The Neighborhood Effects of Foreclosure

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Abstract

Neighborhood quality is an important attribute of housing yet its value is rarely known to researchers. We argue that changes in nearby foreclosures reveal changes in neighborhood quality. Thus estimates of the hedonic price of nearby foreclosures provide a glimpse of values that people hold for local neighborhood quality. The empirical models include controls for both spatial dependence in housing prices and in the errors. The estimates indicate that nearby foreclosures produce externalities that are capitalized into home prices-- an additional foreclosure within 250 feet of a sale negatively impacts selling price by approximately $1,666, *ceteris paribus*.

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1. *Introduction*

"Neighborhood quality" is a local public good that impacts housing values. Houses in "good" neighborhoods command higher sale prices than those in "bad" neighborhoods and neighborhoods in decline often exhibit similar signs of low neighborhood quality; e.g., poorly maintained properties and higher foreclosure rates. In contrast to other housing characteristics such as the square feet of living area or the average test scores at the nearest elementary school however, the value of a home's neighborhood quality is not readily observed. Thus, there is little quantitative information on the relative magnitude of neighborhood quality on home values. The purpose of this paper is to use the theoretical link between foreclosure events and neighborhood quality to specify a hedonic model that reveals the full price impacts of foreclosures on a particular housing market. Our goal is to control for price trends over time and space in order to specifically (through the estimation of foreclosure price impacts) identify the potential loss in home values, a non-pecuniary externality, due to reductions in the supply of neighborhood quality.

By finding a significant monetary impact of foreclosure events on neighborhood home values, even after controlling for local prevailing trends in home prices, we provide rational for a closer inspection of the role of foreclosure on neighborhood quality. By reducing neighborhood quality, foreclosure events might have real, long-term impacts on neighborhoods. Furthermore, reductions in neighborhood quality-- a local public good-- suggest that the social willingness-to-pay for prevention measures that is greater than the private costs incurred by individuals during foreclosure. Thus, there may be efficiency reasons for public policy aimed at reducing foreclosures and for preserving neighborhood quality in the face of foreclosures, perhaps by attacking the degradation of neighborhood quality directly.

We define neighborhood quality as a public good that is produced by neighbors who enhance (or fail to enhance) their lawns, trim their trees (or fail to trim them), maintain their structures (or do not maintain them), etc. These behaviors by people living in close proximity to each other generate spillover costs and benefits to their neighbors. The impact of neighborhood quality and the set of contributors are bounded spatially. However, these spatial boundaries are not necessarily equal. For instance, a property owner who lives a quarter mile from my house may contribute to the neighborhood quality at my house, but that same distant property owner may also contribute to the neighborhood quality of even more distant places that have no effect on me. In other words, each house has, potentially, a different neighborhood definition--its definition ``slides" as different houses are examined (Dubin, 1992 and Paez, Long and Farber, 2008). Usually, very local public goods, such as neighborhood quality, are unobserved and provide a rationale for specifying models with spatially dependent errors or prices to control for unobserved differing provision levels (Can, 1992). However, this does not allow for any measurement of the value of these local public goods.

Rosen (1974) provides a logical framework for using urban housing markets to reveal estimates of the marginal value (hedonic price) of traditionally un-priced goods like local neighborhood quality. However, if the hedonic approach is going to work, there must be some variation in the level of provision and, of course, there must be a way to measure that level. Our behavioral model suggests that foreclosures stifle incentives to contribute to neighborhood quality and, therefore, cause changes in neighborhood quality; hence, the neighborhood cost of foreclosure may be attributed to the cost associated with decreased neighborhood quality. We create geographies for local neighborhoods by using distances of 250, 500, 1000 and 1500 feet from the parcel of interest. This approach facilitates a definition for sliding neighborhoods as well as tests of the spatial reach of foreclosure externalities.

The remainder of this paper is divided into five sections. Section 2 reviews the literature on the effects of foreclosure. Section 3 presents a theoretical model whereby individual incentives for investing in neighborhood quality are explicitly defined. Section 4 describes the data, while Section 5 describes the estimations and empirical results. Finally, section 6 contains concluding remarks.

2. Foreclosure Studies and Policy

Homeownership is an issue of increasing importance across the United States. Affordability products[2] paired with an emergence of more customized mortgage pricing[3] increased

[2] "Affordability" products include subprime loans or mortgages with interest only and payment option features.

[3] According to the literature review in Edelberg (2003), in 1995 bank regulators implemented more stringent measures of CRA (Community Reinvestment Act) compliance that motivated the development of technology to facilitate lending in high-risk neighborhoods. This motivation along with decreasing costs of information storage and computing power resulted in innovations in credit pricing.

homeownership rates in the US beginning in approximately 1995 (US Census Bureau, 2007). In 2006, the number of US households with housing costs accounting for greater than 30% of income reached a historic high of 37.3 million households (Joint Center for Housing Studies of Harvard University, 2007), indicating that with the increases in homeownership came increasing rates of potential default. In fact, foreclosure rates climbed beginning in early 2005 (Gaines, 2007).

The costs associated with foreclosures include costs to the individual in default, the institution holding the failed mortgage, and any negative externalities in the neighborhood of the foreclosed property. The impact of foreclosures on the individual or institution holding the failed mortgage has been studied (see Capone, 2001 and Kau and Keenan, 1995 for a review of mortgage modeling); but the neighborhood externalities of foreclosures have not been fully explored. These negative externalities represent a societal cost of foreclosures that, if not fully assessed, may be ignored by policy makers. Additionally, to the extent that foreclosure is a result of an optimal exercise of the default option, one foreclosure may trigger additional foreclosures because neighborhood externalities lower the put-option value of other properties in the neighborhood.

Foreclosure is the result of a process that lasts at least 60 days and most often significantly longer. When the homeowner fails to pay their mortgage for more than 60 days the property is considered to be in default. Once default status is triggered, the holder of the failed mortgage may act to foreclose on the property. In Texas (the location for our study), there are two methods for foreclosing on a property: judicial and non-judicial. A judicial foreclosure must be enacted when no power of sale is explicitly stated in the mortgage document. In this case, the mortgage holder must file a lawsuit and obtain court approval to foreclose on the property. The property may then be put up for auction. A non-judicial foreclosure is allowed when the power of sale is included in the mortgage document and unless otherwise stated involves the property owner being given a 20 day grace period to get current on their mortgage payments and an additional 20 day notice before the foreclosed property is auctioned (United States Foreclosure Law, 2007). Given the events that must occur between the time a homeowner stops making mortgage payments and the foreclosed home is repurchased by a new owner, there is a considerable length of time during which the condition of the property is likely to deteriorate.

Immergluck and Smith (2005) measured the effects of foreclosures 1 to 2 years after they occurred and found that a foreclosure causes a 0.9 percent decline in house value for all homes within an eighth of a mile radius. Additionally, Cotterman (2001) found that a one percentage point increase in the default rate[4] leads to an estimated 14 percent reduction in home prices within a census tract. However, neither of these studies was able to explore both the time and spatial dimensions of the impact of foreclosures. It is unknown whether Immergluck and Smith's result would have been higher if the effect were measured immediately after the foreclosure or if the default rate examined by Cotterman has more pronounced effects at the parcel rather than census tract level.

Lin et al (2008) improve on the previous analysis by estimating the effects of foreclosure over a five-year time range and at varying distances from the foreclosed property. They find that the largest effect of foreclosure reduces sale prices by 8.7% for closely neighboring properties and that the effect lasts for up to 5 years after the foreclosure. However, Lin et al (2008) do not distinguish between the direct effects of foreclosure and those effects that are propagated due to spatially dependent home prices. Due to neighborhood sorting, spatially dependent home prices, and the endogenous relationship between these and factors which influence default decisions, there remains uncertainty about the mechanics of neighborhood effects and whether they are directly a result of foreclosure due to some real change in home values, or a result of a spatial process whereby a depressed sale price of a foreclosed property artificially lowers neighboring sale prices.

We improve upon these previous studies in three ways. First, our data includes contemporaneous foreclosure and home sales so that the immediate (and arguably largest) foreclosure effect can be estimated. Second, the empirical models we estimate recognize the spatial correlation in the data providing some reassurance that any estimated foreclosure impact is not inflated by extraneous correlation between foreclosure and other spatially dependent processes. Finally, we motivate our empirical analysis with a model that suggests a mechanism through which foreclosure should impact home prices. This model drives our decision to analyze the effect of properties in any stage of the foreclosure process rather than the sale of

[4] Default occurs when a borrower fails to make his/her mortgage payment. Not all defaults result in foreclosure, but all foreclosures necessarily began as a borrower default.

foreclosed properties because we believe that it is the foreclosure process (e.g. the period of time between default and sale of the foreclosed property) which produces the market failure whereby neighborhood quality is neglected.

3. *Theoretical Motivation*

The neighborhood impact of foreclosures may result from changes in contributions to the local public good--neighborhood quality. Consider individual i with utility defined by

$$U^i = U^i(x_i, z_i, N_i) \tag{1}$$

where denotes non-house consumption, z_i denotes a vector of housing attributes and N_i denotes the neighborhood quality for i's neighborhood. The individual's contribution to N_i is n_i; however, n_i is also considered to be a characteristic of the property and is a component of z_i. Thus, it has both direct and indirect benefits--direct because of the intrinsic benefits associated with a well-maintained home (e.g., enjoyment of a nicely maintained lawn) and indirect through its contribution to the public good.

Let

$$y_i + A(z_i, N_i) = x_i + c(n_i) + p(z_i, N_i) + S_i \tag{2}$$

be individual i's budget constraint where y_i is total income, the price of x_i is normalized to 1, and the cost of neighborhood quality contributions is given by the function $c(n_i)$. In this model, $p(z_i, N_i)$ represents the annualized cost of the purchase price of the home.[5] $A(z_i, N_i)$, on the other hand, is annual appreciation and therefore acts as income in the budget constraint. Note that appreciation may be zero, positive or negative depending on the current conditions. For a renter, this term is zero.

Maximizing (1) subject to (2) gives

$$dc / n_i - (\partial A^i / \partial N_i)(\partial N_i / \partial n_i) - \partial A^i / \partial n_i = MRS_{n_i x_i} + MRS_{N_i x_i} \partial N_i / \partial n_i . \tag{3}$$

[5] In this static model, the purchase price does not change.

In (3), the right hand side is the marginal valuation of n_i, while the left hand side is the net marginal cost. The model provides two motivations for why a homeowner in default and eventually foreclosure will decrease his/her contributions to neighborhood quality. First, for the case of an individual who is defaulting on their mortgage loan, the budget constraint is broken. Default means $y_i + A^i(n_i, N_j) < x_i + c(n_i) + p(z_i, N_i)$. Individuals must take steps to satisfy the budget constraint, eliminating any avoidable costs such as $c(n_i)$. Second, when foreclosure is unavoidable, the owner knows that appreciation will be lost; hence, there is no motivation to provide n_i, so (3) becomes

$$dc / dn_i = MRS_{n_i x_i} + MRS_{N_i x_i} \partial N_i / \partial n_i. \tag{4}$$

Note, that for the same cost function and preferences, diminishing MRS implies that optimally chosen n_i is greater in (3) than in (4).[6]

These results are important for motivating our empirical analysis. They suggest that foreclosures should impact neighborhood home prices due to a real change in the neighborhood through lower neighborhood quality contributions. These decreased neighborhood quality contributions occur as soon as a homeowner has difficulty meeting his/her budget constraint and they receive further motivation when foreclosure becomes an inevitable event because in this case appreciation is lost. This implies a local neighborhood price effect of foreclosure that is independent of other spatial home price effects such as the provision of amenities to larger geographic areas (i.e. schools, distance to business districts, etc.) or spatial dependence in home prices due to real-estate pricing practices based on local comparables. The goal of our empirical analysis is to test this implication. Is there a local price impact of foreclosures that exists after other spatially dependent pricing effects have been properly accounted for? If this local price impact of foreclosure exists, then the model suggests a reason for it; i.e., changes in local neighborhood quality provision.

[6] Since N_i is considered a good, we assume that $\partial A / \partial N_i > 0$.

Since we desire to test for the price impacts of nearby foreclosures, we form measures of foreclosures at varying distances from each sale. The model does not specify the spatial boundaries for a neighborhood. It might be that neighborhood quality externalities are so local, that they can only be observed with a sufficiently small geographic boundary. Hence, we employ multiple definitions of sliding neighborhoods to understand the spatial reach of the externalities associated with foreclosure.

The model implies that N_i should decrease as the number of foreclosures increases. We worry, however, about endogeneity confounding the interpretation of the hedonic price. In particular, increases in foreclosure may simply be an artifact of a declining trend in the neighborhood owing to an unobserved factor, such as changing labor market conditions. Similarly, we can imagine that for neighborhoods in decline, foreclosure is a more viable option than in neighborhoods with appreciating values. To control for these effects, we specifically control for the spatial trend in sales prices.

4. Data

The data set used to estimate the hedonic models contains sales prices, characteristics, and location information for 23,218 single-family homes, in and around Dallas County, Texas, that sold during 2006.[7] All of the housing data were obtained from the Dallas Central Appraisal District (DCAD) who determines the certified tax roll for all taxing authorities in Dallas County. DCAD uses a parcel-based GIS; thus, the location of each property is known and it is easy to merge other information with the data. The DCAD file contains information on all of the properties (sold and unsold in 2006) in the DCAD service area. We are analyzing homes sold in market transactions that have a neighboring sale within 2000 feet.

The hedonic model requires measures for the structural and various neighborhood-level characteristics. We consider three neighborhood levels: (1) local, (2) Census block group, and (3) school district. The boundaries for Census block groups and the school districts are

[7] A small percentage of the sales are in Collin, Denton, Ellis, and Tarrant Counties because the boundaries of some of the cities in Dallas County extend into other counties.

externally determined but, the true definition of "local" is unknown. We approach this using sliding neighborhood definitions of 250, 500, 1000 and 1500 feet as discussed below.

The structural or site-specific characteristics, z_i, are square feet of living area, square feet of the lot, number of bathrooms, age of the house, number of fireplaces, the number of stories, the condition of the property as coded by DCAD appraisers, the type of foundation, type of fence (if any), and the existence of a pool, attached or detached garage, attached or detached carport, central air conditioning, and central heat. The age of the house is actually the "effective" age in the sense that homes with significant refurbishing have had their age recoded by the DCAD.

RealtyTrac provided a list of foreclosures at various points in time. Specifically, we have the lists for end of year 2005, end of year 2006, and end of second quarter 2007, containing an overall total of 22,353 different properties. Each list gives the properties that entered into some stage of the foreclosure process during the previous quarter along with a code that identifies the property as entering pre-foreclosure (90 days late in mortgage payments), in auction, or bank owned. The lists often contained several duplicate records for the same property because a property appeared in more than one of the three stages during the quarter. We deleted duplicate entries, keeping only those that could conceivably impact sale prices for 2006; i.e., the properties that were on the 2006 foreclosure list as well as properties which appear on the 2005 list, not on the 2006 list, but again on the 2007 list. It seems likely that the residents of cured defaults in 2005 that reappear in 2007 decreased their contributions to neighborhood quality during default and in the intervening period.[8]

The foreclosure data were geocoded to the DCAD parcel file to facilitate calculating the number of foreclosures within 250 feet, 500 feet, 1000 feet and 1500 feet of sales. Thus, we added the variables *F250*, *F500*, *F1000* and *F1500* to each observation in the sales data set. *F250* is the count of foreclosures that are within 250 feet of the sale; *F500* is a count of foreclosures that are between 250 and 500 feet from the sale, and etc. Thus, consistent with our theoretical model, we are using the foreclosure counts as proxy variables to measure declining local neighborhood quality. It is important to note that the counts are measured for concentric rings extending outward from the sale, thus, the total number of foreclosures within 1500 feet

[8] Ambrose and Capone (2000) found elevated risk of another default within two years of foreclosure.

of the property would be the sum of the counts in each of the separate rings. Additionally, since the area within each ring increases as we move outward from the property, we expect to see that the counts of foreclosures increase and, on average, this does happen-- the average counts of foreclosures are 0.131, 0.352, 1.130 and 1.581, respectively.

We also measure the owner occupancy status and foreclosure status for each observation. A sale is owner-occupied (*OWN* = 1) if the physical address of the property is the same as the owner's mailing address for the tax bills. This assumes that an owner occupant would get the tax bill when the mailing address and physical address matched. For billing, the addresses are accurate as of January 1, 2007; hence, homes sold in 2006 should have the correct assignment of billing addresses.

To isolate the local effects associated with foreclosures, we control for school effects and census block group population characteristics. For the 1700 plus block groups in the study area, we calculated the percentage of the population that is not Hispanic and is African American (*NHBLACK*), the percentage of the population that is Hispanic (*HISPANIC*), the percentage of the population that is greater than 65 years old (*AGE65*), the average household size (*HHSIZE*), and the block group owner occupancy rate *(OWNOCC_BG*). To control for the influence of schools, we tested two geographic definitions based on the public schools. First, we used dummy variables for the 324 elementary school attendance zones in the study area. Second, we used dummy variables representing the 14 independent school districts. Both gave similar results so we report the estimates with the 14 school district dummies to conserve space.

Tables 1-3 display summary information for our data. The average home has approximately 2000 square feet of living area with two bathrooms, is on a lot of approximately 10,000 square feet, is 25 years old and sold for just over $200,000. Most homes are single story with an attached garage, slab foundation, and one fireplace. Almost 75% of the homes sold during 2006 were rated in good or better condition. The left out category for month is December while for school district it is the Carrollton-Farmers Branch District. The counts for foreclosures are somewhat surprising in terms of their size. Adding the means for *F250, F500*, *F1000* and *F1500*, we see that the average sold home in 2006 had at least five homes in some stage of foreclosure within 1500 feet.

5. *Estimation*

The empirical analysis has two primary goals: first, estimate the hedonic price of an increase in foreclosures and second, determine its spatial reach. We begin with ordinary least squares regression; i.e.,

$$S_{06} = \zeta Z + \beta X + \delta D + \eta N + \epsilon \tag{5}$$

The dependent variable S_{06} is the vector of home sale prices in 2006 (expressed as natural log). Z is a matrix of site-specific characteristics, while X contains block group-level controls for percent African American, percent Hispanic, percent over 65 years of age, average household size and percent owner occupied. D is a matrix of dummy variables to control for any fixed effects across school districts and time (month in which the sale took place), while the main interest is on N, the local neighborhood quality as measured by the counts of foreclosures at various distances.

A noticeable shortcoming of the model specified by equation (5) is the inability to control for current trends in home prices. It could be that the foreclosure effects estimated from equation (5) are simply a spurious result caused by localized trends in home prices that induce more foreclosures. Thus, it is important to control for these trends. To do so, we use sales data from 2003, 2004, 2005 and 2006[9] to calculate the "spatial average" or "spatial lag" price of homes sold within 2000 feet of the 2006 sales. Let S_{YY} denote the vector of observed home sales in year *YY*. Then, to make the spatial averages, we constructed four weights matrices, denoted as W_{03}, W_{04}, W_{05}, and W_{06} of sizes S_{06} by S_{YY} where the weights are inverse distance up to and including 2000 feet and zero beyond 2000 feet. Thus, a nonzero entry in W_{YY} means that there is a home that sold in 2006 within 2000 feet of a home that sold in year *YY*. All of the weights matrices are row standardized so that $W_{YY} \times S_{YY}$ can be interpreted as a spatial weighted average.[10]

Adding in the measures of neighborhood trend gives

$$S_{06} = \zeta Z + \beta X + \delta D + \eta N + \rho_1 W_{06} S_{06} + \rho_2 W_{05} S_{05} + \rho_3 W_{04} S_{04} + \rho_4 W_{03} S_{03} + \epsilon. \tag{6}$$

[9] The number of observations was 23,960, 27,273, 28,549, and 26,456 respectively

[10] All of these values are determined with the natural log of price so that they are in the same units as the dependent variable.

Equation (6) indicates a classic spatial lag model (Anselin 1988) because S_{06} appears on the left and the right-hand-side of the equation.

Once again, since our interest is in the local neighborhood variables, we are particularly interested in accounting for any remaining spatial dependence in the errors. After all, our measures may simply be correlated with other unobserved effects that are unrelated to neighborhood quality. If this were the case, presumably, our measures would be insignificant in a model with spatially dependent errors. Thus,

$$\begin{aligned} &S_{06} = \zeta Z + \beta X + \delta D + \eta N + \rho_1 W_{06} S_{06} + \rho_2 W_{05} S_{05} + \rho_3 W_{04} S_{04} + \rho_4 W_{03} S_{03} + \epsilon \\ &\epsilon = \lambda W_{06} \epsilon + \mu \end{aligned} \tag{7}$$

Equation (7) is a spatial autoregressive model with autoregressive disturbances of order (1,1) (SARAR(1,1)) as presented by Anselin and Florax (1995). The idea is to control for very localized spatial error dependence in an attempt to washout all but the direct effects of foreclosure.

The choice of distance thresholds for the nearby foreclosures and the spatial weight matrices was driven both by theory and data limitations. As noted previously, the distance thresholds used for nearby foreclosures (i.e. 250 feet, 500 feet, 1000 feet and 1500 feet), in effect, determine the size of the local neighborhood. For example, if we find that *F250* is statistically significant, but *F500* is not, then foreclosures have neighborhood price impacts that extend only 250 feet. The choice of these distances was simply for ease in interpretation—one can easily envision such increments.

The choice for the distance employed in the spatial weight matrices, on the other hand, were driven by data limitations. The matrix W_{06} needs to be constructed so that every sale in 2006 (the dependent variable) has at least one sale within the specified distance in 2006. If this did not occur, we would have to drop observations from our analysis. Thus, a distance of 2000 feet was selected. The other (W_{YY}) matrices use 2000 feet to maintain consistent geography for the spatial price trends.

To highlight the roles of spatial effects and estimation methods in driving the results, we present four different estimations. First, we use OLS to estimate equations (5) (no controls for spatial dependency or neighborhood pricing trends) and (6) (controls for pricing trends, but still no spatial controls). In order to estimate equation (6) with OLS, we dropped the endogenous S_{06} variable. Next, we use maximum likelihood (ML) estimation for the models specified by equations (6) (spatial lag) and (7) (SARAR(1,1)). Then, we implement the generalized method of moments (GMM) estimator presented by Kelejian and Prucha (1998 and 2006), which makes no distributional assumptions, but requires a large number of observations. This model is particularly appealing because it allows for a heteroskedastic error structure. Kelejian and Prucha (2006) note that if the error structure is heteroskedastic, then the ML estimates are biased and the non-heteroskedastic GMM estimates are no longer normally distributed in the limit. Below, we present limited sets of coefficients for these specifications but all of the estimated coefficients are available from the authors.

6. Results

The results for the OLS estimates are reported in Table 4. OLS1 is simply a hedonic regression to test our basic model specification. All of the housing attributes are of the expected sign and seem to "make sense". For example, central AC is priced more than twice as much as central heat, reflecting the climate in Dallas, and an iron fence commands an approximate 16% premium. OLS2 includes the owner occupancy rate at the block group level and whether or not the owner lives in the house after the sale, *OWN*. The coefficient on *OWN* is significant and positive.[11]

Turning to the foreclosure variables in OLS2 (*F250*, *F500*, *F1000*, and *F1500*), we see the expected effects. Foreclosures are statistically significant in every ring and the hedonic price is greatest in the inner ring and this tails off for the next two rings. The outer-most ring has approximately the same impact as the 500-1000 foot ring. The final OLS model, OLS3, includes controls for previous period sale prices. As expected, all of the coefficient estimates for previous period sale prices are statistically significant and positive. However, the other coefficient estimates remain relatively unchanged.

[11] In a regression without *OWN* but with *OWNOCC_BG*, we found that the addition of *OWN*' to the regression caused the effect of *OWNOCC_BG* to fall by approximately 67%.

Table 5 shows the coefficient estimates from the ML models that include parameters for spatial dependence. Our goal for ML1 is to see if the results are robust to the inclusion of neighborhood price trends. Note that the spatial lag specification allows for inclusion of the full four-year price trend from 2003-2006. If any coefficients lose statistical significance, endogeneity may be a better explanation of the foreclosure effects found in the OLS models. The spatial lag model estimated by ML1 still does not correct for spatially dependent errors, which can lead to inefficient estimates. Thus, the second model in Table 5, ML2, is equation (7). Most of the results are similar across the three models displayed in Table 5. However, the coefficient estimates for some variables, especially those that would seemingly be spatially correlated, do change. For example the housing condition variables have increasingly lower standard errors as we move from OLS3 to ML2. Additionally, two block group level controls, *AGE65* and *OWNOCC_BG*, are no longer statistically significant in ML2. Additionally, the coefficient on *HISPANIC* is positive in ML2. The foreclosure effects remain essentially intact—the outer two rings are not significant in ML2, suggesting very localized impacts from foreclosures.

Next, we compare alternative estimation techniques for the SARAR(1,1) model (equation (7)). The final regression in Table 5 results from a GMM estimation with heteroskedastic errors. First, note the difference in the estimates of ρ and λ, the spatial autoregressive parameters. Both are less than the ML estimates. There is not an obvious way to choose between the models. In terms of requirements on the model, however, the GMM is superior for two reasons. First, it does not seem likely that the errors in a property valuation model are homoskedastic and, second, the strong assumption of normality in finite samples required by ML estimation is potentially problematic. Thus, we favor the GMM estimates.

One of the obvious differences between the spatial models and the OLS models is the lack of robustness in the census block group level measures. In GMM, neither *HISPANIC*, *AGE65*, nor *OWNOCC_BG* is statistically significant. On first inspection, these results are quite surprising. However, one can imagine that, with spatial autocorrelation, the coefficient estimates for *HISPANIC* (for example) are influenced more heavily by isolated block groups with high Hispanic populations than other block groups that are located in close geographic proximity to one another. In our data, concentrated areas of minority block groups are more likely to occur in poorer rather than richer neighborhoods. This points to a problem when using block group level (or larger) aggregations. Because of sorting in residential housing, the majority of the variation in these block group level variables is spatially correlated. Thus, they lack the variation necessary to accurately estimate their impact on house prices when spatial correlation is controlled for.

Of primary interest, are the results for the foreclosure variables. For the GMM model, foreclosures are significant when they occur within 250 feet, between 500 and 1000 feet and between 1000 and 1500 feet of a sale. However, the magnitude of the effect of a foreclosure is five times greater in the inner ring so we focus on these effects. With the log-linear form, the direct effect of an additional foreclosure on the average house may be calculated by multiplying the coefficient for that ring by the average sale price; hence, the hedonic price of an additional foreclosure within 250 feet is \$200,000 × -0.005 = \$1,000. Additionally, with the endogeneity of price in the spatial lag specification, we may calculate the total effect of an additional foreclosure as $(1-\rho)^{-1}$ times the direct effect,[12] giving 1.666 × 1000 = \$1,666. The OLS results do not allow us to distinguish between direct and total effects.

7. Conclusions

Our results indicate that the effects of nearby foreclosures are capitalized in the housing market and that the impact is negative. We found robust evidence that foreclosure within 250 feet of a sale depreciate selling price. This evidence is consistent with our hypothesis that as a result of a foreclosure event neighborhood quality decreases as strapped residents divert their expenditures away from routine maintenance. Researchers rarely observe very local neighborhood quality; hence, this paper provides a unique look at plausible values.

It is important to emphasize that we did not estimate the influence of *sales* of foreclosed properties on nearby sales. The foreclosure variable we use identifies properties in some stage of the foreclosure process which we argue signals a decrease in neighborhood quality provision on the part of the defaulting homeowner. This then facilitated our goal of identifying the

[12] The spatial multiplier for a spatial lag model is calculated as $(1-W_{06}\rho)^{-1}$, but this reduces to $(1-\rho)^{-1}$ when the weight matrix is standardized (Kim et al, 2003).

potential home value loss, a non-pecuniary externality, due to reductions in the supply of neighborhood quality.

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Table 1. Variable Names, Brief Descriptions and Summary Statistics for the House-Specific Characteristics

Variable	Description	Mean	Std. Dev.	Min	Max
SALEPRICE	Sales Price	220,699	261988	9000	5,000,000
LIVAREA	Livinig Area sqft (x1000)	2.091	.942	0.494	17.403
LOTAREA	Lot Area sqft (x1000)	9.467	9.27	0.2486	378.82
BATHS	Number of bathrooms	2.288	0.831	0.5	12.5
EFF_AGE	Age of the house in yrs	25.54	19.17	0	342
STORY1_5	1.5 stories dummy	0.129	0.333	0	1
STORY2	2 or more stories dummy	0.183	0.387	0	1
ONE_FIRE	1 fire place dummy	0.715	0.451	0	1
TWO_FIRE	2 or more fireplaces dummy	0.065	0.247	0	1
COND2	Very poor condition dummy	0.004	0.067	0	1
COND3	Poor condition dummy	0.037	0.188	0	1
COND4	Average condition dummy	0.147	0.354	0	1
COND5	Good condition dummy	0.246	0.431	0	1
COND6	Very good condition dummy	0.275	0.447	0	1
COND7	Excellent condition dummy	0.287	0.452	0	1
PIERBEAM	Pier and Beam dummy	0.225	0.418	0	1
SLAB	Slab foundation dummy	0.760	0.427	0	1
CENTRALHEAT	Central heat dummy	0.968	0.175	0	1
CENTRALAIR	Central air dummy	0.962	0.191	0	1
POOL	Pool dummy	0.143	0.351	0	1
ATGARG	Attached garage dummy	0.805	0.396	0	1
ATCP	Attached carport dummy	0.034	0.181	0	1
DTCP	Detached carport dummy	0.022	0.145	0	1
CHAINFENCE	Chain Fence dummy	0.132	0.339	0	1
IRONFENCE	Iron fence dummy	0.022	0.146	0	1
WOODFENCE	Wood fence dummy	.599	0.490	0	1

Table 2. Variable Names, Brief Descriptions and Summary Statistics for the Census Track, Time and School District Fixed Effects

Variable	Description	Mean	Std. Dev.	Minimum	Maximum
NHBLACK	p. nonHispanic Black in BG*	0.139	0.179	0	0.997
HISPANIC	p. Hispanic in BG*	0.176	0.169	.003	0.968
AGE65	p. older than 65 in BG*	0.073	0.076	0	0.571
HHSIZE	Average household size in BG	2.775	0.511	1.3	4.86
M1	Sold in January dummy	0.057	0.232	0	1
M2	Sold in February dummy	0.071	0.257	0	1
M3	Sold in March dummy	0.099	0.299	0	1
M4	Sold in April dummy	0.085	0.279	0	1
M5	Sold in May dummy	0.100	0.301	0	1
M6	Sold in June dummy	0.109	0.311	0	1
M7	Sold in July dummy	0.090	0.286	0	1
M8	Sold in August dummy	0.093	0.290	0	1
M9	Sold in September dummy	0.079	0.270	0	1
M10	Sold in October dummy	0.077	0.267	0	1
M11	Sold in November dummy	0.069	0.253	0	1
SD2	Carrolton-Farmers B. ISD Dummy	0.073	0.261	0	1
SD2	Cedar Hill ISD dummy	0.027	0.161	0	1
SD3	Coppell ISD dummy	0.034	0.181	0	1
SD4	Dallas ISD dummy	0.278	0.448	0	1
SD5	Desoto ISD dummy	0.029	0.168	0	1
SD6	Duncanville ISD dummy	0.029	0.168	0	1
SD7	Garland ISD dummy	0.140	0.347	0	1
SD8	Grand Prairie ISD dummy	0.053	0.225	0	1
SD9	Highland Park ISD dummy	0.018	0.131	0	1
SD10	Irving ISD dummy	0.049	0.216	0	1
SD11	Lancaster ISD dummy	0.019	0.135	0	1
SD12	Mesquite ISD dummy	0.073	0.260	0	1
SD13	Non Dallas County ISD dummy	0.091	0.288	0	1

*p. denotes proportion of the block group population.

Table 3. Variable Names, Brief Descriptions and Summary Statistics for the Focus Variables

Variable	Description	Mean	Std. Dev.	Minimum	Maximum
OWNOCC_BG	p. Owner occupied in BG*	0.785	0.120	0	1
OWN	Owner occupied dummy	0.791	0.407	0	1
F250	# Foreclosures within 250 ft	0.224	0.534	0	7
F500	# Foreclosures within 500 ft	0.605	1.008	0	13
F1000	# Foreclosures within 1000 ft	1.938	2.336	0	24
F1500	# Foreclosures within 1500 ft	2.705	2.911	0	26
$W_{03}S_{03}$	Spatial lag of 2003 log sale price	11.611	1.916	0	14.89
$W_{04}S_{04}$	Spatial lag of 2004 log sale price	11.706	1.672	0	14.79
$W_{05}S_{05}$	Spatial lag of 2005 log sale price	11.916	0.906	0	14.87

*p. denotes proportion of the block group housing units.

Table 4. OLS Coefficient Estimates and Heteroskedasticity-Consistent Standard Errors in Parentheses

	OLS1		OLS2		OLS3	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
LIVAREA	0.332***	0.007	0.330***	0.007	0.317***	0.007
LOTAREA	0.002***	0.000	0.002***	0.000	0.003***	0.000
BATHS	0.036***	0.006	0.036***	0.006	0.032***	0.006
EFF_AGE	-0.002***	0.000	-0.002***	0.000	-0.003***	0.000
STORY1_5	-0.034***	0.006	-0.034***	0.006	-0.032***	0.006
STORY2	-0.039***	0.006	-0.037***	0.006	-0.027***	0.006
FIRE1	0.101***	0.005	0.102***	0.005	0.087***	0.005
FIRE2	0.197***	0.012	0.197***	0.011	0.174***	0.011
COND2	-0.017	0.082	-0.017	0.081	-0.022	0.080
COND3	0.133*	0.070	0.134*	0.070	0.130*	0.070
COND4	0.219***	0.070	0.219***	0.070	0.214***	0.070
COND5	0.297***	0.070	0.297***	0.070	0.291***	0.069
COND6	0.358***	0.070	0.358***	0.070	0.351***	0.069
COND7	0.399***	0.070	0.399***	0.070	0.398***	0.070
PIERBEAM	0.133***	0.021	0.133***	0.021	0.127***	0.020
SLAB	-0.018	0.022	-0.017	0.022	-0.014	0.021
CENTRALHEAT	0.043***	0.016	0.043***	0.016	0.041***	0.015
CENTRALAIR	0.134***	0.014	0.136***	0.014	0.133***	0.014
POOL	0.089***	0.005	0.088***	0.005	0.083***	0.005
ATGARG	-0.022***	0.006	-0.021***	0.006	-0.021***	0.006
ATCP	-0.028***	0.010	-0.028***	0.010	-0.029***	0.010
DTCP	-0.017	0.014	-0.016	0.014	-0.011	0.013
CHAINFENCE	0.014**	0.006	0.014**	0.006	0.016***	0.006
IRONFENCE	0.165***	0.014	0.165***	0.014	0.156***	0.013
WOODFENCE	0.050***	0.004	0.051***	0.004	0.053***	0.004
NHBLACK	-0.822***	0.014	-0.786***	0.015	-0.722***	0.016
HISPANIC	-0.311***	0.017	-0.302***	0.017	-0.246***	0.017
AGE65	-0.357***	0.030	-0.369***	0.030	-0.321***	0.029
HHSIZE	-0.191***	0.005	-0.188***	0.005	-0.177***	0.005
OWNOCC_BG	0.172***	0.018	0.174***	0.018	0.121***	0.019
OWN	0.040***	0.004	0.040***	0.004	0.042***	0.004
F250			-0.011***	0.003	-0.012***	0.003
F500			-0.006***	0.002	-0.006***	0.002
F1000			-0.003***	0.001	-0.004***	0.001
F1500			-0.003***	0.001	-0.004***	0.001
$W_{03}S_{03}$					0.008***	0.001
$W_{04}S_{04}$					0.004**	0.002
$W_{05}S_{05}$					0.056***	0.007
Constant	11.223***	0.074	11.219***	0.074	10.469***	0.112
Observations	23218		23218		23218	
R-squared	0.88		0.88		0.89	

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Maximum Likelihood and GMM Coefficient Estimates and Standard Errors in Parentheses

	ML_1		ML_2		GMM	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
LIVAREA	0.215***	0.003	0.248***	0.003	0.242***	0.000
LOTAREA	0.002***	0.000	0.004***	0.000	0.003***	0.000
BATHS	0.018***	0.000	0.020***	0.000	0.020***	0.002
EFF_AGE	-0.003***	0.000	-0.002***	0.000	-0.002***	0.000
STORY1_5	-0.028***	0.000	-0.016***	0.000	-0.023***	0.004
STORY2	-0.021***	0.000	-0.007*	0.057	-0.016***	0.003
FIRE1	0.060***	0.000	0.040***	0.000	0.054***	0.003
FIRE2	0.097***	0.000	0.095***	0.000	0.101***	0.006
COND2	-0.008	0.706	-0.034	0.150	-0.017	0.022
COND3	0.174***	0.000	0.152***	0.000	0.166***	0.018
COND4	0.281***	0.000	0.254***	0.000	0.272***	0.017
COND5	0.353***	0.000	0.322***	0.000	0.344***	0.017
COND6	0.408***	0.000	0.374***	0.000	0.399***	0.017
COND7	0.451***	0.000	0.401***	0.000	0.436***	0.017
PIERBEAM	0.102***	0.000	0.123***	0.000	0.113***	0.009
SLAB	0.058***	0.000	0.053***	0.000	0.050***	0.010
CENTRALHEAT	0.042***	0.000	0.044***	0.000	0.043***	0.009
CENTRALAIR	0.080***	0.000	0.093***	0.000	0.087***	0.008
POOL	0.080***	0.000	0.075***	0.000	0.079***	0.003
ATGARG	0.020***	0.000	-0.011***	0.001	0.006*	0.003
ATCP	-0.004	0.411	-0.010	0.104	-0.007	0.006
DTCP	-0.002	0.774	-0.016**	0.031	-0.007	0.007
CHAINFENCE	0.008**	0.023	0.018***	0.000	0.014***	0.004
IRONFENCE	0.089***	0.000	0.087***	0.000	0.092***	0.008
WOODFENCE	0.023***	0.000	0.023***	0.000	0.024***	0.003
NHBLACK	-0.443***	0.000	-0.260***	0.000	-0.378***	0.013
HISPANIC	-0.165***	0.000	0.048***	0.000	-0.014	0.015
AGE65	-0.010	0.763	0.003	0.861	-0.011	0.024
HHSIZE	-0.059***	0.000	-0.094***	0.000	-0.101***	0.004
OWNOCC_BG	0.058**	0.004	-0.007	0.513	0.021	0.015
OWN	0.043***	0.000	0.043***	0.000	0.044***	0.003
F250	-0.004*	0.051	-0.007**	0.002	-0.005***	0.002
F500	-0.001	0.536	-0.003**	0.023	-0.002	0.001
F1000	-0.001*	0.050	-0.001	0.221	-0.001**	0.001
F1500	-0.001*	0.071	-0.000	0.642	-0.001*	0.000
$W_{03}S_{03}$	0.007***	0.000	0.006***	0.000	0.006***	0.001
$W_{04}S_{04}$	0.004**	0.009	0.001	0.175	0.002**	0.001
$W_{05}S_{05}$	0.027***	0.000	0.007***	0.000	0.018***	0.002
Constant	7.704***	0.000	4.553***	0.000	3.482***	0.043
rho	0.242***	0.000	0.542***	0.000	0.410***	0.006
lambda			0.779***	0.000	0.414	NA
Observations	23218		23218		23218	
R-squared	0.893		0.949		0.88	

* significant at 10%; ** significant at 5%; *** significant at 1%