Neighborhood Impact of Foreclosure: A Quantile Regression Approach

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Abstract

This paper uses quantile regression, while accounting for spatial autocorrelation, to examine the simultaneous space-time impact of foreclosures on neighborhood property values. We find that negative price externalities associated with neighborhood foreclosures are greatest (1) among lower-priced homes, (2) within 250 feet of the property and (3) in the 12 months following a foreclosure auction. By using quantile regression, we are able to also investigate changes in the distribution of house prices associated with varying levels of neighborhood foreclosures.

Keywords: Hedonic model; Quantile regression; Foreclosures; Spatial dependence

Classification codes: C2; R2

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1 Introduction

Following the 2007 financial crisis, numerous authors have robustly documented negative neighborhood price externalities associated with foreclosed properties (Immergluck and Smith, 2006; Schuetz et al., 2008; Harding et al., 2009; Leonard and Murdoch, 2009; Lin et al., 2009; Rogers and Winter, 2009; Daneshvary et al., 2011; Daneshvary and Clauretie, 2012). However, the literature has largely only examined mean foreclosure effects, while the policy focus has remained on lower income neighborhoods, which presumably are more likely to suffer significant decline as a result of high foreclosure rates. For example, the federal Neighborhood Stabilization Program, which has been used in many areas to rehabilitate foreclosed properties, has been directed only to low- and middle-income neighborhoods, with an emphasis on very low-income neighborhoods (Joice, 2011). Evidence regarding the heterogeneity in price externalities of foreclosures across high-, middle- and low-income neighborhoods is lacking. We fill this gap in the literature by examining heterogeneity in the neighborhood price impacts of foreclosure across different quantiles of the conditional home price distribution. By examining the space-time variations in price externalities across house price quantiles, we also hope to inform the degree to which observed heterogeneity in foreclosure price externalities is attributable to different mechanisms at work in different types of neighborhoods.

In this paper, quantile regression is used to analyze the neighborhood effects of foreclosures on house prices. To the best of our knowledge, this is the first paper that investigates heterogeneity in the neighborhood price effects of foreclosure on the full (conditional) distribution of house price. A spatial-lag model was applied to control for spatial dependence and unobserved neighborhood features. The results suggest that foreclosure price externalities vary across the conditional house price distribution. We also examine the effects across different time periods and distance thresholds for each quantile. Finally, we discuss how our results can be used to guide the implementation of policy aimed at ameliorating the effects of foreclosures in urban neighborhoods.

2 Background

Hedonic pricing models have been used in housing studies since Lancaster (1966) and Rosen (1974) to explore the relationship between house prices and housing characteristics. Sirmans et al. (2005) provide a review of recent empirical studies that have used hedonic modeling to estimate house prices. The findings indicate variability in both the magnitude and direction of the estimated relationship between housing characteristics and house prices. For example, 62 of their studies showed that square footage was positively related to house price; 4 studies identified a negative relationship; and 3 showed that there was no significant relationship. Liao and Wang (2012) suggest various reasons for the heterogeneity in results: different markets of study, spatial dependence, and “quantile effects”.

“Quantile effects” occur when housing characteristics are valued differently across the conditional distribution of house prices. Quantile regression models allow for estimation of differential effects of a covariate on various quantiles of the dependent variable’s conditional distribution. In contrast, estimations based on the conditional mean (such as ordinary least square (OLS)) may not be able to completely characterize the distribution of house prices and thus produce biased results. Researchers have found that quantile regression is particularly useful when examining segmented markets (such as occurs in most urban residential housing markets) because full characterization of the conditional distribution, rather than the conditional mean, of house prices is properly examined (e.g., Coulson and Mcmillen, 2007; McMillen, 2008; Zietz et al., 2008; Mak et al., 2010; Ebru and Eban, 2011). Zietz et al. (2008) applied a novel spatial quantile regression estimation strategy using Orem/Provo, Utah housing data. Mak et al. (2010), and Ebru and Eban (2011) used quantile regression technique to analyze Hong Kong and Istanbul real estate prices, respectively. All three studies found that housing attributes were valued differently across the conditional price distribution.

Following the financial crisis in 2007, the United States experienced declining house prices and rapidly increasing foreclosures. Considering mean effects only, foreclosed properties are associated with neighborhood price declines(Immergluck and Smith, 2006; Schuetz et al., 2008; Harding et al., 2009; Leonard and Murdoch, 2009; Lin et al., 2009; Rogers and Winter, 2009; Daneshvary et al., 2011; Daneshvary and Clauretie, 2012). However, comparison of the magnitudes of estimated foreclosure price externalities reveals that they are quite diffuse. In all of the previous studies, it was assumed that, on a percentage basis, conditional house prices are all equally affected by nearby foreclosed properties. This assumption may not be realistic.

3 Hypothesis

There are many reasons why one might expect to find differences in the neighborhood impacts of foreclosures. We will focus on two sources which are of significant policy interest: (1) heterogeneity associated with different types of properties, as represented by different quantiles of the house price distribution and (2) heterogeneity created by different channels through which foreclosures might impact neighborhood house prices.

Foreclosures may affect neighborhood housing through three primary channels: blight, valuation, and supply (Lee, 2008). These channels are distinct both in the mechanisms through which the externality is generated and the timing of the external impact. From a policy perspective it is important to understand the channel through which externalities are being produced in order to properly identify potential solutions to ameliorate the negative price impacts.

The blight channel occurs because foreclosed properties are poorly maintained and may produce negative price externalities before the official declaration of foreclosure or at any point in time during the foreclosure process. Poor exterior maintenance produces a negative visual externality that impacts the value of nearby housing. The negative externality can happen before the official declaration of foreclosure because homeowners at high risk of default are less financially capable and poorly incentivized to allocate resources towards home maintenance (Harding et al., 2000). Examining American Housing Survey data from the 2007 financial recession, Leonard (2013) found that homeowners at very high foreclosure risk reported lower routine maintenance expenditures while still occupying their home. During the foreclosure process, properties may be vacant for some time–further attracting vandalism and crime, which may exacerbate the blight. As a result of blight, the neighborhood may become undesirable for buyers. Therefore, the blight channel produces neighborhood price externalities through real changes in neighborhood condition.

The valuation channel occurs because foreclosed homes often sell at a discount and may produce negative neighborhood price externalities only after a market sell of a foreclosed property. The lower market valuation of foreclosed properties may cause significant downward price pressure on nearby sales (Vandell, 1991).

The supply channel occurs because foreclosed homes "recycle" back to the market and increase the supply of houses on the market. The negative price externalities created by the supply channel may occur anytime after the foreclosure event because foreclosed properties can re-enter the market at auction or when properties sale out of REO stock. The increase in supply can lead to lower prices for nearby home sales.

Considering the timing of the 3 channels through which foreclosures might produce neighborhood price externalities, we note that only the blight channel is at work prior to the initiation of foreclosure and only the valuation and supply channels are at work after a market sale of the foreclosed property. By breaking the foreclosure process into different time periods, we are able to roughly differentiate the foreclosure impacts through different channels.

Different channels may function differently for different housing or neighborhood types. In a standard OLS regression, the distribution of the dependent variable is assumed to undergo a parallel shift in response to changes in one of the explanatory variables. This "parallel shift" assumption may not be well-founded for the case of foreclosure price externalities. Neighborhoods associated with low foreclosure rates are more likely to be associated with higher-income and stable communities (Edmiston, 2009). Thus, the conditional distribution of house prices may be different in neighborhoods with high/low foreclosure rates. Similarly, foreclosure externalities might exhibit heterogeneity across the conditional price distribution.

We propose two hypothesis which will be tested. First, foreclosed properties will produce different magnitudes of neighborhood price externalities across the conditional distribution of house prices. This heterogeneity in the price impacts will help to reconcile why we might see different estimated price impacts in the literature. Second, the timing of foreclosure impacts will vary across the conditional distribution of house prices. This heterogeneity in the timing of price externalities will inform how different quantiles of the conditional distribution of house prices are affected through different channels.

4 Data

In order to address our hypothesis we will use a hedonic modeling approach to analyze foreclosure and sales data from Dallas County Texas. Our sales data comes from the University of Texas at Dallas Real Estate Research Database and includes all arms-length real-estate transactions that transacted through the multiple listing service in Dallas County, Texas. This database also contains historical records on housing characteristics, appraised values, sale prices, month of sale, and physical address of the house. Table 1 displays the summary statistics of major housing characteristics in the sales data.

A list of foreclosures from RealtyTrac over the period from 2007 to 2009 was used to identify homes that foreclosed. Each foreclosure record indicates the date of the foreclosure auction and we will use this date as the "foreclosure date". Both sales and foreclosure data were geocoded to facilitate geographic matching of foreclosures and sales; the foreclosure auction date was used to temporally match the sales and foreclosure data. For each house that was sold in 2008, neighborhood foreclosure counts were assessed by counting the number of foreclosures in several time and distance threshold categories.

First, we constructed the foreclosure distance categories. For each house sold, we drew four concentric rings with different radii measured by Euclidean distance in feet: 0-250 feet (Ring 1), 250-500 feet (Ring 2), 500-1000 feet (Ring 3), and 1000-1500 feet (Ring 4). Ring 1 included the nearest neighboring houses, which are likely visible from the sale property. Ring 2 covered properties in roughly the same block, which might not be visible from the the sale property but might be seen by potential buyers driving through the community. Properties in the the two outer rings are more distant and may not be seen by potential buyers–or if seen may not be considered as part of the same neighborhood. However they might affect the community environment or increase the housing supply, and further affect the sale property.

To measure time effects, we categorized the foreclosures by 8 phases covering from 12 months before the foreclosure auction to 12 months after the foreclosure auction. We broke the time before foreclosure auction (pre-foreclosure) and the time after foreclosure auction (post-foreclosure) into four quarterly periods. Figure 1 provides a visual description of the time period definitions. For example, $F - 12$ represents 12 months before the foreclosure auction.

Finally, after constructing the different distance and time categories, we calculated the foreclosure count variable by counting the number of foreclosures in each different distance ring, each different time phase, and each combination of distance ring and time phase.

5 Methodology

To estimate neighborhood foreclosure price externalities, we began with a classic spatial lag model that included both current and historical neighborhood price trends. The spatial lag model had the following form:

$$y_{08} = \lambda W_{08} y_{08} + X\beta + F\delta + \rho_{07} W_{07} y_{07} + \rho_{06} W_{06} y_{06} + \rho_{05} W_{05} y_{05} + \epsilon \tag{1}$$

y_{08} is the vector of natural log of sale prices in 2008 for all properties that transacted through the multiple listing service. y_{07}, y_{06}, and y_{05} are similarly defined with subscripts indicating the year in which sales occurred. X is a matrix of property characteristics (e.g., living area in thousands of square feet, number of bathrooms, age of the house in 10 years, etc.), and dummy variables that control for institutional (e.g., school districts) and temporal (e.g., month of sale) fixed effects. β is a vector of regression parameters. F is a matrix containing neighborhood foreclosure counts tallied for varying distance and time buffers around each 2008 sale. δ is a vector of estimated spillover effects associated with the neighborhood foreclosure counts in each buffer.

Because foreclosures are more likely in neighborhoods with declining home prices, historical house price trends may impact current sale prices and the likelihood of foreclosure. This presents a likely omitted variable problem. We followed the approach of Leonard and Murdoch (2009) and included spatial averages of past house sale prices within 2000 feet of each 2008 sale. We took this measure to account for endogeneity between the occurrence of foreclosures and lower sale prices; later we also discuss additional robustness checks related to the potential endogeneity problem.

Four weight matrices, W_{08}, W_{07}, W_{06}, and W_{05}, were constructed by calculating the distances between houses sold in 2008 and houses sold in 2008, 2007, 2006, and 2005, separately. The weights were based on inverse distance up to and including 2000 feet and zero beyond 2000 feet. All of the weights matrices were row standardized. $W_{08}y_{08}$, $W_{07}y_{07}$, $W_{06}y_{06}$, and $W_{05}y_{05}$ are the spatially weighted average of neighborhood sale prices in years 2008, 2007, 2006 and 2005, respectively. λ, ρ_{07}, ρ_{06}, and ρ_{05} are the spatial lag parameters. ϵ is a vector of random disturbance terms.

(1) is usually estimated via a "traditional" spatial lag estimation approach that accounts for the endogenous spatial lag term $\lambda W_{08}y_{08}$. "Traditionally", the estimation approach is concerned with estimating conditional mean relationships (LeSage and Pace, 2009). However, for many reasons, these approaches are inappropriate for our purposes (Hao and Naiman, 2007). First, the traditional approaches estimate conditional mean functions by minimizing

the sum of squared residuals–ignoring the differential effects of the explanatory variables across the conditional distribution. These differential effects are precisely what we are most interested in estimating. Second, traditional spatial lag models require that the dependent variable's conditional variance remain constant (homoskedastic) for all values of the covariates. According to a Breusch-Pagan / Cook-Weisberg test for heteroskedasticity on a simplified model (1), the null hypothesis of constant variance was rejected. Third, outliers in the traditional spatial lag model tend to have undue influence on the fitted line. The usual treatment is to eliminate outliers, which would not allow us to investigate foreclosure effects on the *full* conditional distribution of house prices.

Following the work of Liao and Wang (2012), we first used a two-stage least squares approach to estimate parameters based on the conditional mean. This allowed us to assess differences between conditional mean parameter estimates and quantile regression parameter estimates. Next, we used a quantile regression approach. The quantile regression's conditional quantile function was estimated by minimizing the weighted sum of absolute residuals. In doing so it allowed for unobserved heterogeneity across quantiles (τ) and heteroscedasticity among the disturbances (Koenker, 2005). The quantile regression model was formulated as follows:

$$y_{08} = \lambda(\tau)W_{08}y_{08} + X\beta(\tau) + F\delta(\tau) + \rho_1(\tau)W_{07}y_{07} + \rho_2(\tau)W_{06}y_{06} + \rho_3(\tau)W_{05}y_{05} + \epsilon \quad (2)$$

Since the spatial lag dependent variable is present on the right-hand side of equation (2), the conventional quantile regression estimator will be inconsistent. Thus, instrumental variables for $W_{08}y_{08}$ are needed. Two methods have been used to form the instrumental variables needed for quantile regression: two-stage quantile regression (2SQR) (Kim and Muller, 2004), and instrumental variable quantile regression (IVQR) (Chernozhukov and Hansen, 2006). Both methods are not specific to the endogeneity issues associated with spatially lagged dependent variables; rather, they focus more generally on endogeneity in quantile regressions. Even so, the two methods can still be applied to spatial models to circumvent the endogeneity problem (McMillen, 2013). IVQR requires more computation time and is preferred when one is dealing with relatively small data sets (Kostov, 2009). Given that we have a large sample size (12,465 observations), we used 2SQR. The 2SQR approach is similar to traditional instrumental variables approaches.

For each quantile, the estimation involved two stages. In the first stage, we estimated a quantile regression for the spatial endogenous variable $W_{08}y_{08}$ using $W_{07}y_{07}$, $W_{06}y_{06}$, $W_{05}y_{05}$, X, F, and the instruments of $W_{08}y_{08}$ as explanatory variables. Following Kelejian and Robinson (1993) and Kelejian and Prucha (1999), we used spatial lags of the explanatory variables X and F as the instruments of $W_{08}y_{08}$. The predicted $\widehat{W_{08}y_{08}}$ was then substituted for $W_{08}y_{08}$ in equation (2) to solve the endogeneity problem. In the second stage, we estimated another quantile regression. This time we regressed y_{08} on $\widehat{W_{08}y_{08}}$, $W_{07}y_{07}$, $W_{06}y_{06}$, $W_{05}y_{05}$, X, and F. Standard errors for the vector of coefficients were obtained by using the bootstrap method described in Gould (1993, 1998). We employed three quantiles (0.25, 0.5, and 0.75), and further extended the analysis to 19 quantiles ranging from 0.05 to 0.95. In addition, we followed McMillen (2013) and investigated predicted changes in the full distribution of house prices associated with varying amounts of neighborhood foreclosures.

6 Estimation and Results

Three sets of models were estimated with different assumptions for distance/time effects. First, we explored distance effects in which neighborhood foreclosure counts for each distance ring included foreclosures at any stage of the foreclosure process (Model A). Next, we examined only the time effects (Model B). Finally, we combined the distance and time effects and analyzed simultaneous space/time impacts of foreclosures (Model C).

Before we proceed, we need to clarify a language issue. The higher/medium/lower-priced houses mentioned later in this paper are properties that are located at higher/medium/lower positions in the conditional house price distribution, or the house price distribution *conditioned* on the values of the explanatory variables. Therefore, they are properties which are of higher/medium/lower prices relative to other properties with similar characteristics.

6.1 Model A: Distance Effects Only

In Model A, the foreclosure variables include the number of foreclosure counts in each ring at any stage of the foreclosure process. We start with estimation of standard OLS and quantile regressions which do not account for spatial autocorrelation. Results are reported in Table 2. The estimation results for OLS are reported in column (1), and the estimates of the standard quantile regression are in columns (2) to (4). The last column of the table shows the estimates of an interquantile regression between the 0.25 and 0.75 quantiles. These estimates test for statistically significant differences in coefficients of two quantile models (McMillen, 2013). All standard errors are reported in parentheses.

Next, we test for spatial autocorrelation in the model's residuals. The Moran's I statistic was 190.2 and the null hypothesis of no spatial autocorrelation was rejected. Therefore, in the next step, we estimated models that accounted for spatial autocorrelation.

Estimation results are shown in Table 3. The model in column 1 is based upon a two-stage least squares approach, and parameter estimates are based upon conditional mean effects[1]. Estimates of the spatial quantile regression are in columns (2) to (4). All standard errors for quantile regressions are obtained through 500 bootstrap replications and reported in parentheses.

First we compare results of OLS and 2SLS (Column (1) in Tables 2 and 3, respectively). The coefficient of the spatial lag variable is statistically significant at a 1% level, but inclusion of the spatial lag variable did not change other parameter estimates substantially. Coefficient

[1]The estimation procedure is similar to 2SQR. In the first stage, we estimate an OLS regression for the spatial endogenous variable $W_{08}y_{08}$ using $W_{07}y_{07}$, $W_{06}y_{06}$, $W_{05}y_{05}$, X, F, and the instruments of $W_{08}y_{08}$ as explanatory variables. We use spatial lags of explanatory variables X and F as the instruments. The predicted $\widehat{W_{08}y_{08}}$ is then saved. In the second stage, we regress y_{08} on $\widehat{W_{08}y_{08}}$, $W_{07}y_{07}$, $W_{06}y_{06}$, $W_{05}y_{05}$, X, and F.

estimates have the expected signs. Larger houses, those with more bathrooms, pool, better condition, and central air conditioning are associated with higher sale prices.

Comparing the results of OLS (Table 2, column (1)) and standard quantile regression (Table 2, columns (2)-(4)) we find that the estimated relationships between the explanatory variables and house price vary across quantiles. We observe similar differences when comparing the results of 2SLS and 2SQR in Table 3. The interquantile regression results in Table 2 indicate that differences between many of the 0.25 and 0.75 quantile coefficient estimates are statistically significant. In particular, the estimated coefficients for foreclosure counts in rings 1-3 are statistically different across quantiles.

Next, we focus on the 2SQR results (Table 3). Comparing the estimates across quantile regressions, some increase while others decrease. For example, the coefficient of living area increases from 0.1707, to 0.2112, then to 0.2389 for 0.25, 0.50 and 0.75 quantiles, respectively. The increasing slope indicates a widening of the conditional house price distribution as living area increases, which reflects the increasing conditional variance (evidence of heteroskedasticity) of the regression among houses with larger living area. The 0.25 and 0.75 quantiles of the conditional price distribution are much further apart among houses with larger living area. Thus, the houses with larger living area are more expensive but there is also greater dispersion of the prices among them. The spatial lag variable is statistically significant for all three quantiles and increases in magnitude with increasing quantile. Living area, lot area, and number of bathrooms are valued more for higher-priced homes. Central heat and fireplaces are valued more for lower-priced homes. Additionally, two or more stories (the omitted category) is more important for lower-priced home buyers than higher-priced home buyers.

Focusing on the 2SQR results for neighborhood foreclosure counts, we observe the largest estimated relationships between foreclosures and home prices in the first ring. This is consistent with previous work (Leonard and Murdoch, 2009; Harding et al., 2009; Lin et al., 2009). Within the first ring, lower-priced homes have a larger price penalty associated with neighborhood foreclosures and this penalty decreases as quantile increases. To further examine the quantile effects of neighborhood foreclosures, we estimated another model allowing for quantiles at 0.05 increments.[2] Figure 2 presents a summary of quantile regression results for foreclosure distance effects. For each of the four foreclosure covariates, we plot 19 quantile regression estimates for τ ranging from 0.05 to 0.95, which is shown as the solid curve. The two dashed lines in each panel represent 95 percent confidence intervals for the quantile regression estimates. The solid straight line in each panel shows the 2SLS estimate of the conditional mean effect. The two dotted lines represent conventional 95 percent confidence intervals for the 2SLS estimate.

The results plotted in Figure 2 highlight the same basic patterns observed in Table 3. The negative relationship between neighborhood foreclosures and home prices is strongest for all quantiles within 250 feet (Ring 1). Across quantiles, neighborhood foreclosures have a stronger negative effect in Ring 1 for lower-priced homes, but the different impacts among quantiles become less noticeable in the outer rings. A comparison of mean regression (2SLS) and quantile regression shows that the signs of the coefficients of foreclosure variables are similar, but magnitudes are quite different, especially in outer rings (Rings 2 to 4). This indicates that outlier observations likely do drive the 2SLS results.

The graphs of the 19 quantile regression coefficients clearly show significant differences in coefficients across quantiles. To further disentangle how the distribution of house price changes when the number of foreclosures takes on different values, we follow McMillen (2013) and examine the full distribution of house prices when the number of foreclosures within Ring 1 changes from 0 to 3[3]. Figure 3 exhibits Kernel density functions for predicted log sales prices at alternative values of Ring 1 foreclosure counts. As the number of foreclosures in Ring 1 increases, the distribution of log of sales prices shifts to the left. Table 4 provides summary statistics for the predicted log sales price distribution. The distribution of house prices with fewer foreclosures is less negatively skewed, and has a higher peak than those

[2]Full regression results are available from the authors upon request.
[3]We chose 0 to 3 because 92% of the houses have 0 to 3 foreclosing houses within 250 feet.

with more foreclosures. On average, the sale price for houses in neighborhoods with fewer foreclosures tend to be higher and less volatile than those with more foreclosures in the neighborhood. This finding is consistent with the conclusion found in the literature that neighborhoods associate with fewer foreclosures tend to be more stable and well-established (Edmiston, 2009).

6.2 Model B: Time Effects Only

In order to examine the time effects in Model B, the foreclosure variable now includes the number of foreclosure counts in 8 time periods within 1500 feet of a market non-distressed sale. Figure 4 reports the foreclosure impacts on neighborhood sales from 12 months before the foreclosure auction to 12 months after the auction.[4] Each solid curve represents the plot of the coefficient of a foreclosure variable in a specific quantile. Dotted curves indicate 95% confidence intervals. In the pre-foreclosure stages, foreclosures have a negative impact on nearby sales, but most of the impacts are not statistically significant. In addition, differential effects among the 3 quantiles are not noticeable. However, in the post-foreclosure stages, the negative price impacts of foreclosure are stronger than in the pre-foreclosure stages. Furthermore, point estimates indicate that foreclosure impacts on lower-priced homes are stronger than medium and higher priced homes; however, they are not statistically distinguishable.

6.3 Model C: Distance and Time Effects

Finally, we focus on the combination of distance and time effects. In Model C, the foreclosure variables include 32 foreclosure counts representing each different distance (4 categories) and time (8 categories) combination.

Figure 5 shows the foreclosure time effects within Rings 1 to 4, respectively.[5] After the foreclosure auction, the foreclosed property impacts all types of nearby homes in Ring 1. The

[4]Full regression results are available from the authors upon request.
[5]Full regression results are available from the authors upon request.

impact is stronger on lower-priced houses and the effect becomes more homogenous across the quantiles as the foreclosure auction becomes more distant (i.e. as we move from period $F+3$ to $F+6$, etc.). However, in Rings 2-4, there are almost no statistically significant effects of neighborhood foreclosures, or discernible trends in foreclosure effects across the quantiles. The results of the combined space-time categorizations of neighborhood foreclosures are consistent with estimates from Models A and B whereby the strongest effects are found for lower-priced homes, within 250 feet, and in the post-foreclosure periods. The cross-quantile heterogeneity in post-foreclosure effects were not evident in outer rings.

7 Robustness Checks

7.1 Foreclosure Endogeneity

A major concern relating to the analysis of neighborhood foreclosure effects is the issue of causation. The model we proposed implies that foreclosure effects are exogenous after controlling for historical neighborhood price trends. However, this may not be the case. To further investigate potential endogeneity between the occurrence of nearby foreclosures and home prices, we followed a strategy proposed by Campbell et al. (2011). We estimated only the relationship between past foreclosures (i.e. foreclosures that occurred before the market sale) and house prices. Past foreclosures have an impact on the price of subsequent sales, while the subsequent sales have limited impact on past foreclosures. By including only past foreclosures, we can break the simultaneity between foreclosures and property values. However, we are not able to examine the pre-foreclosure impacts on house prices because all the pre-foreclosures will necessarily have foreclosed after the market sales.

Table 5 reports the 2SQR estimation results for foreclosure variables for Model A.[6] Please note that the number of foreclosures in each ring is the sum of all the foreclosure counts in post-foreclosure stages only. The results are consistent with what we reported in Table 3:

[6]Full regression results are available from the authors upon request.

the impact of foreclosure is stronger on lower-priced houses and the effect becomes more homogenous across the quantiles as the foreclosure event becomes more distant.

7.2 Monotonic Foreclosure Variables

Another major concern is related to the definition of foreclosure variables. We used a simple count of foreclosures by ring distance, which imposed an implicit weight on more distant foreclosures because the area (and hence likelihood of having a higher foreclosure count) increases with ring size. For example, on average there were 1.03 foreclosures in Ring 1, 2.15 in Ring 2, 7.04 in Ring 3, and 9.75 in Ring 4. To deal with this foreclosure monotonicity problem, we standardized the foreclosure variables by subtracting the mean and dividing by the standard deviation. The standardized foreclosure variables measure the relative intensity of foreclosures within each ring. A value of 1 for the standardized foreclosure variable in Ring 1 indicates that the house has 1 standard deviation more foreclosures in Ring 1 than the "average" Ring 1 foreclosure count for the sample. Standardized foreclosure counts for Rings 1, 2, 3 and 4 are now comparable. We used the standardized foreclosure variables and re-ran Model A. Table 6 shows the estimation results for the standardized foreclosure variables.[7] Our major findings were not impacted.

8 Discussion and Conclusions

In this paper, we applied spatial quantile regression to examine how neighborhood foreclosures affected nearby house sale prices across the conditional distribution of house prices. The quantile regression method allowed us to differentiate the foreclosure impacts on higher-priced versus lower-priced homes across different time periods and distance thresholds. Returning to our hypothesis, we found that foreclosed properties did produce different neighborhood price impacts at different quantiles of the conditional house price distribution. In

[7] Full regression results are available from the authors upon request.

particular, the price impacts for lower-priced homes were larger (in absolute value); and based on estimates for Model C (our most complete model), they were statistically distinguishable. However, we did not find variation in the timing of foreclosure effects across the conditional house price distribution.

The timing of the price effects may provide clues regarding the mechanisms through which foreclosures produce neighborhood price externalities. Neighborhood foreclosure effects occurring before the foreclosure auction are most likely associated with blight, which has been proposed as a leading mechanism through which foreclosures impact nearby home prices (Harding et al., 2009). We did not estimate any statistically significant price impacts prior to the foreclosure auction; however, estimated price externalities in the F to F+3 period may be a lagged effect of blight that occurred prior to the foreclosure auction. After the foreclosure auction, the negative price impacts of neighborhood foreclosures may increase (in absolute value) because all three channels for transmittal of neighborhood price externalities are likely: homes may continue to be inadequately maintained (blight channel), foreclosed properties increase the supply of homes (supply channel) and foreclosed properties are usually sold at significant discounts (valuation channel).

For all quantiles, we observed similar temporal patterns of foreclosure impacts within ring 1: Statistically significant negative foreclosure price externalities appeared in the F to F+3 period, intensified in the F+3 to F+6 period, and then attenuated in subsequent periods. Due to the similarity in the timing of foreclosure impacts across quantiles, we cannot infer differences in the mechanisms generating the foreclosure externalities that might vary across the conditional house price distribution. However, the observed statistically significant differences in the magnitude of the price externalities may be a result of cross-quantile differences in the severity or relative impacts of the three channels through which foreclosures are hypothesized to impact neighboring home prices after the foreclosure auction. Clarifying our understanding of heterogeneity in how the foreclosure price externality channels operate across different neighborhoods is an important area for future research. Our estimation results indicate that the most sever neighborhood price externalities were associated with houses in the lower quantiles and occurred in Ring 1, 3 to 6 months after the foreclosure auction.

These results should be viewed in light of the study's limitations. The principle limitation relates to external validity. The data from this study came from a single, urban Texas county. As a whole, Texas experienced a less volatile housing market during the financial recession and as a result the density and degree of clustering of foreclosures may be less than in other cities. Additionally, the dependent variable was only observed when properties sold, which may be considered a choice variable. To the extent that owners of properties in higher quantiles of the conditional price distribution had greater ability to delay sales when market prices were less than optimal, the estimated foreclosure price externalities will be biased towards zero in these quantiles. The extent to which the bias is problematic is unknown; however, we can observe the degree to which sales decreased across low-, middle-, and high-income neighborhoods during the time period when foreclosure rates were high in Dallas County. These data indicate that the drop off in sales affected all types of neighborhoods, and sales volume declined only slightly more in high- and middle-income neighborhoods (compared to low-income neighborhoods) in Dallas County (Leonard et al., 2014).

From a policy perspective, the results suggest the importance of foreclosure mitigation for lower-priced homes (i.e. homes within the lower quantiles of the *conditional* price distribution). These homes are likely located in poorer neighborhoods, likely represent a smaller proportion of a banks' balance sheet (compared to other homes with similar characteristics), and will likely sell at a higher penalty (in percentage terms) than higher-priced foreclosed properties. However, debt forgiveness or mortgage work-out measures in absolute terms may be smaller (because of the relatively smaller underlying asset value) for lower priced homes. Therefore our results suggest there may be additional benefits associated with foreclosure mitigation in poor neighborhoods because the benefits (i.e. reduced price externalities) are larger while the absolute costs of mitigation may be less.

Our results also suggest that policy efforts focussed on ameliorating the negative consequences of foreclosures in poorer neighborhoods likely target neighborhoods where the impact of foreclosure is most sever. In particular, Figure 2 illustrates the degree to which perviously reported mean neighborhood foreclosure effects likely under-estimate (in absolute value) the neighborhood price impacts of foreclosures in the lower quantiles, while over-estimating these same effects in higher quantiles. Therefore, programs such as the federal Neighborhood Stabilization Program (NSP) grants that stipulate funding must be used to the benefit of low- and moderate-income households, with an emphasis on household making less than 50% of the area median income, were likely effectively targeting areas where foreclosure externalities are most severe.

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Table 1: Summary Statistics for Housing Characteristic Variables

Variable	Description	Mean	Std. Dev.	Min.	Max.
Living area	Size of living area in thousands of square feet	2.147	1.088	0.552	31.100
Lot area	Size of lot area in thousands of square feet	10.108	10.177	0.249	324.850
Baths	Number of baths	2.296	0.878	0	10
Effective age	Number of years (in 10 years) since house has significant refurbishing	3.667	2.189	0.5	11.3
Pool	House with swimming pool	0.140	0.347	0	1
Story 1	House with one story	0.711	0.453	0	1
Story 1.5	House with one and a half stories	0.116	0.320	0	1
Slab	House with slab foundation	0.697	0.460	0	1
Central heat	House with central heat	0.953	0.213	0	1
One fire	House with one fireplace	0.698	0.459	0	1
Two fires	House with two fireplaces	0.073	0.260	0	1
Attached garage	House with attached garage	0.789	0.408	0	1
Attached carport	House with attached carport	0.020	0.139	0	1
Detached carport	House with detached carport	0.008	0.089	0	1

Table 2: Model A: OLS and quantile regression estimates

	(1) OLS	(2) 0.25 quantile	(3) 0.50 quantile	(4) 0.75 quantile	(5) 0.75-0.25 quantile
Constant	9.0557***	3.5017***	4.7386***	9.3565***	5.8547***
	(0.0645)	(0.2140)	(1.1011)	(0.9039)	(0.8208)
Living area	0.1803***	0.1717***	0.2127***	0.2729***	0.1012***
	(0.0054)	(0.0119)	(0.0091)	(0.0115)	(0.0114)
Lot area	0.0034***	0.0011***	0.0014***	0.0022**	0.0011
	(0.0003)	(0.0004)	(0.0004)	(0.0009)	(0.0008)
Baths	0.1502***	0.0402***	0.0485***	0.0501***	0.0098
	(0.0068)	(0.0084)	(0.0064)	(0.0068)	(0.0084)
Effective age	0.0010	0.0015	0.0082***	0.0036	0.0022
	(0.0026)	(0.0024)	(0.0019)	(0.0027)	(0.0030)
Pool	0.0649***	0.0543***	0.0515***	0.0483***	-0.0060
	(0.0097)	(0.0070)	(0.0059)	(0.0070)	(0.0086)
Story 1	-0.0631***	-0.0212***	-0.0018	0.0018	0.0230**
	(0.0105)	(0.0081)	(0.0069)	(0.0088)	(0.0091)
Story 1.5	-0.0437***	-0.0281***	-0.0087	-0.0151	0.0130
	(0.0121)	(0.0086)	(0.0076)	(0.0092)	(0.0108)
Slab	-0.1458***	-0.0765***	-0.0820***	-0.1142***	-0.0377***
	(0.0102)	(0.0094)	(0.0077)	(0.0121)	(0.0130)
Central heat	0.3855***	0.4710***	0.2203***	0.1607***	-0.3102***
	(0.0162)	(0.0452)	(0.0310)	(0.0222)	(0.0448)
One fireplace	0.2300***	0.1075***	0.0900***	0.0868***	-0.0207*
	(0.0087)	(0.0094)	(0.0083)	(0.0098)	(0.0114)
Two fireplaces	0.3510***	0.1322***	0.1330***	0.1456***	0.0134
	(0.0171)	(0.0148)	(0.0151)	(0.0167)	(0.0173)
Attached garage	-0.0296***	0.0049	-0.0352***	-0.0827***	-0.0876***
	(0.0100)	(0.0100)	(0.0100)	(0.0127)	(0.0139)
Attached carport	-0.0789***	-0.0329	-0.0633***	-0.0870***	-0.0540
	(0.0231)	(0.0315)	(0.0198)	(0.0251)	(0.0331)
Detached carport	-0.0665*	-0.0840**	-0.0583**	-0.0566	0.0274
	(0.0350)	(0.0383)	(0.0274)	(0.0350)	(0.0460)
Foreclosure count in Ring 1	-0.0441***	-0.0355***	-0.0226***	-0.0164***	0.0191***
	(0.0022)	(0.0023)	(0.0016)	(0.0018)	(0.0023)
Foreclosure count in Ring 2	-0.0045***	-0.0011	-0.0022***	-0.0043***	-0.0032**
	(0.0014)	(0.0011)	(0.0008)	(0.0011)	(0.0013)
Foreclosure count in Ring 3	-0.0049***	-0.0018***	-0.0021***	-0.0034***	-0.0016***
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0006)
Foreclosure count in Ring 4	-0.0083***	-0.0020***	-0.0019***	-0.0026***	-0.0007
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
$W_{07}y_{07}$	0.1191***	0.4652***	0.4091***	0.1820***	-0.2833***
	(0.0037)	(0.0684)	(0.0716)	(0.0569)	(0.0534)
$W_{06}y_{06}$	0.0664***	0.1511**	0.1335*	0.1947***	0.0437
	(0.0039)	(0.0700)	(0.0714)	(0.0713)	(0.0594)
$W_{05}y_{05}$	0.0362***	0.0108***	0.0157***	0.0229***	0.0120***
	(0.0027)	(0.0016)	(0.0017)	(0.0026)	(0.0024)
Condition dummies	Yes	Yes	Yes	Yes	Yes
Monthly sold dummies	Yes	Yes	Yes	Yes	Yes
School district dummies	Yes	Yes	Yes	Yes	Yes
N	12465	12465	12465	12465	12465
Adjusted/Pseudo R^2	0.816	0.6257	0.6551	0.6872	-

Standard errors in parentheses

The standard errors for quantile regression were obtained through 500 bootstrap replications.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Model A: 2SLS and 2SQR estimates

	(1) 2SLS	(2) 0.25 quantile	(3) 0.50 quantile	(4) 0.75 quantile
Constant	8.6880***	3.4887***	4.7191***	5.8568***
	(0.0684)	(0.2151)	(0.9367)	(0.6977)
$\widehat{W_{08}y_{08}}$	0.0556***	0.0107*	0.2054***	0.4772***
	(0.0037)	(0.0062)	(0.0409)	(0.0519)
Living area	0.1730***	0.1707***	0.2112***	0.2389***
	(0.0054)	(0.0118)	(0.0089)	(0.0086)
Lot area	0.0045***	0.0013***	0.0022***	0.0037***
	(0.0003)	(0.0004)	(0.0004)	(0.0008)
Baths	0.1438***	0.0404***	0.0460***	0.0427***
	(0.0067)	(0.0084)	(0.0064)	(0.0067)
Effective age	-0.0013	0.0013	0.0069***	0.0055**
	(0.0025)	(0.0025)	(0.0020)	(0.0022)
Pool	0.0645***	0.0541***	0.0550***	0.0539***
	(0.0096)	(0.0070)	(0.0060)	(0.0072)
Story 1	-0.0650***	-0.0215***	-0.0027	-0.0154*
	(0.0104)	(0.0080)	(0.0072)	(0.0080)
Story 1.5	-0.0447***	-0.0278***	-0.0087	-0.0155
	(0.0120)	(0.0087)	(0.0078)	(0.0101)
Slab	-0.1379***	-0.0755***	-0.0764***	-0.0792***
	(0.0102)	(0.0094)	(0.0079)	(0.0102)
Central heat	0.3707***	0.4517***	0.2032***	0.1463***
	(0.0161)	(0.0449)	(0.0284)	(0.0219)
One fireplace	0.2166***	0.1066***	0.0775***	0.0638***
	(0.0087)	(0.0094)	(0.0076)	(0.0080)
Two fireplaces	0.3347***	0.1321***	0.1210***	0.1179***
	(0.0170)	(0.0148)	(0.0150)	(0.0149)
Attached garage	-0.0318***	0.0038	-0.0338***	-0.0542***
	(0.0099)	(0.0099)	(0.0093)	(0.0104)
Attached carport	-0.0797***	-0.0341	-0.0606**	-0.0680***
	(0.0229)	(0.0322)	(0.0240)	(0.0253)
Detached carport	-0.0711**	-0.0851**	-0.0620**	-0.0553*
	(0.0347)	(0.0389)	(0.0257)	(0.0324)
Foreclosure count in Ring 1	-0.0431***	-0.0349***	-0.0218***	-0.0147***
	(0.0022)	(0.0023)	(0.0016)	(0.0017)
Foreclosure count in Ring 2	-0.0037***	-0.0010	-0.0021**	-0.0011
	(0.0013)	(0.0011)	(0.0009)	(0.0010)
Foreclosure count in Ring 3	-0.0049***	-0.0017***	-0.0021***	-0.0029***
	(0.0007)	(0.0005)	(0.0004)	(0.0004)
Foreclosure count in Ring 4	-0.0081***	-0.0020***	-0.0016***	-0.0017***
	(0.0005)	(0.0004)	(0.0003)	(0.0003)
$W_{07}y_{07}$	0.1011***	0.4673***	0.2511***	-0.0183
	(0.0038)	(0.0671)	(0.0804)	(0.0378)
$W_{06}y_{06}$	0.0596***	0.1416**	0.0888	0.0308
	(0.0039)	(0.0706)	(0.0653)	(0.0534)
$W_{05}y_{05}$	0.0332***	0.0099***	0.0145***	0.0200***
	(0.0027)	(0.0017)	(0.0018)	(0.0026)
Condition dummies	Yes	Yes	Yes	Yes
Monthly sold dummies	Yes	Yes	Yes	Yes
School district dummies	Yes	Yes	Yes	Yes
N	12465	12465	12465	12465
Adjusted/Pseudo R^2	0.819	0.6259	0.6579	0.7005

Standard errors in parentheses
The standard errors for quantile regression were obtained through 500 bootstrap replications.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Summary Statistics for Log of Sale Price Distribution

# of foreclosures	Mean	Std. Dev.	Skewness	Kurtosis
0	12.0801	0.8269	-0.5421	18.3189
1	12.0525	0.8304	-0.5450	18.1705
2	12.0249	0.8342	-0.5478	18.0045
3	11.9973	0.8382	-0.5504	17.8221

This table provides summary statistics for the log of sale price distribution with varying ring 1 foreclosure counts.

Table 5: Estimated Foreclosure Externalities Considering Only Past Foreclosures

	0.25 quantile	0.50 quantile	0.75 quantile
Foreclosure count in Ring 1	-0.0533***	-0.0330***	-0.0228***
	(0.0031)	(0.0017)	(0.0000)
Foreclosure count in Ring 2	-0.0023*	-0.0020***	-0.0026***
	(0.0012)	(0.0007)	(0.0004)
Foreclosure count in Ring 3	-0.0029***	-0.0029***	-0.0038***
	(0.0000)	(0.0007)	(0.0004)
Foreclosure count in Ring 4	-0.0027***	-0.0028***	-0.0028***
	(0.0002)	(0.0007)	(0.0004)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The standard errors (in parentheses) were obtained through 500 bootstrap replications.

The number of foreclosure counts in each ring is defined as the sum of all the foreclosure counts in post-foreclosure stages. We re-ran Model A by using the new set of foreclosure variables. Estimates for the foreclosure variables are reported here. Full regression results are available from the authors upon request.

Table 6: Estimated Foreclosure Externalities Based On Standardized Foreclosure Counts

	0.25 quantile	0.50 quantile	0.75 quantile
Foreclosure count in Ring 1	-0.0586***	-0.0366***	-0.0246***
	(0.0038)	(0.0027)	(0.0029)
Foreclosure count in Ring 2	-0.0030	-0.0064**	-0.0034
	(0.0035)	(0.0026)	(0.0030)
Foreclosure count in Ring 3	-0.0128***	-0.0152***	-0.0213***
	(0.0034)	(0.0033)	(0.0032)
Foreclosure count in Ring 4	-0.0188***	-0.0151***	-0.0158***
	(0.0040)	(0.0032)	(0.0032)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The standard errors (in parentheses) were obtained through 500 bootstrap replications.

The number of foreclosure counts in each ring was standardized by subtracting the mean and dividing by the standard deviation. We re-ran Model A by using the new set of foreclosure variables. The estimates of the foreclosure variables are reported here. Full regression results are available from the authors upon request.

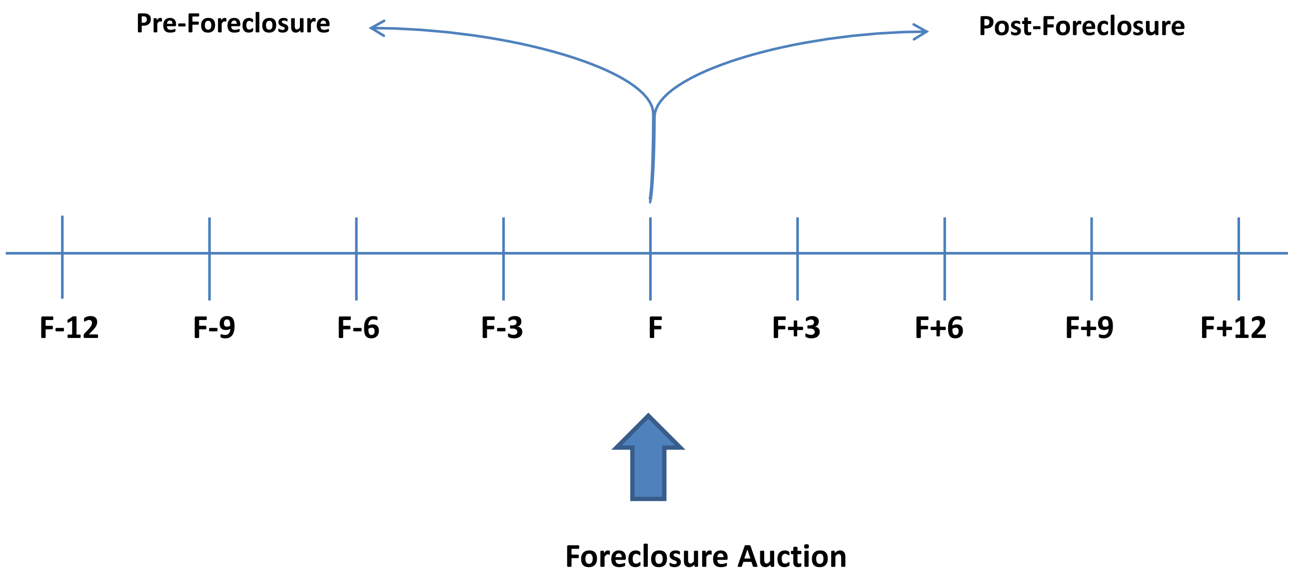

Figure 1: Foreclosures by Time. We break the time before foreclosure sale (pre-foreclosure) and the time after foreclosure sale (post-foreclosure) each into four quarterly periods. Then we calculate the number of foreclosures in each time period.

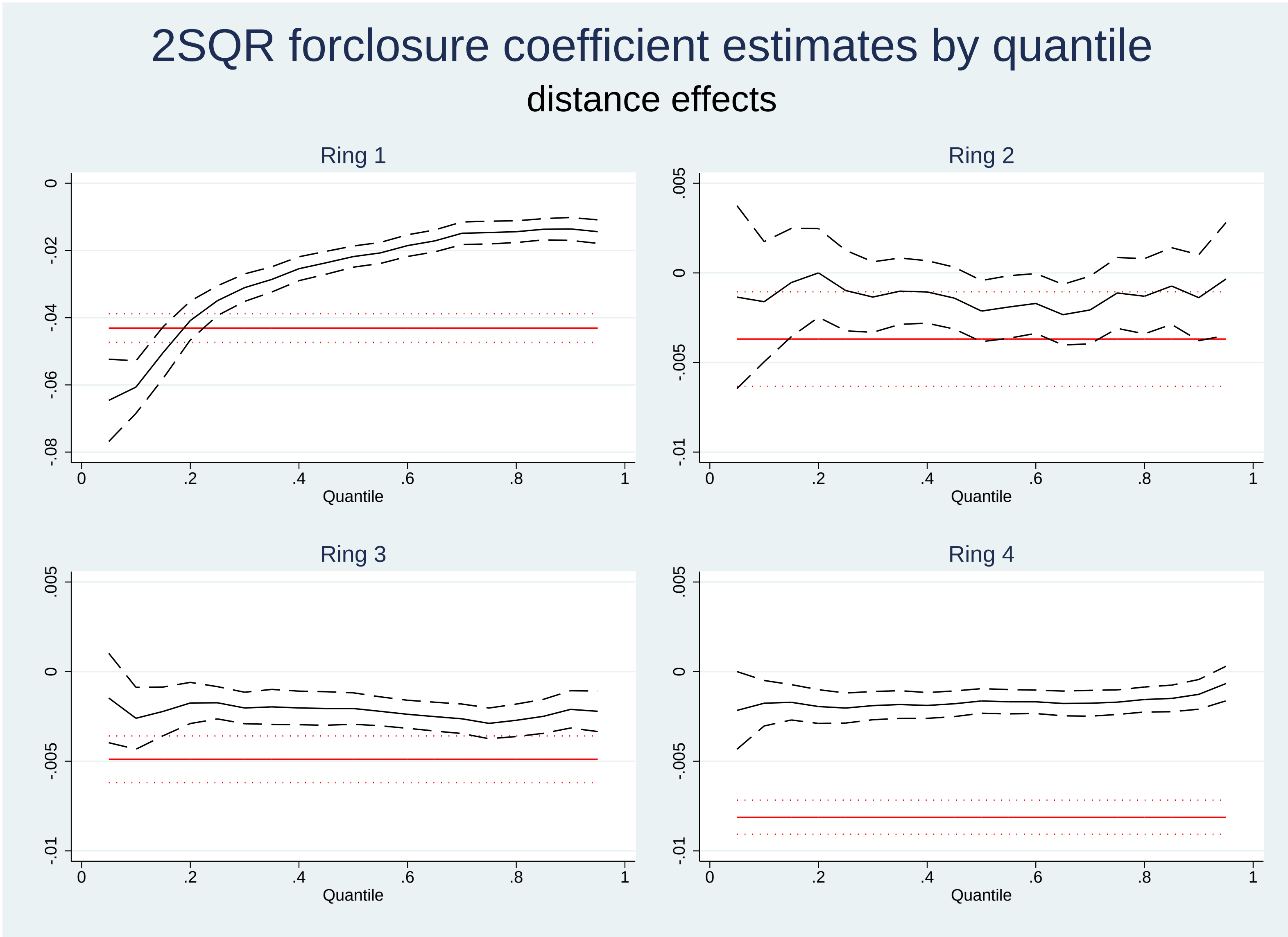

Figure 2: Distance Effects. This figure displays the estimated foreclosure externalities associated with foreclosures occurring at any time in each different distance ring. Each panel plots an explanatory variable's 2SQR coefficient estimates and their associated 95% confidence intervals (dashed line) at 19 quantile points from the 5th to 95th percentile. The solid horizontal line in each figure is the 2SLS coefficient estimate and associated 95 percent confidence interval (dotted line). Note: Scale for Ring 1 is different from Rings 2-4.

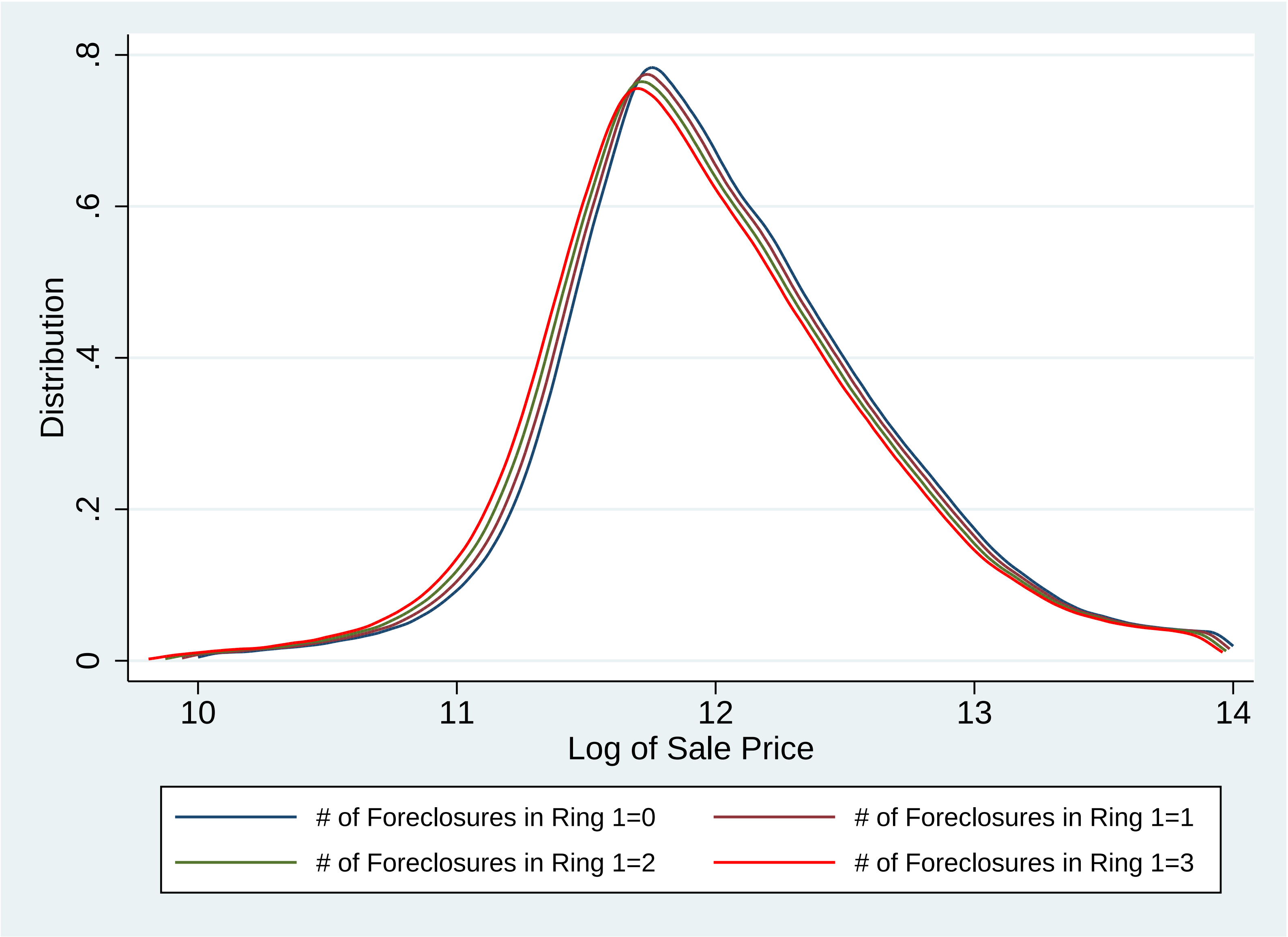

Figure 3: Predicted Densities from Spatial Quantile Regression Estimates. This figure exhibits kernel density functions for predicted log sales prices at alternative values of the number of foreclosures in Ring 1.

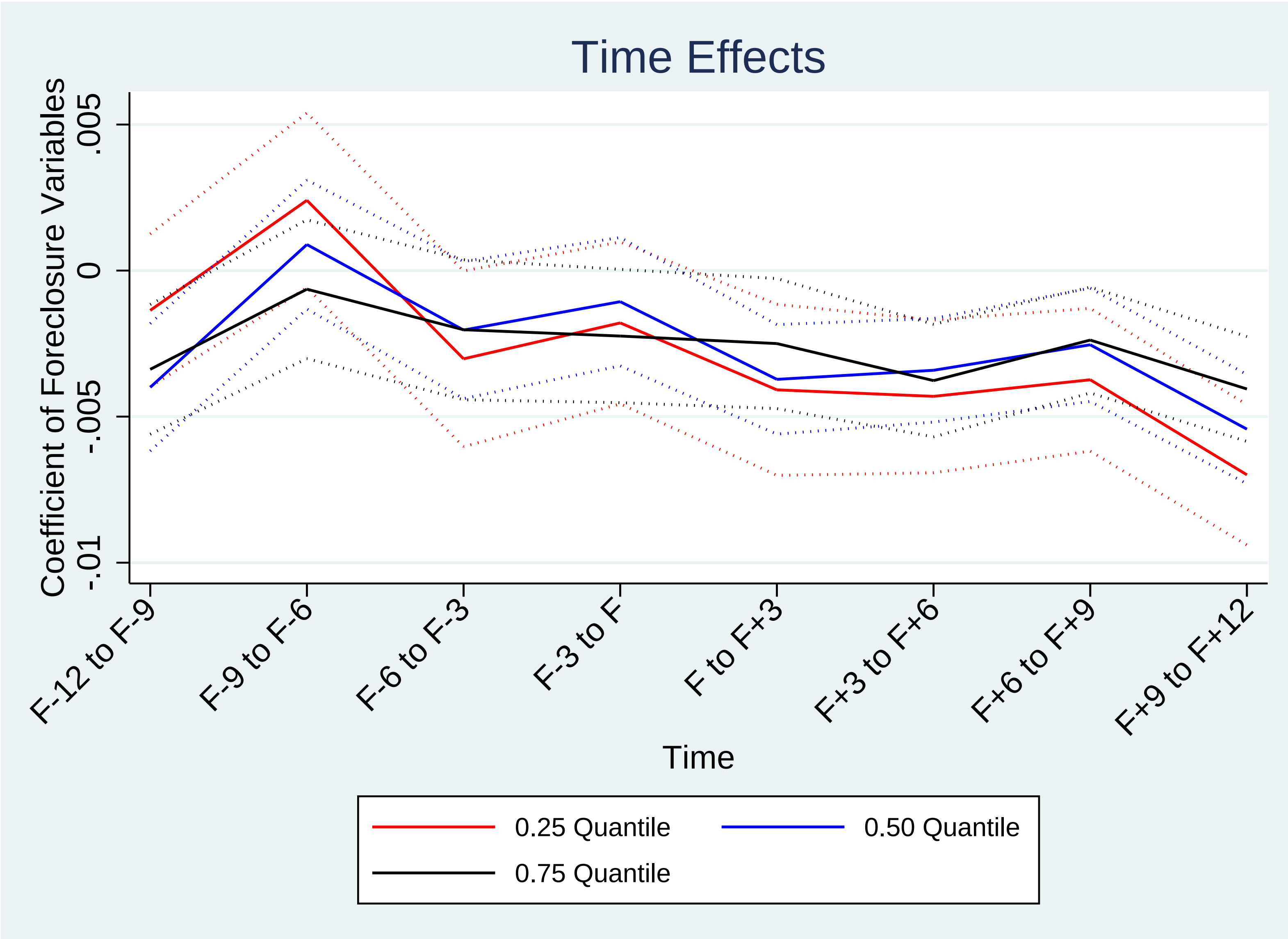

Figure 4: Foreclosure Time Effects. This figure displays the estimated foreclosure effects from foreclosures within 1500 feet of a non-distressed sale from 12 months before the foreclosure auction to 12 months after the foreclosure auction. Each solid curve in different color represents the plot of the coefficient estimates for foreclosure variables in a specific quantile. The two dotted curves with same color are the related 95% confidence intervals.

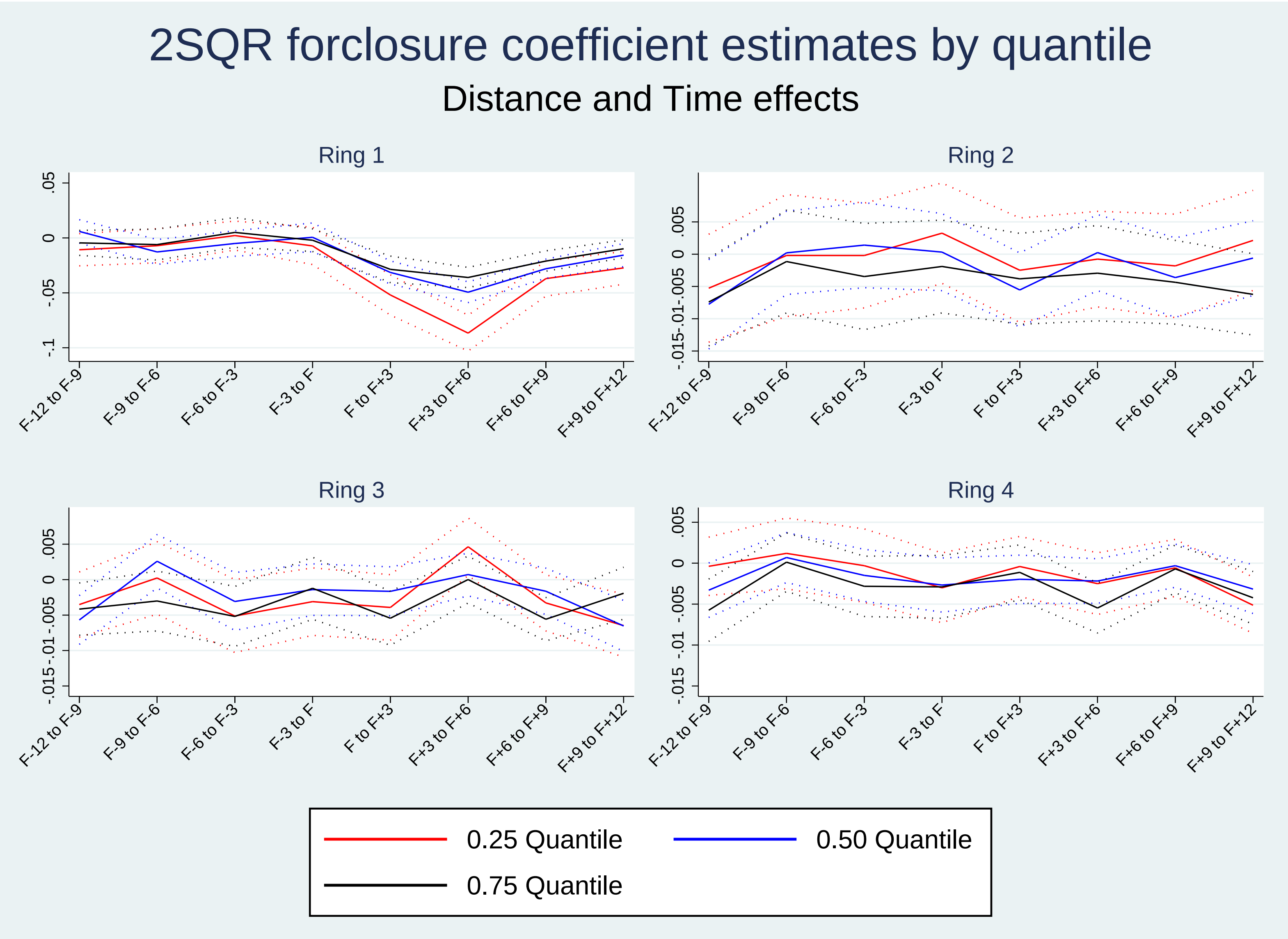

Figure 5: Distance and Time Effects. This figure displays the estimated neighborhood effects of foreclosures in different rings from 12 months before the foreclosure auction to 12 months after the foreclosure auction. Each solid curve in different color represents the plot of the coefficient estimates of foreclosure variables in a specific quantile. The two dotted curves with same color are the related 95% confidence intervals. Note: Scale for Ring 1 is different from Rings 2-4.