and Bockstael (2000).

Causation and Biased Selection

An additional methodological issue relating to the analysis of foreclosures is the issue of causation. The hedonic model proposed above implies that the foreclosure effect is exogenous. However, there exists a large literature that identifies the causes of foreclosures including the loan-to-value ratio (LTV).[3] Lower prices also will increase the chances of future foreclosures, so the process is to some degree endogenous, with foreclosures potentially causing lower neighborhood prices and then lower neighborhood prices causing more foreclosures. While falling prices, which will increase the LTV, increase the probability of default, there are a variety of other factors that impact foreclosure including unemployment and divorce (Capozza, Kazarian, and Thomson, 1997).

Separating out these two different effects can be accomplished using an instrumental variables approach. The difficulty is in finding an instrument or instrument set that is correlated with the foreclosure but not correlated with the errors of the hedonic model. We found no such instrument, and it is unlikely that without detailed household information any instrument exists. Consequently, claims of causation must be made cautiously.

Another methodological issue related to foreclosure spillover effects is the problem of a biased sample. In one sense, sample selection bias cannot be a concern because we are estimating a model using the full population of arms-length sales. However, as foreclosed housing builds up in a neighborhood, home sellers may delay the sale of their house in order to avoid a loss. If the loss-avoidance choice is not distributed randomly within the neighborhood, then the above estimator may be biased.

Lin, Rosenblatt, and Yao (2009) used a simple two-step procedure, developed by Heckman (1979),[4] to test and correct for sample bias. The authors used nine exclusion variables describing the characteristics of the loan and financial situation of the borrower. They find a statistically significant bias but the effects on the hedonic model are quite small, which suggests no economically significant bias. Still, Harding, Rosenthal, and Sirmans (2003) argue that due to the uniqueness of the housing market, some characteristics of the buyers and sellers are observed in the unit sales price; which suggests that some of the sample selection variables used by Lin, Rosenblatt, and Yao may also be house price predictors.

Data

St. Louis County, the study area for this analysis, is an older urban county located on the eastern side of the state in the St. Louis Metropolitan Statistical Area. While the county has seen a large increase in foreclosures since 1998, comparative data suggests that the area's foreclosure problem is not attributable to the housing bubble impacts that have preceded an increase in foreclosures in other parts of the country. The 2007 foreclosure rate for the county is slightly lower than that for the nation as a whole (RealyTrac, 2008). Housing prices in the county increased 75% since the first quarter of 1998, as compared to 87% for the nation, and, in 2008, standardized prices for the county were only half of that of the nation (Office of Federal Housing Enterprise Oversight, 2008). The county's relatively low performing housing market is related to the state of the local economy. St. Louis County's 2007 unemployment rate was 50% higher than that of the United States (U.S. Census Bureau, 2008). From 1998 through 2006, the county lost 2% of its total jobs, compared to 11% increase for the nation as a whole (U.S. Census Bureau, 2006).

Data describing single-family housing sales and foreclosures were collected from the St. Louis County Recorder of Deeds and the St. Louis County Assessor. The dataset includes 98,828 single-family sales considered arms-length by the Assessor's Office[5] for the years 2000 through 2007, and 23,334 single-family housing foreclosures and liquidations for the years 1998 through 2007. All sales and foreclosure data originates from deeds, not mortgage information; thus, all foreclosures events are final in the sense that the situation has moved beyond default, and a bank, trustee or new owner has taken over ownership of the property.

Exhibit 1 presents the total foreclosures of single-family housing in St. Louis County and the single-family housing foreclosure rate. The foreclosures include all foreclosures and liquidations of single-family housing as identified by the St. Louis County Assessor's office. The foreclosure rate is a count of single-family housing foreclosures divided by the total number of single-family housing units in the county; thus our calculation is not a default rate. By contrast, most private real estate firms use total mortgages or households in the denominator, a statistic unavailable at the county level. The exhibit shows that the count of foreclosure has increased 260% since 2000, with the foreclosure rate nearly tripling since 2003. As shown in Exhibit 2, while foreclosures have been seen in all parts of St. Louis County, there are high clusters of them in the mid-north county area.

Since foreclosures are expected to have weaker effects at greater spatial and temporal distances, several spatial-temporal concentric rings were calculated to count foreclosures at various bands. For each house sale, 12 concentric rings (four 100 yard by three 6 month) were calculated, and foreclosures within each ring were counted. Therefore, each ring represents foreclosures farther in time and space from the observed sale. Means for all foreclosure rings are presented in Exhibit 3. The exhibit shows that mean foreclosure counts more or less uniformly increase in both space and time around sales; alternatively, there is a more pronounced clustering of foreclosures in spatial terms within the first 100-yard band, with more uniform decreases in temporal terms past the first six months.

Exhibit 4 reports the mean and standard deviation of dependent and control variables. Control variables were chosen based on what we believe to be important factors in the St. Louis housing market. We found our foreclosure results to be robust to a variety of control variable choices.

Exhibit 1 | St. Louis County Single-Family Foreclosure Counts and as a Percentage of Single-Family Housing Stock

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Foreclosures	751	1,231	1,693	1,469	1,459	1,979	2,407	2,249	3,840	6,256
Foreclosure Rate	na	na	0.6%	0.5%	0.5%	0.7%	0.8%	0.8%	1.4%	2.2%

Notes: Foreclosures include all foreclosures and liquidations of single-family housing as identified by the St. Louis County Assessor's office. The foreclosure rate is a count of single-family housing foreclosures divided by the total number of single-family housing units in the county; thus our calculation is not a default rate. Most private real estate firms use total mortgages or households in the denominator.

Exhibit 2 | Density of Foreclosures in St. Louis County: 1998–2007

Exhibit 3 | Mean Foreclosure Count by Spatial-Temporal Ring

	Foreclosure Months from Sale			
Yards from Sale	6	12	18	24
100	0.0821	0.0706	0.0584	0.0530
200	0.1784	0.1595	0.1429	0.1319
300	0.2726	0.2378	0.2153	0.1966
400	0.3462	0.3069	0.2752	0.2520
500	0.4173	0.3640	0.3303	0.3016
600	0.4917	0.4283	0.3851	0.3498

Note: Means are calculated from the 98,828 single-family sales. Foreclosure density is the number of foreclosures per single-family housing unit in the same ring.

Exhibit 4 | Variables, Notes, and Basic Statistics

Variable	Description	Type	Mean	Std. Dev.
Real Price	Real price in 2007 dollars (CPI Urban)	Continuous	204,800	170,330
Age	In years from sale	Discrete	38.7	21.7
Area	In acres	Continuous	0.274	0.381
Living Area	In square feet	Discrete	1,641.8	814.6
Stories		Discrete	1.261	0.440
Bedrooms		Discrete	3.074	0.797
Bathrooms		Discrete	1.691	0.701
HalfBath		Discrete	0.441	0.551
AC	Air conditioning	Dichotomous	0.945	0.228
Chimney		Discrete	0.348	0.534
Pools	Private lot pools	Discrete	0.043	0.211
Tennis	Private lot tennis courts	Discrete	0.001	0.027
ArtRoad	In miles from center of property to nearest arterial road	Continuous	0.224	0.229
Ramp	In miles from center of property to nearest interstate onramp	Continuous	1.545	1.210
Metro	In miles from center of property to nearest light-rail station	Continuous	7.190	4.696
FEMA 100	In 100 year flood zone	Dichotomous	0.016	0.125

Hedonic Results

Regression results for all three models are presented in Exhibits 5 through 7, where each model includes two estimations: (1) OLS with foreclosure counts; (2) spatial GMM with foreclosure counts. Each exhibit reports the coefficients on the foreclosure variables, λ when applicable, and selected diagnostics and control variable coefficients are summarized in the Appendix. The foreclosure variables are labeled by distance and time (i.e., *y200m06* counts all foreclosures within 200 yards and 6 months since the observed sale). Exhibit 5 includes the quadratic and Exhibit 6 includes interaction terms respectively so the quadratic and interaction coefficients are reported in the same row as the unadjusted variable.

All models tested significant for heteroscedasticity using a Breusch-Pagan test; thus all *t*-scores were adjusted for heteroscedasticity using a HC_3 type correction.[6] All models also tested significant for spatial dependence using the Lagrangian Multiplier (LM) test, where the robust LM tests favor the spatial error estimator over the spatial lag estimator. The spatial lag model, similar to an autoregressive

Exhibit 5 | Marginal Neighborhood Effect of Foreclosures on Housing Prices (Models 5 and 6)

	Model 5		Model 6					
Variable	$\beta_{t,s}$	$\beta_{t,s}B^2_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}B^2_{t,s}$	$\beta_{t,s}$*D_{0305}	$\beta_{t,s}B^2_{t,s}$*D_{0305}	$\beta_{t,s}$*D_{0607}	$\beta_{t,s}B^2_{t,s}$*D_{0305}
y200m06	−0.0192	0.0021	−0.0335	0.0051	0.0121	−0.0028	0.0244	−0.0045
	(−7.45)*	(2.94)*	(−7.58)*	(3.64)*	(1.95)	(−1.37)	(4.23)*	(−2.77)*
y200m12	−0.0177	0.0034	−0.0294	0.0063	0.0139	−0.0035	0.0168	−0.0037
	(−8.08)*	(5.62)*	(−7.01)*	(5.30)*	(2.56)*	(−2.31)*	(3.06)*	(−2.55)*
y200m18	−0.0177	0.0032	−0.0156	0.0014	−0.0072	0.0032	0.0031	0.0021
	(−7.25)*	(4.41)*	(−3.76)*	(1.11)	(−1.29)	(1.95)	(0.50)	(1.11)
y200m24	−0.0206	0.0020	−0.0189	0.0008	−0.0055	0.0028	0.0025	−0.0005
	(−8.10)*	(2.60)*	(−4.27)*	(0.58)	(−0.92)	(1.48)	(0.39)	(−0.27)
y400m06	−0.0110	0.0009	−0.0219	0.0024	0.0094	−0.0011	0.0136	−0.0020
	(−8.58)*	(4.85)*	(−8.53)*	(4.85)*	(2.97)*	(−2.05)*	(4.25)*	(−3.78)*
y400m12	−0.0115	0.0011	−0.0172	0.0021	−0.0019	−0.0016	0.0138	−0.0016
	(−6.87)*	(4.15)*	(−8.76)*	(8.00)*	(−0.91)	(−4.40)*	(4.81)*	(−2.42)*
y400m18	−0.0129	0.0012	−0.0167	0.0019	0.0051	−0.0006	0.0048	−0.0013
	(−7.06)*	(3.52)*	(−6.55)*	(4.17)*	(1.50)	(−1.10)	(1.23)	(−1.93)
y400m24	−0.0159	0.0014	−0.0164	0.0010	0.0007	0.0005	0.0023	−0.0001
	(−10.10)*	(5.16)*	(−5.15)*	(1.47)	(0.18)	(0.67)	(0.55)	(−0.09)

Exhibit 5 | (continued)

Marginal Neighborhood Effect of Foreclosures on Housing Prices (Models 5 and 6)

	Model 5		Model 6					
Variable	$\beta_{t,s}$	$\beta_{t,s}B^2_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}B^2_{t,s}$	$\beta_{t,s}{*}D_{0305}$	$\beta_{t,s}B^2_{t,s}{*}D_{0305}$	$\beta_{t,s}{*}D_{0607}$	$\beta_{t,s}B^2_{t,s}{*}D_{0305}$
y600m06	−0.0050	0.0001	−0.0217	0.0018	0.0126	−0.0012	0.0203	−0.0018
	(−1.51)	(0.17)	(−11.80)*	(7.35)*	(5.03)*	(−3.70)*	(7.79)*	(−6.32)*
y600m12	−0.0073	0.0004	−0.0157	0.0016	0.0043	−0.0008	0.0144	−0.0016
	(−4.03)*	(1.64)	(−7.55)*	(5.17)*	(1.63)	(−2.11)*	(5.14)*	(−4.43)*
y600m18	−0.0116	0.0011	−0.0156	0.0017	0.0079	−0.0009	0.0039	−0.0010
	(−8.66)*	(5.81)*	(−7.82)*	(5.75)*	(2.92)*	(−2.41)*	(1.37)	(−2.78)*
y600m24	−0.0155	0.0012	−0.0157	0.0012	0.0023	−0.0002	−0.0012	−0.0002
	(−12.23)*	(7.19)*	(−7.03)*	(3.30)*	(0.82)	(−0.49)	(−0.37)	(−0.42)
R^2	0.907		0.908					

Notes: This table provides OLS estimates of Models 5 and 6. For Model 5, k = 127; for Model 6, k = 174. Coefficients on the interaction terms are reported in the adjacent columns. The heteroscedasticity robust *z*-statistics are in parentheses. *N* = 98,828.

*Statistically significant at the 5% level.

Exhibit 6 | Marginal Neighborhood Effect of Foreclosures on Housing Prices (Models 7 and 8)

Variable	Model 7 $\beta_{t,s}$	Model 7 $\beta_{t,s}B^2_{t,s}$	Model 8 $\beta_{t,s}$	Model 8 $\beta_{t,s}B^2_{t,s}$	Model 8 $\beta_{t,s}{}^{*}D_{0305}$	Model 8 $\beta_{t,s}B^2_{t,s}{}^{*}D_{0305}$	Model 8 $\beta_{t,s}{}^{*}D_{0607}$	Model 8 $\beta_{t,s}B^2_{t,s}{}^{*}D_{0305}$
y200m06	−0.0070	0.0004	−0.0139	0.0023	0.0018	−0.0017	0.0144	−0.0029
	(−4.98)*	(1.22)	(−4.55)*	(2.54)*	(0.46)	(−1.53)	(3.73)*	(−2.99)*
y200m12	−0.0062	0.0016	−0.0172	0.0043	0.0153	−0.0043	0.0137	−0.0031
	(−3.87)*	(3.91)*	(−5.92)*	(5.61)*	(3.88)*	(−4.10)*	(3.36)*	(−3.11)*
y200m18	−0.0059	0.0015	−0.0059	0.0007	−0.0036	0.0013	0.0029	0.0013
	(−3.27)*	(3.04)*	(−1.93)	(0.81)	(−0.87)	(1.12)	(0.64)	(1.02)
y200m24	−0.0035	−0.0004	−0.0027	−0.0006	−0.0035	0.0014	−0.0017	−0.0008
	(−1.92)	(−0.72)	(−0.84)	(−0.69)	(−0.81)	(1.15)	(−0.37)	(−0.59)
y400m06	−0.0036	0.0001	−0.0091	0.0009	0.0027	−0.0005	0.0074	−0.0011
	(−4.12)*	(1.08)	(−5.02)*	(2.90)*	(1.17)	(−1.36)	(3.18)*	(−3.25)*
y400m12	−0.0048	0.0006	−0.0067	0.0011	−0.0028	−0.0007	0.0048	−0.0007
	(−5.16)*	(5.00)*	(−4.80)*	(5.74)*	(−2.02)*	(−2.97)*	(2.25)*	(−2.01)*
y400m18	−0.0047	0.0003	−0.0085	0.0010	0.0053	−0.0008	0.0028	−0.0007
	(−4.47)*	(2.09)*	(−4.67)*	(3.24)*	(2.15)*	(−2.04)*	(1.07)	(−1.72)
y400m24	−0.0159	0.0014	−0.0164	0.0010	0.0007	0.0005	0.0023	−0.0001
	(−10.10)*	(5.16)*	(−5.15)*	(1.47)	(0.18)	(0.67)	(0.55)	(−0.09)

Exhibit 6 | (continued)

Marginal Neighborhood Effect of Foreclosures on Housing Prices (Models 7 and 8)

	Model 7		Model 8					
Variable	$\beta_{t,s}$	$\beta_{t,s}B^2_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}B^2_{t,s}$	$\beta_{t,s}$*D_{0305}	$\beta_{t,s}B^2_{t,s}$*D_{0305}	$\beta_{t,s}$*D_{0607}	$\beta_{t,s}B^2_{t,s}$*D_{0305}
y600m06	−0.0050	0.0001	−0.0217	0.0018	0.0126	−0.0012	0.0203	−0.0018
	(−1.51)	(0.17)	(−11.80)*	(7.35)*	(5.03)*	(−3.70)*	(7.79)*	(−6.32)*
y600m12	−0.0073	0.0004	−0.0157	0.0016	0.0043	−0.0008	0.0144	−0.0016
	(−4.03)*	(1.64)	(−7.55)*	(5.17)*	(1.63)	(−2.11)*	(5.14)*	(−4.43)*
y600m18	−0.0116	0.0011	−0.0156	0.0017	0.0079	−0.0009	0.0039	−0.0010
	(−8.66)*	(5.81)*	(−7.82)*	(5.75)*	(2.92)*	(−2.41)*	(1.37)	(−2.78)*
y600m24	−0.0155	0.0012	−0.0157	0.0012	0.0023	−0.0002	−0.0012	−0.0002
	(−12.23)*	(7.19)*	(−7.03)*	(3.30)*	(0.82)	(−0.49)	(−0.37)	(−0.42)
λ	0.6573		0.6522					
R^2	0.939		0.939					

Notes: This table provides GMM estimates of Models 7 and 9. The GMM procedure was used to control for spatial autocorrelation with autocorrelation parameter λ and 10 nearest-neighbors spatial weight (Kelejian and Prucha, 1999). Coefficients on the interaction terms are reported in the adjacent columns. For Model 7, k = 128; for Model 9, k = 173. *N* = 98,828.

*Statistically significant at the 5% level.

Exhibit 7 | Comparison of Implied Marginal Neighboring Foreclosure Impact on Sales Price (OLS)

	Distance	2000	2003	2006
Immergluck and Smith (2006b)	220 Yards	−0.9%		
Lin, Rosenblatt, and Yao (2009)	100 & 200 Meters		−5.0%, −4.8%	−8.7%, −4.7%
Rogers and Winter	200 Yards	−1.4%	−1.4%	−0.6%

Notes: Table presents the implied price impacts of a neighboring foreclosure within the reported distance and two years time. For comparison purposes, only the OLS models are reported. Lin, Rosenblatt, and Yao's (2009) results are reported based on visual inspection of their Figure 8.

parameter in time series, includes the weighted average of neighboring sales prices as an alternative to the spatial error model. The spatial lag estimator was still run for all models using spatial two-stage least squares (Anselin, 1988), but the results were quite similar to OLS and thus were not reported.

As expected, all estimations of all models report economically and statically significant negative neighborhood impacts of single-family foreclosures on single-family sale prices. The Appendix summarizes the model control variables. Beyond the expected negative impacts, we believe there are three points worth highlighting. First, the marginal neighborhood foreclosure impact is about 1% or less, depending on the spatial-temporal distance and estimator used. Our results are similar to Immergluck and Smith (2006a) but far less than Lin, Rosenblatt, and Yao's (2009) results. Second, again in contrast to Lin, Rosenblatt, and Yao, the marginal neighborhood foreclosure impact is the greatest in the relatively stable years of 2000 through 2002. Finally, our quadratic model demonstrates that the marginal neighborhood foreclosure impact is non-linear.

Marginal Neighborhood Foreclosure Impact

Model 1 in Exhibit 8 reports the marginal foreclosure impact on neighboring sales prices. All coefficients are negative and significant. Furthermore, as expected, for any given time frame (*m*), foreclosures have a larger negative impact when closer: the coefficients on the 200 yard rings are more negative than their corresponding coefficients on the 400 and 600 yard rings.

Our OLS estimates in Model 1 are quite similar to Immergluck and Smith's (2006a,b). Immergluck and Smith used one year of Chicago sales data (1999) and two years of foreclosure counts[7] (1997, 1998) to estimate the foreclosure impact using independent spatial rings of 1/8 mile and 1/4 mile, which would be approximately equivalent to Model 1 if the *y200s* and *y400s* were each combined

Exhibit 8 | Marginal Neighborhood Effect of Foreclosures on Housing Prices (Models 1–4)

	OLS				GMM			
	Model 1	Model 2			Model 3	Model 4		
Variable	$\beta_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}{}^{*}D_{0305}$	$\beta_{t,s}{}^{*}D_{0607}$	$\beta_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}{}^{*}D_{0305}$	$\beta_{t,s}{}^{*}D_{0607}$
y200m06	−0.0114	−0.0196	0.0040	0.0137	−0.0055	−0.0078	−0.0026	0.0053
	(−8.75)*	(−7.90)*	(1.23)	(4.24)*	(−6.28)*	(−4.80)*	(−1.23)	(2.44)*
y200m12	−0.0061	−0.0091	0.0022	0.0073	−0.0007	−0.0034	0.0018	0.0051
	(−4.35)*	(−3.51)*	(0.66)	(2.01)*	(−0.71)	(−2.13)*	(0.84)	(2.12)*
y200m18	−0.0083	−0.0111	0.0025	0.0094	−0.0013	−0.0036	0.0003	0.0070
	(−5.56)*	(−4.22)*	(0.72)	(2.50)*	(−1.24)	(−2.08)*	(0.13)	(2.70)*
y200m24	−0.0144	−0.0166	0.0044	0.0017	−0.0043	−0.0044	0.0009	−0.0038
	(−9.20)*	(−6.06)*	(1.21)	(0.43)	(−4.17)*	(−2.56)*	(0.38)	(−1.45)
y400m06	−0.0042	−0.0106	0.0054	0.0062	−0.0025	−0.0051	0.0010	0.0021
	(−5.40)*	(−7.06)*	(2.80)*	(3.12)*	(−4.54)*	(−5.07)*	(0.76)	(1.52)
y400m12	−0.0030	−0.0057	−0.0001	0.0083	−0.0006	−0.0011	−0.0019	0.0021
	(−3.35)*	(−3.56)*	(−0.03)	(3.80)*	(−1.10)	(−1.05)	(−1.35)	(1.42)
y400m18	−0.0060	−0.0063	0.0026	−0.0006	−0.0024	−0.0033	0.0016	−0.0003
	(−6.46)*	(−3.77)*	(1.21)	(−0.24)	(−3.92)*	(−3.09)*	(1.12)	(−0.17)
y400m24	−0.0080	−0.0117	0.0060	0.0028	−0.0037	−0.0061	0.0035	0.0006
	(−8.41)*	(−6.78)*	(2.65)*	(1.14)	(−5.82)*	(−5.63)*	(2.41)*	(0.36)

Exhibit 8 | (continued)

Marginal Neighborhood Effect of Foreclosures on Housing Prices (Models 1–4)

	OLS				GMM			
	Model 1	Model 2			Model 3	Model 4		
Variable	$\beta_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}$*D_{0305}	$\beta_{t,s}$*D_{0607}	$\beta_{t,s}$	$\beta_{t,s}$	$\beta_{t,s}$*D_{0305}	$\beta_{t,s}$*D_{0607}
y600m06	−0.0037	−0.0101	0.0046	0.0085	−0.0014	−0.0058	0.0030	0.0057
	(−6.25)*	(−8.36)*	(2.97)*	(5.50)*	(−3.42)*	(−7.34)*	(2.91)*	(5.46)*
y600m12	−0.0031	−0.0052	−0.0002	0.0057	−0.0016	−0.0025	−0.0006	0.0016
	(−4.41)*	(−3.96)*	(−0.14)	(3.18)*	(−3.40)*	(−2.92)*	(−0.54)	(1.32)
y600m18	−0.0047	−0.0056	0.0036	−0.0006	−0.0015	−0.0033	0.0034	0.0005
	(−6.19)*	(−4.10)*	(2.02)*	(−0.33)	(−2.89)*	(−3.81)*	(2.96)*	(0.40)
y600m24	−0.0077	−0.0085	0.0029	−0.0023	−0.0032	−0.0047	0.0022	−0.0003
	(−10.25)*	(−6.32)*	(1.63)	(−1.24)	(−6.22)*	(−5.37)*	(1.84)	(−0.25)
λ					0.6582	0.6580		
R^2	0.906	0.906			0.939	0.939		

Notes: Coefficients on the interaction terms are reported in the adjacent columns. The GMM procedure was used to control for spatial autocorrelation with autocorrelation parameter λ and 10 nearest-neighbors spatial weight (Kelejian and Prucha, 1999). For OLS, the heteroscedasticity robust z-statistics are in parentheses, GMM estimates report also asymptotic z-statistics. For Model 1, k = 115; for Model 2, k = 139; for Model 3, k = 116; for Model 4, k = 140. *N* = 98,828.

*Statistically significant at the 5% level.

and the *y600s* dropped. Immergluck and Smith found a marginal impact of −0.0114 and −0.0033 for their respective rings; however, when they added the median block group of self-reported single-family house values from the 2000 Census, the marginal impact fell to −0.0091 for the 1/8 mile ring and insignificant for the 1/4 mile ring. For example, assume a foreclosure has happened within the last six months and 200 yards. Model 1 implies a decline of 1.1% or about $2,200 off the sales price of an otherwise $200,000 unit, while Immergluck and Smith's estimates imply the same decline.

By contrast, our Model 1 estimates suggest a much smaller foreclosure impact compared to Lin, Rosenblatt, and Yao (2009). Lin, Rosenblatt and Yao also use Chicago sales (2006) and foreclosure data (1996 through 2006) and employ a similar hedonic model. They estimate a marginal foreclosure impact of about 8.7% for foreclosures within 100 meters and two years and about 4.7% within 200 meters and two years. For the same neighboring $200,000 housing unit as described above, a single foreclosure would lower the sales value by about $7,400 to $17,400 depending on the exact distance.

The GMM estimates reported as Model 3 in Exhibit 8 suggest that foreclosures have a smaller impact than the OLS results suggest by about half. All coefficients are still negative but three are not statistically significant at the 5% level, which suggest that the standard errors in the OLS models are biased downward (Bell and Bockstael, 2000).

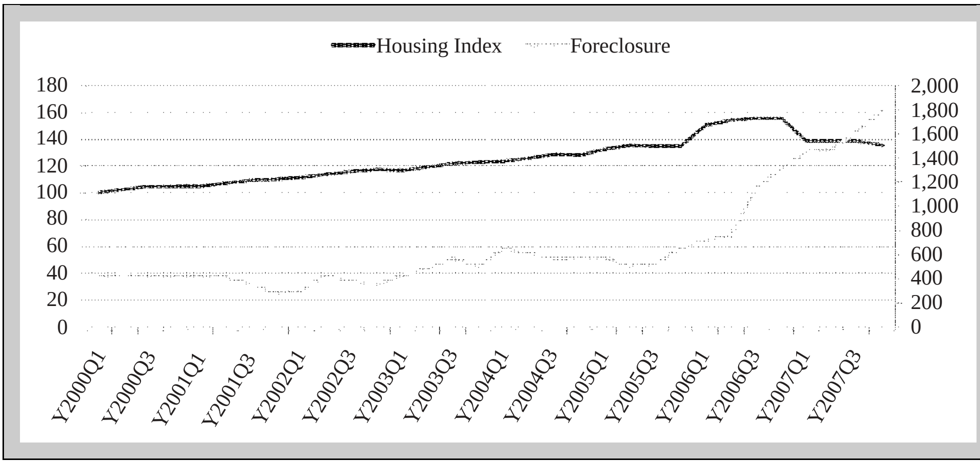
It is not clear why our results are similar to Immergluck and Smith but much smaller compared to Lin/Rosenblatt/Yao. All three studies employ a similar hedonic model and report at least one OLS estimation. Immergluck and Smith and Lin, Rosenblatt and Yao use the Chicago housing market but different periods, while we use the St. Louis housing market and a period that overlaps both of the above studies.

Temporal Interactions

Lin, Rosenblatt, and Yao (2009) argue that the marginal foreclosure impact should be larger in ''bad'' markets therefore they estimate a model using sales data from 2003 and compare the results to the 2006 sample. They find a larger marginal foreclosure impact for foreclosures within two years and 100 meters in 2006 but a negligible difference among all other foreclosure rings.

Model 2 (OLS) and Model 4 (GMM), in Exhibit 8, test the foreclosure coefficients for a structural change over two time periods: 2003–2005 and 2006–2007. To provide a sense of the housing market dynamics in St. Louis County, Exhibit 9 charts the number of foreclosures by quarter and the housing index produced by Model 1. The foreclosure count was fairly stable from 2000 through 2002. From 2003 through 2005 foreclosures began to rise and in 2006 and 2007 rose dramatically. Thus, the foreclosure rings were interacted with temporal dummy

Exhibit 9 | St. Louis County Housing Price Index and Foreclosures by Quarter



variables such that the ring coefficients are now $\beta_{t,s}B_{t,s} + \beta_{t,s}B_{t,s}{*}D_{0305} + \beta_{t,s}B_{t,s}{*}D_{0607}$.

The OLS and GMM results still suggest a negative marginal foreclosure impact but the marginal impact is smaller in 2006 and 2007. All coefficients in column $\beta_{t,s}B_{t,s}$ of Model 2 in Exhibit 8 are negative and significant at the 5% level. Not all coefficients in the interaction columns ($\beta_{t,s}B_{t,s}{*}D_{0305}$ and $\beta_{t,s}B_{t,s}{*}D_{0607}$) are positive but all the significant coefficients are positive, which suggests that the marginal impact has declined. Furthermore, all significant coefficients in column $\beta_{t,s}B_{t,s}{*}D_{0607}$ of Model 2 (7 of 12) nearly offset the coefficients in column $\beta_{t,s}B_{t,s}$. Thus, Model 2 suggests that the marginal foreclosure impact from 2000 through 2005 was between about 0.5% and 2% depending on the spatial-temporal distance but the marginal foreclosure impact from 2006 through 2007 was negligible. This result is echoed in Model 4, although Model 4 has fewer significant coefficients.

Model 2 allows for a complete temporal comparison of our OLS results to Immergluck and Smith (2006a,b) and Lin, Rosenblatt, and Yao (2009). Assuming a foreclosure has happened within the last six months and 200 yards, Model 2 implies a decline of almost 2% in the years 2000 through 2005 or about $4,000 off the sales price of an otherwise $200,000 unit, while Immergluck and Smith's estimates a decline of about $2,200 in the year 2000 (using 2007 prices via the CPI). Lin, Rosenblatt, and Yao's results imply a decline of about $10,000 in the year 2003 and about $7,400 to $17,400 in 2006 depending on the exact distance, while our results imply a decline of about 0.6% or $1,200 in 2006 and 2007.

Quadratic Form

The final implication of this study is that foreclosures, at least in the St. Louis County market, have a diminishing marginal impact within a given time period.

To test this, Models 1–4 were re-estimated with a quadratic term to create Models 5–8. The quadratic term allows the marginal foreclosure impact to change based on the level of foreclosures; thus the quadratic term differentiates the high-foreclosure neighborhoods from the low-foreclosure neighborhoods.

Exhibit 5 presents the OLS estimates for Models 5 and 6. The quadratic coefficients in Model 5 imply a diminishing marginal impact of foreclosures. It should be noted that not all coefficients are statistically significant at the 5% level; of the 12 pairs, 10 are significant. This result is somewhat surprising because it suggests that neighborhoods are self-stabilizing, at least with respect to foreclosures, which is in contrast to the scenario of neighborhood tipping points.

Model 6, in Exhibit 5, introduce the temporal structural tests. As in Model 5, all $\beta_{t,s}$s are negative and all $\beta_{t,s}B^2_{t,s}$s are positive. Roughly half of the temporal interactions are significant at the 5% level but those that are tell the same story: the marginal foreclosure impact is flatter in the later years especially from 2006 through 2007.

Exhibit 6 presents the GMM estimates in Models 7 and 8. Although there are generally fewer statistically significant results, the pattern in the same as in Exhibit 5. Foreclosures in St. Louis County have a negative but diminishing marginal impact on neighboring house sale prices.

In the context of the literature of foreclosure spillovers, Models 5–8 are unique and consequently should be tested by an examination of other markets. Obviously, the finding could be a result of the subject market, along with a stable but older urban market and time period and the beginning and initial impact of a national credit and housing crisis. In other words, because the rise of foreclosures is a fairly recent phenomenon and one would expect that a full effect would take a number of years, it may be that this analysis is too early to capture the marginal effects of foreclosures in St. Louis County. On the other hand, the structural tests suggest that neighborhood foreclosure impacts are moving in the direction of insignificance.

Conclusion

The conventional view among many policy analysts has been that the rising tide of foreclosures will cause deep declines in the sales values of neighboring properties, extending the housing crisis into local fiscal policy. This analysis provides a more robust specification of the foreclosure impact than past studies, including specifying a hedonic price model that corrects for spatial error and selection bias and has a robust set of neighborhood controls. In doing so, however, the analysis suggests that the impact may be much smaller and more local than previously thought in both spatial and temporal terms. Most significantly, our findings suggest that there does not appear to be a tipping point where at some threshold the neighborhood sales decline rapidly. In fact, the marginal impact of foreclosures seems to decline with an increase in the number of foreclosures, suggesting that at some point neighborhoods are self-stabilizing; although, we are unable to control for causality.

Our analysis points out the importance of replicated studies at different time points and within different markets. Some of the variance in results presented here, as opposed to past studies of foreclosure effects, could be due to the models employed or due to the different housing markets at different points in time. For example, our Model 1 (OLS) results are similar to Immergluck and Smith (2006b): the marginal foreclosure impact is about 1% of the sales price when the foreclosure is within 200 yards (roughly 1/8 of a mile). However, our Model 2 (OLS) estimates are far smaller and in contrast to Lin, Rosenblatt and Yao's (2009) estimates: we estimate the marginal foreclosure impact to be smaller in bad markets (2006 and 2007). Exhibit 7 compares our 200 yard OLS results from Model 2 to Immergluck and Smith and Lin, Rosenblatt, and Yao. Since both previous studies counted all foreclosures within two years, Exhibit 7 reports the weighted average of all four 200 yard coefficients from Model 2.

The regression results point to a declining marginal neighboring-foreclosure effect both in cross-section and over time; however, due to data limitations, we were unable to explore the reasons for the decline. That is, we only measure the quantity of distressed properties and not other qualitative effects of the foreclosure process.[8] This declining impact could be a function of the characteristics of the deed prior to the default, the characteristics of the property after foreclosure or the changing characteristics of local actors within submarkets in the region. Full exploration of a neighborhood foreclosure effect, then, would require data on the property owner's finances, detailed description of the properties condition, and vacancy status—data that is all unavailable at this time. Without such data, we can only speculate about the specific mechanism connecting a foreclosed property to a neighboring sale.

These results could be limited to housing markets that are relatively stable: St. Louis County experienced a relatively small housing boom and bust. The relative stability could allow for a more efficient market clearing process of foreclosures. On the other hand, the increased experience market participants have had with foreclosures may have improved their skill. The market, in St. Louis County or even nationally, is now dealing with the foreclosure process better, which may lead to better pricing and/or less capital deterioration.

Appendix

Remaining Regression Results

	OLS	OLS	GMM	GMM	OLS	OLS	GMM	GMM
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
FEMA 100	−0.0928	−0.0935	−0.0462	−0.0466	−0.0926	−0.0932	−0.0466	−0.0470
	(−15.20)	(−15.31)	(−8.94)	(−9.04)	(−15.32)	(−15.45)	(−9.03)	(−9.12)
Age	−0.0121	−0.0120	−0.0140	−0.0139	−0.0121	−0.0120	−0.0140	−0.0138
	(−61.73)	(−61.55)	(−105.31)	(−104.36)	(−61.36)	(−61.15)	(−105.37)	(−104.20)
Age^2	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(36.19)	(36.03)	(79.93)	(79.05)	(36.10)	(35.87)	(79.99)	(78.85)
Log(*Area*)	0.1343	0.1339	0.1332	0.1327	0.1317	0.1316	0.1329	0.1326
	(71.71)	(71.57)	(79.08)	(78.89)	(70.19)	(70.41)	(79.00)	(78.96)
Log(*Living*)	0.4291	0.4238	0.3058	0.3040	0.4272	0.4203	0.3070	0.3040
	(113.60)	(112.18)	(112.08)	(111.02)	(113.75)	(111.64)	(112.48)	(110.81)
Log(*Stories*)	0.0587	0.0562	0.0372	0.0367	0.0557	0.0541	0.0374	0.0368
	(13.78)	(13.28)	(11.73)	(11.58)	(13.19)	(12.87)	(11.78)	(11.63)
Log(*Bedrooms*)	0.0493	0.0503	0.0771	0.0776	0.0488	0.0502	0.0768	0.0776
	(11.92)	(12.20)	(27.08)	(27.27)	(11.86)	(12.26)	(26.96)	(27.25)
Log(*Bathrooms*)	0.1585	0.1603	0.1209	0.1216	0.1568	0.1585	0.1210	0.1220
	(55.62)	(56.49)	(53.47)	(53.81)	(55.38)	(56.20)	(53.48)	(53.98)

Appendix (continued)

Remaining Regression Results

	OLS	OLS	GMM	GMM	OLS	OLS	GMM	GMM
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
HalfBath	0.0693	0.0693	0.0463	0.0464	0.0686	0.0686	0.0463	0.0465
	(43.52)	(43.75)	(36.81)	(36.93)	(43.36)	(43.63)	(36.82)	(37.02)
AC	0.1029	0.0980	0.0695	0.0684	0.1010	0.0972	0.0695	0.0683
	(25.01)	(23.86)	(29.46)	(29.00)	(24.79)	(23.96)	(29.41)	(28.90)
Chimney	0.0772	0.0769	0.0589	0.0589	0.0766	0.0765	0.0590	0.0589
	(43.58)	(43.62)	(40.68)	(40.67)	(43.42)	(43.59)	(40.71)	(40.74)
Pool	0.0963	0.0973	0.0785	0.0787	0.0964	0.0973	0.0786	0.0789
	(27.80)	(28.09)	(31.22)	(31.33)	(27.81)	(28.06)	(31.24)	(31.41)
Tennis	0.1651	0.1691	0.1442	0.1456	0.1680	0.1725	0.1443	0.1463
	(4.22)	(4.37)	(7.73)	(7.82)	(4.34)	(4.51)	(7.73)	(7.85)
Log(*Metro*)	−0.0050	−0.0138	0.0104	0.0044	−0.0064	−0.0146	0.0100	0.0024
	(−2.02)	(−5.60)	(5.00)	(2.08)	(−2.61)	(−5.97)	(4.79)	(1.12)
Log(*Ramp*)	−0.0099	−0.0085	−0.0074	−0.0063	−0.0078	−0.0062	−0.0069	−0.0055
	(−8.76)	(−7.55)	(−3.16)	(−2.68)	(−6.84)	(−5.53)	(−2.95)	(−2.38)
Log(*ArtRoad*)	0.0049	0.0052	0.0111	0.0113	0.0051	0.0052	0.0110	0.0111
	(7.46)	(7.89)	(10.87)	(11.05)	(7.76)	(7.92)	(10.83)	(11.00)

Appendix (continued)

Remaining Regression Results

	OLS	OLS	GMM	GMM	OLS	OLS	GMM	GMM
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
λ			0.6582	0.6580			0.6573	0.6522
R^2	0.906	0.906	0.939	0.939	0.907	0.908	0.939	0.939
k	115	139	116	140	127	174	128	173

Notes: $N = 98{,}828.9$. This table reports the remaining results of the hedonic estimations from all models except dummy variables controlling for data of sale (by quarter), ZIP Code, and house style (as determined by the St. Louis County Assessor) but were included in the estimation. All coefficients are significant at the 5% level except for Log(*NrMetro)* in Model 8. The GMM procedure was used to control for spatial autocorrelation with autocorrelation parameter λ and 10 nearest-neighbors spatial weight (Kelejian and Prucha, 1999). For OLS, the heteroscedasticity robust z-statistics are in parentheses; GMM estimates report also asymptotic z-statistics. The following variables were included but not reported: dummy variables controlling for data of sale (by quarter), ZIP Code, and house style (as determined by the St. Louis County Assessor).

Endnotes

[1] We do not have the appropriate data to measure vacancies, maintenance, or crime. We leave this to future study.

[2] Alternative weights of 5 and 15 nearest neighbors were also tested using a Lagrangian Multiplier test (Anselin, 1988) but use of other weights did not change the results in any significant way.

[3] See LaCour-Little (2004) for a recent mortgage default literature review.

[4] See Dye and McMillen (2007) for a recent implementation of the Heckman procedure with respect to a housing model.

[5] The St. Louis County Assessor's office excludes from arms-length housing sales all foreclosures, liquidations, transfers, and ''quit-claim'' deeds. According to the County Assessor's offices, the foreclosure category includes all foreclosures and liquidations but not estate sales and other sales with unusual amounts of personal property.

[6] See Long and Ervin (2000) for details.

[7] Immergluck and Smith (2006a) differentiate foreclosures by type of loan (conventional single-family, government-backed, and commercial/multi-family). They found the marginal impact of foreclosures to differ depending on the type of mortgage defaulted on. Commercial/multi-family produced the greatest marginal impact followed by conventional, while government-backed foreclosures had no significant impact. We do not have data on the type of loan homeowners possess, and so consequently cannot verify this aspect of their findings.

[8] We thank an anonymous reviewer for making this point.

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