The Contagion Effect of Foreclosed Properties

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Abstract

Although previous research shows that prices of homes in neighborhoods with foreclosures are lower than those in neighborhoods without foreclosures, it remains unclear whether the lower prices are the result of a general decline in neighborhood values or whether foreclosures reduce the prices of nearby non-distressed sales through a contagion effect. We provide robust evidence of a contagion discount by simultaneously estimating the local price trend and the incremental price impact of nearby foreclosures. At its peak, the discount is roughly one percent per nearby foreclosed property. The discount diminishes rapidly as the distance to the distressed property increases. The contagion discount grows from the onset of distress through the foreclosure sale and then stabilizes. This pattern is consistent with the contagion effect being the visual externality associated with deferred maintenance and neglect.

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Introduction

After an extended period of house price appreciation, in 2008 the United States experienced declining house prices and rapidly increasing foreclosures. It is widely accepted that home foreclosures have significant negative externalities.[1] Recent studies (e.g., Immergluck and Smith, 2006 and Lin et al., 2009) have reported that the presence of foreclosed properties is associated with lower sales prices for nearby non-distressed properties. These results are often interpreted as supporting the idea that nearby foreclosed properties lower the prices of neighboring houses (e.g., Center for Responsible Lending, 2008 and 2009). There are several possible mechanisms through which a foreclosed property can affect the values of nearby properties. The first is through a negative visual externality as the appearance of the neglected property deteriorates. In addition to normal depreciation, many properties undergoing foreclosure experience gross neglect, abandonment and vandalism which significantly alter their exterior appearance. A second mechanism, social interaction, is described by Ioannides (2002) who shows that individuals' valuations of their own homes are influenced by those of their immediate neighbors. As a result, a decline in value of a nearby foreclosed property can result in lower seller reservation prices and lower sales prices for nearby non-distressed properties. Foreclosed properties also increase the supply of homes and the sellers of foreclosed properties are highly motivated to sell quickly putting downward pressure on local prices. Finally, the prospect of imminent foreclosure reduces the incentive of homeowners to invest in socially desirable individual and community activities which can reduce the attractiveness of the neighborhood to potential buyers. Concern about such negative externalities has helped shape public policy since the 1930's. In 2008, the Bush Administration, Congress and various regulators introduced new programs to aid troubled homeowners, reduce foreclosures and fund the acquisition of distressed properties by local governments. In 2009, the

[1] For example, in a May 5, 2008 speech, Federal Reserve Board Chairman, Ben Bernanke, stated "High rates of foreclosure can have substantial spillover effects on the housing market, the financial market and the broader economy."

Obama Administration introduced a $275 billion program to shore up the housing markets and aid homeowners deemed to be "at risk" of foreclosure. The justification for the use of public funds for such efforts is based on the negative externalities of foreclosures.

Three recent papers (Lin et al., 2009, Immergluck and Smith, 2006, and Shlay and Whitman, 2004) have documented a negative relationship between non-distressed sales prices and the number of nearby foreclosures.[2] Significantly, none of these studies have focused on whether foreclosed properties cause a decline in the value of nearby homes or whether all homes in the neighborhood experienced a decline in value which, in turn, led to more local foreclosures. A general decline in home values would trigger defaults at some houses in the neighborhood, but not all, making it difficult to distinguish cause and effect.[3] The critical question is whether the presence of nearby foreclosures causes an incremental decline in values of nearby properties or is just a symptom of a general decline in house prices.

All three recent papers derive their estimates using hedonic models. The contagion effect is estimated by including measures and/or indicators of nearby distressed properties as additional independent variables. A general problem with the hedonic specification is that it is impossible to observe all house, location and local market characteristics and thus the coefficient estimates of the included variables are subject to omitted variable bias. The omitted variable problem arises very frequently in the study of urban externalities, including the impact on home values of environmental problems, schools, and commercial development. A recent example is the analysis by Pope (2008) of the impact of the presence of a registered sex offender on the prices of nearby homes. Pope finds that sex offenders tend to locate in lower valued areas and shows that estimating the impact of a nearby sex

[2] See Schwartz et al. (2003) for a summary of earlier literature on housing spillover effects.

[3] Theory suggests that although a decline in house value that creates negative equity is a necessary condition for a foreclosure, the foreclosure is triggered by a cash flow or income problem that reduces the ability of the household to make the mortgage payments. Thus, the incidence of foreclosure in a neighborhood undergoing a general decline in value depends on the distribution of loan-to-value ratios in the area and the incidence of income disruption (e.g., illness, divorce, loss of job). It is reasonable to assume that the distribution of original loan to value ratios and the incidence of trigger events are independent of the local price changes. See Avery et al. (1996) for more discussion.

offender using an indicator variable significantly overstates the effect of the sex offender. Measures of the number of nearby foreclosures in a cross-sectional hedonic model are especially vulnerable to the omitted variable problem because it is likely that the number of nearby foreclosures is correlated with unobserved property and location characteristics and especially the local trend in market prices.[4]

The repeat sales approach provides an alternative estimation procedure that substantially reduces the omitted variable problem of hedonic models and is well-suited to identify the separate effects of the overall price trend and the contagion effect of nearby foreclosures. We use an extension of the repeat sales model (first suggested by Bailey et al., 1963, and later utilized by Schwartz, et al., 2003, and Harding et al., 2007) that explicitly controls for property characteristics that are expected to change between sales and thus do not difference out of the repeat sales regression. We treat the number of nearby foreclosures as such a variable.

We use a sample of approximately 400,000 repeat sales transactions to study this issue. At each sale, we collect information about the number and distance of distressed properties in the vicinity of the subject property. Because the foreclosure process includes three distinct phases (a period of delinquency leading to a foreclosure sale, the period after the lender takes title through foreclosure and the period after the REO sale to a new permanent owner), for each foreclosed property, we collected information about the foreclosure sale date and the subsequent REO sale date. This information enables us to identify the phase of the foreclosure process the nearby property was in when the subject property sold and thereby estimate whether the contagion effect differs with the phase of foreclosure. The results provide insights into the mechanism by which foreclosed properties affect nearby values.

Our results confirm that nearby distressed properties have significant negative contagion effects over and above the local trend in house prices. We estimate a peak contagion effect from the closest

[4] Immergluck and Smith (2006) discuss this problem and try to address it by including a very large set of neighborhood characteristics. However, they do not control for the overall market trend in prices.

foreclosures of approximately one percent. The estimated contagion effect varies from one MSA to another but in all cases it diminishes quickly with the distance between the subject property and the foreclosed property. We also find that the strongest contagion effect generally increases quickly during the year preceding the foreclosure sale. In general, after the foreclosure sale, the trend slows or stops, but the negative effect remains well after the lender resells the property. We find that the maximum negative effect of a single foreclosure on a nearby sale occurs around the time of the foreclosure sale. At that point, a single foreclosure reduces the value of a house located within 300 feet of the foreclosure by approximately one percent. We estimate the model for seven different MSAs with different rates of price appreciation in the 2000's and find a significant negative contagion effect in all seven, although the magnitude of the effect varies by MSA.

Our estimate of the peak contagion effect of a single nearby foreclosed property is smaller than the previous hedonic estimates. We also find a sharper decline with distance than did earlier studies. Based on our estimates, a foreclosed property $1/8^{th}$ of a mile away would have a peak negative effect of less than .5% or roughly half that estimated by Immergluck and Smith (2006). The cumulative effect of all nearby foreclosures can be significantly higher. We find that if there are three or more foreclosed properties within 300 feet of a non-distressed sale, the non-distressed property sells at a price approximately three percent below market.

Historically, lender forbearance and foreclosure moratoria have been popular policy responses to high levels of mortgage delinquency and foreclosures. The current housing and financial crisis has renewed interest in these responses.[5] However, because our results suggest that the root cause of the contagion effect may be reduced maintenance, neglect and vandalism, the most efficient way to reduce the negative externality of foreclosures would be to avoid extended periods of reduced maintenance and

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[5] For information on the use of foreclosure moratoria in the 1930s, see Wheelock (2008). In early 2009, many large mortgage lenders implemented voluntary foreclosure moratoria and in June, 2009, the state of California imposed a 90-day moratorium on housing foreclosures.

neglect. One way to achieve this would be to negotiate a permanent loan modification assuring that the homeowner has both the resources and incentive to maintain and protect the property. Failing that, the best solution is a quick resolution of the problem through foreclosure and subsequent transfer of the property to a new owner who has the capacity and incentive to properly maintain and protect the home.

The remainder of the paper is organized as follows. Section 2 presents the methodology used to estimate the contagion effect. The next section presents the data and discusses the base estimation results while Section 4 explores the cumulative effect of multiple nearby foreclosures. Section 5 discusses robustness tests and Section 6 concludes the paper.

2. Methodology

We begin with the standard log-linear hedonic specification for modeling house prices based on the premise that the price of a bundled good such as a specific house can be expressed as a function of the inner product of a vector of characteristics and the market-determined shadow prices of those characteristics (see Griliches, 1971, Rosen, 1974 and Epple, 1987).

$$P_t = e^{[sC]} \quad \text{or} \quad \ln(\mathrm{P_t}) = s'C \tag{1}$$

In equation (1), P_t represents the price of a house at time t. The house and its locational attributes are fully described by the vector of characteristics, C. The important insight of Rosen (1974) was that under the assumption of sufficient variation in the traded bundles, the vector of shadow prices is revealed to agents in the economy through trades that differ in a single characteristic. If the presence of nearby distressed properties affects the value of the house, in theory, we should simply include the presence of distressed properties in the vector of attributes.

In practice, the vector of shadow prices, s, is estimated by regressing observed house prices on the vector of observed characteristics. A problem arises, however, because we do not observe all characteristics of the subject house and its neighborhood and market. To describe this problem, consider partitioning the vector C into two components -- $C = \begin{pmatrix} C_1 \\ C_2 \end{pmatrix}$, where C_1 denotes the vector of observed characteristics (including the presence of a nearby distressed property) and C_2 the vector of unobserved characteristics, including the local trend in house prices and other unobserved property and location attributes. If C_1 and C_2 are independent, then estimating equation (1) using only C_1 provides unbiased estimates of the corresponding shadow prices, s_1. However, if an element of C_1 is correlated with elements of C_2, then the estimated coefficient on that characteristic will be a combination of the effects of the unobserved characteristics on price and the direct effect (i.e., shadow price) of the observed characteristic. Specifically, consider including the number of nearby distressed properties in C_1. It is well established that the likelihood of foreclosure of a given property increases with the contemporaneous loan-to-value (LTV) ratio. If the overall trend in prices is downward, that will directly lower the price of the subject home and also trigger nearby foreclosures.[6] If the empirical model does not control for the overall price level, a large number of nearby foreclosures may proxy for an overall decline in home prices and thus a negative coefficient on the measure of foreclosures could actually be an estimate of the local decline in prices and not a true contagion effect.

The repeat sales model derived by Bailey et al. (1963) and Case and Shiller (1989) provides a way to jointly estimate the overall trend in prices and the direct contagion effect of nearby distressed properties. The basic idea of a repeat sales specification is that most elements of the characteristic vector (both observed and unobserved) remain constant between the two sales and consequently difference out when we model the rate of price appreciation instead of the price. This greatly simplifies the estimation of the model because those characteristics can be deleted from the model as shown below.

[6] Nearby foreclosures would increase because the current LTV ratio depends on past financing decisions as well as the current price. Different households will have taken out loans with different LTV ratios and made different use of secondary financing. Consequently, the same house price decline will leave some properties with prices in excess of the current debt while other households are "under water" because they owe more than their home is currently worth. For "under water" borrowers, random trigger events (e.g., divorce, job loss, sickness etc.) are more likely to result in default and foreclosure.

We begin with a slightly expanded version of equation (1), describing the price at time t for property i:

$$P_t^i = e^{\gamma_t} e^{\left[s_1 C_1^i + s_2 C_2^i\right]} e^{aN_t^i} e^{\eta_t^i} \quad \text{or } \ln(P_t^i) = \gamma_t + s_1 C_1^i + s_2 C_2^i + aN_t^i + \eta_t^i \tag{2}$$

C_1^i and C_2^i include observed and unobserved explanatory variables related to the price of an individual property. The error term, η_t^i, is assumed to be independent and identically distributed and captures pure random shocks to the transaction price. There are two new elements in equation (2)—γ_t and aN_t^i. The first term, e^{γ_t}, represents the overall market price level and adjusts the base value of the bundle of house attributes to current market price. The second term, $e^{aN_t^i}$, adjusts the price of the particular house for the effects of nearby distressed properties; N_t^i equals the number of nearby (to property i) distressed properties.[7] While N_t^i is technically a location characteristic, we separate it from the other elements of C because we anticipate that it will change between sales and is thus different from the other elements of C. Using the same notation, equation (3) describes the price at the time of the next sale of the same property. The second sale occurs at time t +τ.

$$P_{t+\tau}^i = e^{\gamma_{t+\tau}} e^{\left[s_1 C_1^i + s_2 C_2^i\right]} e^{aN_{t+\tau}^i} e^{\eta_{t+\tau}^i} \quad \text{or } \ln(P_{t+\tau}^i) = \gamma_{t+\tau} + s_1 C_1^i + s_2 C_2^i + aN_{t+\tau}^i + \eta_{t+\tau}^i \tag{3}$$

Following the standard derivation of the repeat sales equation, we difference the log versions of the two equations, assuming s_1C_1 and s_2C_2 are unchanged between t and t+τ for a particular property *i*:

$$\ln\left(P_{t+\tau}^i \big/ P_t^i\right) = \left(\gamma_{t+\tau} - \gamma_t\right) + a(N_{t+\tau}^i - N_t^i) + \varepsilon_{t,t+\tau}^i \tag{4}$$

[7] To simplify the presentation of the basic approach, we use the imprecise notion of "nearby" at this point. The reader can think of nearby being defined as a distance of less than three hundred feet. When we implement the approach, we use several different classes of distance.

The assumption that s_1C_1 and s_2C_2 are unchanged between t and $t+\tau$ is essential to the repeat sales model. While this assumption is common to all repeat sales applications (including research papers such as Harding et al., 2007, and the widely cited Case-Shiller and OFHEO price indices), it is also common to screen the repeat sales pairs to eliminate those where the assumption is questionable. Our standard filter screens out repeat sales pairs that have a high rate of appreciation (ten percent per quarter) combined with a short holding period (less than two years) as well as pairs with an appreciation rate of eight percent per quarter and a holding period longer than two years. Nevertheless, to the extent that property characteristics change between observations, the effect of such changes will be included in the error term and the resulting coefficients would be biased if the variables on the right hand side of equation (4) are correlated with the error term.[8]

The estimates of γ_t and $\gamma_{t+\tau}$ provide an estimate of the change in the local price level between t and $t+\tau$. The contagion effect of distressed properties is measured by the coefficient a, which in this specification, is assumed to be constant over time.[9] The ability of the repeat sales specification to jointly estimate the overall price level change and the contagion effect is a significant advantage over the hedonic specification for this application.

The estimated contagion effect will be unbiased as long as $(N^i_{t+\tau}-N^i_t)$ is uncorrelated with the error term. Given the assumptions underlying equations (2) and (3), N^it is independent of the random idiosyncratic variation in individual house prices, η^i_t. The random shock to the value of house i at time t cannot influence the number of nearby distressed properties. Therefore, if the error term in equation (4), $\varepsilon^i_{t,t+\tau}$ is the just the difference in the two price equation error terms, then the change in the number of

[8] The repeat sales methodology also assumes no change in attribute prices between sales. If the attribute vector is fixed, then this assumption reduces to assuming that the inner product of shadow prices and attributes remains constant. The model allows for an overall shift in price levels and so changes in tastes that lower one price and raise another can have offsetting effects which do not alter the inner product. Even if the effects do not offset, it is unlikely that such shifts in attribute prices relative to the overall price level will be correlated with the change in the number of nearby foreclosures.

[9] The specification also implies that the contagion effect is linear in the number of foreclosures. Although the linearity assumption proves to be reasonable, we later estimate models with different specifications and discuss the impact of multiple nearby foreclosures in Section 4 later in the paper.

nearby foreclosed properties will be independent of the error term. However, it is possible that the error term, $\varepsilon^{i}_{t,t+\tau}$ includes a component attributable to the changes in other elements of the vector, C, that are not explicitly included in the model. If these omitted variables were correlated with the change in the number of foreclosed properties, the estimate of the contagion effect could be biased. As mentioned above, one defense against this potential problem is to screen out repeat sales pairs where it is likely that there has been some unobserved change in characteristics. A second solution is to use instrumental variables to estimate the model. In Section 5 we discuss the application of different filters for screening unusual observations and the use of instrumental variables to address the possible endogeneity issue. Briefly summarizing our findings, the results presented in Section 3 are robust to changes in data filters and further we do not find evidence of significant endogeneity.

3. Data and Results

3.1 Data

In order to estimate equation (4), we need to identify local markets where we have both a large sample of repeat sales and the ability to identify all nearby foreclosures that could potentially influence the transaction price. It is critical that the data include a complete inventory of all foreclosures near each sale with enough information about the foreclosure to precisely locate the foreclosed property in both space and time. At a minimum, one needs the latitude and longitude of the property, the foreclosure date and the REO sale date.

We begin with a large proprietary mortgage database, containing approximately half of all national mortgage transactions over the period from 1989 through 2007. From this mortgage data, we can identify home purchase and sale transactions and the outcome of the mortgage: prepaid, foreclosed or still active at the end of the sample period. For the housing transactions in this database, it is known with near certainty whether the ownership of the underlying property was transferred through a foreclosure sale. For these foreclosed properties, the data include both the foreclosure sale date and the

REO sale date. However, since the database does not contain all mortgages, and particularly since it does not contain many subprime mortgages, it does not provide a complete record of foreclosures in any given area. To augment that record, additional data were acquired from vendors of housing transactions data. This purchased data includes information on foreclosure sales and REO sales as well as normal purchase transactions. Unfortunately, even the purchased transactions data have gaps in coverage of foreclosures and as a result we must restrict our analysis to those geographic areas where we are highly confident that we have complete coverage of foreclosure activity.

We use the proprietary data in conjunction with the purchased data to identify zip codes where the purchased data provides close to complete coverage of foreclosures by finding those zips where the purchased transaction data correctly identifies at least eighty percent of the foreclosure sales from the proprietary database. We assume that if the purchased data can identify at least eighty percent of the known foreclosure sales in the mortgage database for a particular zip code, its coverage of foreclosures in that location resulting from other mortgages is similarly good. For the 296 zip codes that met this criterion, we combine all foreclosures from the proprietary mortgage database with those from the purchased transaction database to create a local inventory of foreclosures which we believe provides a coverage rate well above eighty percent.

To estimate equation (4), we need information on repeat sales pairs as well as the foreclosure information discussed above. The basic source for the repeat sales pairs is the GSE loan database used to generate the Federal Housing Finance authority (FHFA) home price indices augmented with the previously discussed purchased transactions data covering non-GSE home purchase transactions. The repeat sales pairs were restricted to single-family detached houses and include only true market transactions. Refinancings and all foreclosure-related sales were excluded.[10] In addition, we filter the

[10] Leventis (2009) provides evidence that the inclusion of distressed sales has a small but significant negative effect on repeat sales indexes. In the analysis presented here, we exclude all properties that are included in the foreclosure sample (i.e., experience a foreclosure at any time during the sample period) from the repeat sales sample.

repeat sales pairs to eliminate outliers and records where the holding period returns appear abnormal and suggest that the underlying assumption of no change in property and neighborhood characteristics is questionable. Our primary screen eliminates any observation with price appreciation greater than eight percent per quarter – although the return threshold is somewhat higher (ten percent) when the holding period is less than two years.[11] Finally, imposing the requirement that each zip code has sufficient transactions (post screening) to compute a robust repeat sales index for the period from 1990 through 2007 reduced the number of zip codes to 140. For each repeat sales observation in these zip codes we collected the property address, the initial purchase date and price, and the second sale date and price.

The final step in building the data base was to geocode all records in both files so that we could identify nearby foreclosures for each repeat sales transaction using the geocoded locations. We categorized the distance between the subject property in the repeat sales pair and a foreclosure using four concentric rings with different radii around each subject property.[12] The rings we selected were: 1) 0 to 300 feet (Ring 1); 2) 300 feet to 500 feet (Ring 2); 3) 500 feet to 1000 feet (Ring 3); 4) 1000 feet to 2000 feet (Ring 4). The innermost ring can be thought of as including the two to three nearest neighboring properties in each direction (which are probably visible from the sale property), while the second ring can be thought of as having a foreclosure on the same block as the subject property. Properties in this ring might be seen by potential buyers visiting the home for sale but are not likely to be visible from the property. Foreclosures in the two outer rings would not be visible from the subject property but could influence the subject price by altering a potential buyer's perception of the neighborhood and/or by providing competition for buyers. For each sale in the repeat sales sample, we

[11] As a robustness check we also estimated the model using other more restrictive screens. The results of these robustness checks are discussed in Section 5.

[12] For computational reasons, the count of foreclosures in a ring is restricted to include only those in the same zip code as the subject property. This truncation of the rings creates measurement error in the count of nearby foreclosures for some properties. We check the robustness of our results to this potential problem using instrumental variables and also by estimating a model for a single zip code area where we are able to calculate the estimates with and without this restriction. The results are very similar.

searched the foreclosure file to identify all foreclosed properties that were somewhere in the foreclosure process[13] on the date of the sale and also were located in one of the concentric rings.

In addition to identifying the distance of the foreclosed property from the subject property, we categorized each foreclosed property by the phase of the foreclosure process it was in at the date of the repeat sale transaction. To do this, we considered thirteen windows of time linked to either the foreclosure sale date, F, or the REO sale date, S. Figure 1 shows how we identified the different phases of the foreclosure process. We break the time before F into four quarterly periods or "windows" and the time after F and before S into at most five windows. Because the time between F and S varies from loan to loan, not all loans pass through all the indicated post-foreclosure windows. In our classification scheme, as soon as S occurs (which can be shortly after F, but on average occurs approximately ten months after F) we assign the date to one of the four post-S categories and not the post-F categories.[14] For example, consider a foreclosure sale, F, that occurred on July 1 with an REO sale, S, to a third party on August 15. If we observed a nearby repeat sales transaction on August 30, we would classify the foreclosed property as falling into the {S to (S+3months)} window as opposed to the {F to (F+3 months)} category. If the repeat sales date had been August 1 (falling before S), the foreclosed property would be classified as falling into the {F to (F+3)} window.[15]

The 104 zip codes with good foreclosure coverage represent thirty-seven MSAs and thirteen states. The distribution of observations across states is provided in Table 1. Because we want to control as well as possible for local market conditions, we further limit our sample to the seven MSAs with at least 7,500 repeat sales pairs. We estimate equation (4) for each of the seven selected MSAs. These

[13] The foreclosure process is defined as the period beginning twelve months before the foreclosure sale and ending twelve months after the REO sale.
[14] As a result of this convention, the number of foreclosures observed in the windows after F declines with time. For this reason, we define the last post-foreclosure window to include all properties where more than twelve months have passed without an REO sale.
[15] To simplify notation in future discussions of the phase windows, we describe a window using only the later date, as long as the meaning is clear.

MSAs represent different economic and housing market conditions ranging from those that are often cited as examples of "boom" areas (e.g., Las Vegas) to those that experienced more modest price changes and less robust economic growth (e.g., Memphis and Columbus). These seven local markets include 72 zip codes and more than sixty-five percent of the total repeat sales transactions in our data. In most cases, the zip codes in these MSAs that passed the earlier screens for good foreclosure coverage represent a small fraction of the total zip codes in the whole MSA. Further, the selected zip codes are not necessarily contiguous.

Table 2 presents summary statistics for the foreclosure sample. The first column provides data on the combined sample of foreclosures for all seven MSAs while the next seven columns report the data for each of the selected MSAs. The table shows a dramatic increase in foreclosures over the sample period but also shows significant variations across MSAs.[16] In the Los Angeles MSA, foreclosures were quite high in the local housing recession of the mid -1990s and although they are increasing at the end of the sample, they remain below the peak of 1997. In Atlanta, Charlotte, Columbus and Las Vegas, the number of foreclosures in the 2005-2007 period is much higher than at any other period in the sample. The data for Memphis and St. Louis show a history of chronic foreclosure problems related to local economic conditions. The bottom portion of the table provides data from the Mortgage Bankers Association (MBA) for the rate of new foreclosure filings in the nation (column one) and the state corresponding to each of the seven MSAs. These numbers are provided to give an overall perspective on foreclosure rates but it is important to keep in mind that in addition to the geographic differences between state and MSA, the numbers in the top portion of the table represent the stock of homes

[16] The apparent decline in foreclosures in 2007 is the result of lags in recording data related to the foreclosure process — especially the key foreclosure and REO sale dates. We do not include foreclosures for which we do not have both the foreclosure date and the REO sale date. Because the foreclosure sample was drawn in the summer of 2008, some foreclosures from the second half of 2007 still had incomplete information and were excluded from the sample. We tested for sensitivity of our findings to the exclusion of these foreclosures by estimating our models using repeat sales through 2006 instead of 2007. Our parameter estimates were essentially the same.

somewhere in the foreclosure process while those in the bottom panel report the flow of new foreclosure filings.

Table 3 presents descriptive statistics for the repeat sales sample. The purchase price ($140,600) reported in the table represents the average price at the time of the initial purchase in the repeat sales pair, while the sale price ($171,377) reflects the second sale of the pair. The typical holding period (a measure of local mobility) was just under five years. Homeowners in the sample earned an average nominal annual return from price appreciation of approximately four percent. The data for the individual MSAs confirms that these seven MSAs represent a diverse sample of housing markets. The average purchase price ranges from $93,752 in St. Louis to $194,537 in Los Angeles. The average holding period ranges from 3.4 years in Las Vegas to 5.4 years in St. Louis and annual holding period returns averaged 2.6% per year in Charlotte and 9.2% per year in Las Vegas. The repeat sales were generated by 281,088 distinct properties. More than two-thirds of the properties had a single repeat sale and the properties with at most two repeat sales account for more than ninety percent of the sample. This pattern is typical for large repeat sales samples such as those used by FHFA. Panel B of Table 3 provides information about the timing of the sales in the repeat sales pairs.

3.2 Model Specification

We follow the standard repeat sales methodology (see Case and Shiller, 1989), to implement the OLS estimation of equation (4). As discussed in the previous section, we measure the contagion discount using a total of fifty-two "buckets"; where each bucket contains the difference in the number of nearby foreclosures that are within the specified ring and are at the specified phase of the foreclosure process (see Figure 1). The resulting equation to be estimated by OLS is:

$$\ln\left(P^{i}_{t+\tau} \big/ P^{i}_{t} \right) = \sum_{j=1}^{72} \gamma_j D_{i,j} + \sum_{d=1}^{4} \sum_{p=1}^{13} a_{dp} B^{i}_{dp} + \varepsilon^{i}_{t,t+\tau} \tag{5}$$

where $B^{i}_{dp} \equiv (N^{idp}_{t+\tau} - N^{idp}_{t})$ and $N^{idp}_{t} \equiv$ the number of foreclosures at distance d from property i in phase p at t.

In equation (5), D is the standard matrix of indicators that identify sales dates. In estimating equation (5), we use the Case and Shiller (1989) GLS approach which allows for an increase in the variance of the disturbance term, $\varepsilon_{t,t+\tau}$, with increases in the holding period, τ.

3.3 Results

We estimated the parameters of equation (5) separately for each of the seven selected MSAs. We present the estimated indices in graphical form where all indices are normalized to a value of 100 in the first quarter of the plot. Figure 2 shows the indices for each MSA, estimated with and without controlling for nearby foreclosures (i.e., dropping the terms in the double summation of equation (5)). Because the scale would be significantly compressed by plotting the index from 1990 through 2007 (typical prices have more than doubled), the plots in Figure 2 show the indices for the last five years (2003 through 2007). The figures confirm the previously discussed variation in housing market conditions represented by the seven MSAs. Four markets show steady but moderate increases in prices through mid-2007 (Atlanta, Charlotte, Memphis and St. Louis). Las Vegas and Los Angeles exhibit much steeper rates of price appreciation prior to 2006 followed by steep declines.

In six of the seven MSAs (the exception being Los Angeles), the index estimated without controlling for the nearby foreclosures shows less market-based appreciation than the indices estimated with such controls. This is consistent with the recent sharp increase in foreclosures in those MSAs because when nearby foreclosures are more common for the second sale of the repeat sale pair, the observed holding period returns are lower and the unadjusted index underestimates the true appreciation rate because it is "pulled down" by the large number of foreclosure discounts at the second sale. The model with controls for nearby foreclosures correctly reflects a higher market appreciation rate and an offsetting negative contagion effect. When the estimation does not control for contagion effects, the negative contagion effect is erroneously attributed to the general price level, γ_t. When foreclosures affect the first and second sales with roughly the same frequency (as in Los Angeles), the contagion effect on the price index is minimal.

We turn next to the estimates of the contagion effects in the seven models. Because we have seven MSAs, four different rings and thirteen time windows, we need to review the results by selected categories. We focus first on the estimated contagion effect for the nearest foreclosed properties – those in Ring 1. Table 4 presents the estimated Ring 1 contagion effects for all thirteen different phases of foreclosure for each MSA. At the bottom of the Table, we aggregate the thirteen different windows of the foreclosure process into three categories: 1) the twelve months before foreclosure, 2) the time between foreclosure sale and REO sale and 3) the twelve months following the REO sale. Nineteen of the twenty-one aggregated contagion parameters are negative and, of those, sixteen are significantly different from zero at the five percent significance level or better. The estimated effects for properties in the post-foreclosure, pre-REO sale phase are uniformly negative (and significant) and generally larger in absolute value than the estimated pre-foreclosure effects. The average of the seven different MSA estimates is reported in the far right column and shows that the average effect for the post-foreclosure phase is approximately twice as large as the pre-foreclosure effect. The average effects for properties in the post REO sale period are generally negative and somewhat larger in magnitude than the estimated effects for the post foreclosure phase. This shows that the stigma effect is persistent and not easily reversed, even after the property is sold by the lender.

The individual contagion effects reported in the top portion of the table show significant variation across MSAs and across the different phase windows within an MSA. Furthermore, given the limited sample sizes for certain MSA models, the individual parameters are not always estimated precisely enough to achieve statistical significance. The sample size issue is especially significant for the properties that have spent more than twelve months without a lender sale and we place little confidence in those estimates – only one of which is statistically significant at normal confidence levels.

Turning to the average over the seven MSAs for each phase window, all but one of the estimated phase effects are negative. Figure 3 plots this average effect and shows that the estimated contagion effect is negligible a year before the foreclosure sale.[17] At that time, most properties are occupied by their owners and most owners still have an expectation of retaining ownership, even if they are facing financial challenges. Hence, they still have an incentive to maintain the property, albeit at a somewhat lower intensity than owners with more certainty of long-term ownership.[18] The negative effect grows in magnitude as the delinquency extends and foreclosure nears. During this period, the hope of retaining ownership diminishes as the borrower falls further behind in payments and the foreclosure process begins (on average around {F-9}). A homeowner with little prospect of curing the default has no incentive to maintain the property and the lender does not yet have control of the property or the authority to undertake needed repairs. The sharp increase in discount related to foreclosures less than three hundred feet away over the period just preceding the foreclosure sale is consistent with a growing negative externality arising from serious neglect and an increased frequency of abandonment and/or vandalism. By the time of the foreclosure sale, the estimated contagion effects for the two windows that bracket F suggest an approximate one percent discount in price for nearby non-distressed sales. After the foreclosure sale, the property is under the control of the lender who has an incentive to maximize the net proceeds from the disposition of the property. In some cases, the best strategy for the lender is to repair the property, but in other situations the best strategy is to sell the property in “As Is” condition. Generally speaking, the property is left vacant during the marketing period and may be at risk of vandalism. Figure 3 shows that the average contagion effect generally stabilizes while the property is under the control of the lender. Even when the property is resold to a new owner there is little immediate improvement. This could be because it takes the new owner some time to repair the home

[17] In Figure 3 we exclude the window for properties that have been in the post-foreclosure phase for more than a year. The average for that window is dominated by the large positive but insignificant estimate for Los Angeles.
[18] See Harding et al. (2000) for a discussion of how current LTV influences an owner’s maintenance decisions.

and offset the previous owner's neglect, but it could also reflect a tendency for purchasers of foreclosed properties to either rent the home or invest less in maintenance and renovation than would the purchaser of a non-distressed property.

Table 5 presents similar results for Ring 2 where the foreclosed property is between three hundred and five hundred feet of the non-distressed sale. Looking at the results for the aggregated windows (near the bottom of the table), we again see a preponderance of negative contagion effects. However, now five of the twenty-one estimates are positive. More than half of the significant negative effects are from the Charlotte and Columbus MSAs. In the other MSA models, most of the significant estimated coefficients are negative, but many of the estimated effects are quite small. The average effect for all seven MSAs is negative for all three aggregate windows, but less than half the magnitude of the average effects in Ring 1. Shifting attention to the top portion of the table, only Charlotte and Columbus consistently show statistically significant negative contagion effects. Taken as a whole, the estimated coefficients reported in top portion of Table 5 suggest a weak negative effect from these more distant foreclosures.

Figure 4 provides a graph comparing the average phase effects from the seven MSAs (shown in the far right column) for all four Rings. The figure shows that the largest negative effect in Ring 2 occurs around the time of the REO sale by the lender, not the foreclosure sale date as was the case for Ring 1. The figure also shows that the estimated contagion coefficients for Rings 3 & 4 are much smaller in magnitude than those for the inner rings.

In summary, our results show that foreclosed properties within 300 feet of the subject property create a significant negative externality effect which is approximately one percent per distressed property at its peak. This contagion discount diminishes rapidly with distance and falls to approximately .5% for properties that are between 300 feet and 500 feet from the non-distressed sale. Beyond five hundred feet (.1 mile), we find very small negative effects. Our results with respect to the phase of foreclosure show that the contagion discount is negligible a year before the foreclosure sale but increases sharply and peaks in Ring 1 around the time of the foreclosure sale. In Ring 2, the effect is small until close to the lender's REO sale date.

The different time patterns for Ring 1 and Ring 2 suggest different transmission mechanisms for the negative externality. It is reasonable to assume that owner neglect of a property undergoing foreclosure peaks just before the foreclosure sale and eviction. At about the same time, many foreclosed properties become vacant and subject to vandalism. As a result, the visual negative externality of having a neighboring property in foreclosure peaks at about the same time. Because of the close proximity, potential buyers of the non-distressed property will observe the effects of neglect and also face the uncertainty about the future owner and whether the property will be repaired and reasonably maintained in the future. This suggests that the transmission mechanism for how a foreclosed property influences the value of its immediate neighbors is largely visual – visitors to the non-distressed property are confronted with the problem each time they visit the non-distressed property. More distant properties, even those on the same block, have a less direct visual impact on potential buyers. However, such properties can still affect the value of non-distressed properties that are being sold through increased competition for buyers as highly motivated sellers try to sell REO as quickly as possible—often with ready financing. Thus, our finding that the effect of these more distant properties peaks during the lender's REO marketing time is consistent with the hypothesis that the primary transmission mechanism for these more distant properties is through increased competition for a limited number of buyers.[19]

Our results confirm that the presence of a nearby distressed property has a significant, negative effect on the prices of nearby homes over and above the overall trend in market prices. The finding that

[19] Turnbull and Dombrow (2006) argue that greater concentrations of sellers in a local market have two potentially offsetting effects on a given seller: a negative competition effect and a positive shopping externality. They find empirical support for both effects and also find that a higher concentration of vacant houses has a consistent negative effect on the prices (and a generally positive effect on marketing time) of nearby homes. This suggests that the competition effect from nearby vacant homes generally dominates the shopping externality. This is consistent with the results reported here.

the contagion effect diminishes rapidly with distance is intuitive and consistent with the estimated effect being truly a contagion effect. An effect that exhibited persistence with distance would be more consistent with an unobserved trend in local house prices.

4. **Multiple Foreclosures**

The model specification of equations 2-5 and the results discussed in the preceding section assume that the contagion discount increases linearly with the number of nearby foreclosures. In this section, we relax that restriction in two different ways. First, we estimate a model with indicators for exactly one, exactly two and three or more nearby foreclosures in each concentric ring around the subject property. Second, we use an alternative specification that allows for a quadratic effect in the number of nearby foreclosures. To better focus the results and discussion, we reduce the number of contagion parameters estimated in each model by combining the thirteen phase buckets used earlier into a single bucket spanning the period from twelve months before the foreclosure to twelve months after the REO sale.

Indicator Models

We first establish a baseline by estimating a model with a single indicator for each concentric ring; the indicator flags the presence of one or more distressed properties in the ring. The initial specification of the underlying price hedonic (the equivalent of equation (2) without the disturbance term) using these four indicators is given below:

$$P_t = e^{\gamma_t} e^{\left[s_1 C_1 + s_2 C_2\right]} e^{\left[\sum_{d=1}^{4} a_d I_t^d\right]} \tag{6}$$

In equation (6), d indicates the specific ring and I^d_t takes on a value of one if there is one or more distressed properties at time t in Ring d. A distressed property is defined as any property that falls in the range from {F-12} to {S+12} on the sale date, t. In this specification, a_d represents the cumulative effect of nearby foreclosures and is influenced by the distribution of the observed number of nearby foreclosures. For example, if there are typically two nearby foreclosures when I^d_t equals one, then a_d will reflect the average effect corresponding to two nearby foreclosures. In this specification, the effect of nearby foreclosures is summarized by four coefficients not fifty-two. As in the previous section, to derive the final OLS model to be estimated, we write an equation similar to equation (6) for time t + τ, take logs of both equations and difference the two. The resulting OLS specification is:

$$\ln\left(P^i_{t+\tau} \middle/ P^i_t \right) = \sum_{j=1}^{72} \gamma_j D_{ij} + \sum_{d=1}^{4} a_d \left(I^{id}_{t+\tau} - I^{id}_t \right) + \varepsilon^i_{t,t+\tau} \qquad (7)$$

where $I^{id}_t = 1$ if there are one or more distressed properties in Ring d around property i at t.

The results of estimating a_d using equation (7) are presented in the top panel of Table 6. We focus our discussion on the rightmost column that reports the average of the estimates for the seven MSAs. As expected, the contagion coefficients in Table 6 are larger in absolute value than those in Tables 4 and 5. The effect of one or more nearby foreclosures in Ring 1 is -1.5%. The estimated contagion effect in this specification is larger than the earlier estimated coefficients because it represents the cumulative effect summed over all thirteen phases as well as the average number of foreclosures in each phase bucket. Second, the reported contagion effect appears to be more persistent as the distance from the subject property increases. This is because each of the outer rings contains a larger total area and consequently the frequency of foreclosures in each ring increases. The coefficients estimated with equation (7) reflect the combination of a declining marginal effect per foreclosure that is partially offset by an increase in the average number of foreclosures in the bucket.

To further study the effect of multiple foreclosures, we extend equations (6) and (7) to include three different indicators for each ring: one that indicates the presence of exactly one foreclosure in the specified ring, a second to identify cases where there are exactly two foreclosures in the indicated ring and a third to flag the cases with three or more foreclosures. The estimates of these twelve discount effects are reported in Panel B of Table 6. The results are generally consistent with a linear effect over the range from zero to two. For example, the effect of exactly one nearby foreclosure in Charlotte is -1.64% while the effect of having exactly two is -3.6%. The table also shows that several of the individual MSA effects are not significantly different from zero. This is likely the result of a limited number of occurrences in an MSA where only one sale in the repeat sales pair had exactly two nearby foreclosures.[20] As conventional wisdom predicts, the effect of having three or more nearby foreclosures in Ring 1 is quite severe -- roughly three percent based on the average of all MSAs and as high as six percent in Charlotte. Significantly, however, even this effect diminishes quickly with distance. For example, looking at the average of the seven MSAs, the effect declines to -1.3% in Ring 2, despite the fact that the area of Ring 2 is much larger than that of Ring 1 and the average number of foreclosures increases with the area of the ring.

Quadratic Specification.

The indicator specifications discussed above suggest that a linear model for the effect of nearby foreclosures may be appropriate, but does not shed much information on the "tail" of the distribution or the effect of a large number of nearby foreclosures. Therefore, to further explore this issue, we modified equation (2) to include a quadratic effect (while still using a single phase bucket).

$$P_t = e^{\gamma_t} e^{\left[s_1 C_1 + s_2 C_2\right]} e^{\sum_{d=1}^{4} a_d N_t^d + b_d (N_t^d)^2} \tag{8}$$

Following the same procedure of taking logs and differencing, generates equation (9):

$$\ln\left(P^i_{t+\tau} / P^i_t\right) = \sum_{j=1}^{72} \gamma_j D_{ij} + \sum_{d=1}^{4} a_d (N_{t+\tau}^{id} - N_t^{id}) + b_d ((N_{t+\tau}^{id})^2 - (N_t^{id})^2) + \varepsilon_{t,t+\tau} \tag{9}$$

where N_t^{id} = the number of distressed properties in Ring d around property i at t.

[20] The parameter a_d is identified by the cases where only one pair in the sale has an indicator equal to one because if both indicators are one or both are zero, the term differences to zero.

The estimates of a_d and b_d for each of the four rings are presented in Panel C of Table 6. Figure 5 plots the resulting average effect as a function of N_t^{id}. To avoid extrapolating a quadratic function beyond the range of the estimating data, the lines for the various rings are truncated at four, five, seven and ten foreclosures, respectively. The table and figure provide further confirmation of the fact that foreclosures in the innermost ring have a very significant negative externality and that the effect is roughly linear over the observed range of the number of nearby foreclosures. The quadratic term has a significant positive coefficient in all four rings, suggesting that the marginal effect of each new foreclosure is somewhat smaller, but the offsetting quadratic effect is small relative to the linear effect for all rings.

In summary, these alternative specifications suggest that the linear assumption for the contagion effect used in equations (2) to (5) is reasonable. The finding of a rapid decline in the contagion effect with distance is also robust to these different model specifications.

5. Robustness

Although the repeat sales methodology for estimating the contagion effect is preferable to estimating the effect in a hedonic model without controls for local price trends, there is a price associated with that advantage -- the assumption that there is no change in property and neighborhood characteristics between the paired sales. One way to test for robustness to this assumption is to apply different filters to the repeat sales pairs used to estimate the model. The results discussed in the previous section were based on a sample that excluded observations with unusually high holding period returns. This filter serves to screen out property "flips" where an owner/investor buys a property, renovates it and resells the renovated property. To test the sensitivity of our findings to the specific terms of this screen, we re-estimated the models for all seven MSAs using alternative screens. Table 7 describes the various filters used in the estimation. The Base filter is the one described earlier in the paper and is used for all of the previously discussed results. The rows of the table describe the alternative filters applied to the data and the resulting additional exclusions relative to the base sample. While most of the alternative screens reduce the sample size by two to three percent, the most stringent (Screen 6) reduces the total sample by approximately eight percent.

The results of estimating the seven MSA models are robust to varying the filter applied to the repeat sales pairs. Figure 6 shows the estimated Ring 1 phase coefficients (averaged over all seven MSAs) for the various screens. The figure clearly shows that the coefficients are not sensitive to the various screens. We also reviewed the individual MSA estimated coefficients and found them to be similarly robust. The largest single change in a Ring 1 coefficient (from -.0108% to -.0068%) was observed in Los Angeles.

Another possible concern is that the change in the number of foreclosures between the two sales dates of a repeat sales pair is correlated with changes in other variables not explicitly included in the model specification. If this were the case, then the change in the number of foreclosures in equation (5) would be correlated with the error term.[21] As a robustness check for this possible endogeneity, we used the instrumental variables (IV) technique. IV estimation can address both the possibility of endogeneity and the problem of measurement error.[22] To implement this approach we need to predict the number of nearby foreclosures using variables that are uncorrelated with the disturbance term. Previous mortgage research and traditional underwriting rules have shown that borrower credit histories, original loan-to-value ratios and income are important predictors of foreclosure. Consequently, we developed estimates of the distribution of FICO scores, loan-to-value ratios and homeowner incomes in the four rings surrounding each property at each transaction date. We created these estimates using data from loan originations in each ring for each date. We selected the Los Angeles MSA because it had the smallest

[21] Using the change in foreclosures for fifty-two different phase/distance buckets already provides some degree of control for this problem because changes in other house or location characteristics are less likely to be correlated with these very fine measures of foreclosure change.

[22] Although our inventory of nearby foreclosures is quite good, it is nevertheless not perfect. To the extent that our inventory of nearby foreclosed properties is incomplete, our measure of the change in the number of nearby foreclosures in each phase bucket will have measurement error. Another source of measurement error arises because of the boundaries of the zip codes used as the basic geographic unit. This latter problem is discussed below.

number of repeat sales transactions which kept the effort required to create the instruments manageable. We used the 90th percentile of FICO score and loan-to-value ratio, the median income level along with the housing stock in each ring and the subject property size as instruments in a first stage regression to predict the change in the number of foreclosures in each ring for each repeat sales pair (equation 5). We are able to use the property size as an instrument because the property characteristics difference out in the derivation of the repeat sales OLS specification. The property size proxies for average neighborhood house characteristics.

The first stage regression uses the change in the number of foreclosures as the dependent variable and the set of all exogenous variables, including the five instruments described above as the independent variables. In the second stage regression, we used the predicted change in the number of foreclosures in place of the actual number of foreclosures to estimate equation (5). The estimated contagion parameters and index values were qualitatively similar to the original estimates. We tested for the presence of significant endogeneity using the Hausmann endogeneity test.[23] The test rejects the presence of significant endogeneity in the Los Angeles model and provides support for using OLS to estimate the models. We did not repeat this robustness check for the other MSAs because gathering the necessary data on census tract credit scores and loan-to-value ratios is difficult and the results from Los Angeles suggest that endogeneity is not a significant problem.

Another potential problem with our data is that we measure the number of nearby foreclosures looking at only those foreclosures that fall in the same zip code as the non-distressed sale. Thus for a sale that is near the border of its zip code, the concentric circles around the property will cross the zip code boundary leading to an underestimate of the number of nearby foreclosures and therefore introduce measurement error in the change in nearby foreclosures variable. To test whether this influences our

[23]The Hausman endogeneity test provides a test of whether a variable in an OLS specification is endogenous. The test entails projecting the variable to be tested (in our case the change in the number of foreclosures) on the set of all exogenous variables, including the instruments. The residuals from this first stage regression are then added to the original OLS specification and if the estimated coefficient is significant, the test rejects the null hypothesis of no endogeneity.

results,[24] we identified a cluster of zip codes in the Atlanta MSA where there was a central core zip code (30044) that had passed our screens and was fully surrounded by zip codes that had also passed our criteria for having full foreclosure inventories. We re-estimated the model for the central zip code only, treating it as a stand-alone zip code and therefore excluding all foreclosures outside the zip code in the count of nearby foreclosures. We then re-estimated the model for the same zip code (30044) including foreclosures from the surrounding zip codes in the count of nearby foreclosures. We found that the measurement error in the count of nearby foreclosures was quite small for this zip code and that the resulting contagion effect estimates were essentially the same as those estimated using the zip code as a stand-alone location.

6. **Conclusion**

We use the repeat sales methodology to provide joint estimates of the local trend in house prices and the contagion discount associated with selling a home with a foreclosed property nearby. Using the repeat sales approach reduces the omitted variable bias that is likely a problem when using hedonic models for this purpose. We find that having a neighboring property in the process of foreclosure can result in a discount to market value of up to one percent per nearby distressed property. We find that for small numbers of foreclosures the discount is approximately linear in the number of nearby distressed properties.

The estimated contagion effect declines rapidly with distance between the foreclosed property and the non-distressed sale. The effect of a foreclosed property in a ring 300 to 500 feet from the subject property is roughly half that of an immediate neighbor. The size of the discount continues to fall as the distance increases; beyond five hundred feet we find almost no statistically significant contagion

[24] Note that instrumental variables estimation can also be used to address measurement error and as discussed previously we do not find significant differences in Los Angeles using instrumental variables.

effect. These results showing a rapid decline of the contagion effect with distance are different than those reported by previous researchers.

Because of the size of our database, we are also able to study how the contagion effect varies with the phase of the foreclosure process which, in turn, sheds light on the transmission mechanism. For properties within three hundred feet of a foreclosed property, we find that the contagion discount is negligible a year before the foreclosure sale but increases rapidly as the delinquency becomes more serious. The peak negative externality occurs near the time of the foreclosure sale. Between the foreclosure sale and the REO sale, the discount stabilizes as the lender resumes maintenance of the property and markets the property. Despite some improvement after the REO sale, the contagion discount resulting from immediate neighbors lingers for at least a year after the REO sale. The pattern of effects from foreclosed properties between three hundred and five hundred feet (Ring 2) is different in several respects. First, it does not increase as rapidly during the delinquency phase and second it peaks near the time of the REO sale by the lender. We interpret these different patterns as suggesting that the negative externality from immediate neighbors is attributable to property neglect and uncertainty about the future owner. Properties located further away affect the sale prices of non-distressed properties largely through a competition effect.

From a policy perspective, our results confirm the existence of a significant negative externality associated with foreclosed properties and support publicly funded efforts to reduce the problem. However, our estimates of that externality controlling for the local trend in house prices are generally smaller than previous estimates in the literature and we provide evidence that the most significant externalities are attributable to immediate neighbors. As a result, a million additional foreclosures would significantly affect three to five million homes not the forty million that has been estimated using earlier estimates of contagion effects. Finally, our analysis of the impact by phase shows that the externality grows rapidly during the period required for the lender to take control of the property. This suggests that when foreclosure is inevitable, efforts to speed the foreclosure process would be effective at reducing the costs associated with the contagion effect.

References

Avery, R., Bostic, R., Calem, P., Canner, G., 1996. Credit Risk, Credit Scoring, and the Performance of Home Mortgages, *Federal Reserve Bulletin* 82: 621-648.

Bailey, M. J.; Muth, R. F., Nourse, H. O., 1963. A Regression Model for Real Estate Price Index Construction, *Journal of the American Statistical Association* 58(304): 933-942.

Case, K., Shiller, R., 1989. The Efficiency of the Market for Single-Family Homes, *The American Economic Review* 79(1): 125-137.

Center for Responsible Lending, 2008. Subprime Spillover: Foreclosures Cost Neighborhoods $202 Billion; 40.6 Million Homes Lose $5,000 on Average, CRL Issue Paper.

Center for Responsible Lending, 2009. Soaring Spillover: Accelerating Foreclosures to Cost Neighbors $502 billion in 2009 alone; 69.5 million homes lose $7,200 on average, CRL Issue Paper.

Epple, D., 1987. Hedonic Prices and Implicit Markets: Estimating Demand and Supply Functions for Differentiated Products, *Journal of Political Economy,* 95(1):59-80.

Griliches, Z., ed., 1971. *Price Indexes and Quality Change,: Studies in New Methods of Measurement.* Cambridge, MA: Harvard University Press.

Harding, J., Knight, J., Sirmans, C. F., 2003. Estimating Bargaining Effects in Hedonic Models: Evidence from the Housing Market, *Real Estate Economics* 31(4): 601-622.

Harding, J., Rosenthal, S., Sirmans, C. F., 2007. Depreciation of Housing Capital, Maintenance and House Price Inflation: Evidence from a Repeat Sales Model, *Journal of Urban Economics* 61(2): 193-217.

Harding, J., Miceli, T., Sirmans, C.F., 2000. Do Owners Take Better Care of Their Housing Than Renters? *Real Estate Economics* 28(4): 663-681.

Immergluck, D., Smith, G., 2006. The External Costs of Foreclosure: The Impact of Single-Family Mortgage Foreclosures on Property Values, *Housing Policy Debate* 17(1):57-79.

Ioannides, Y., 2002. Interactive Property Valuations. *Journal of Urban Economics.* 53: 145-170.

Leventis, A., 2009. The Impact of Distressed Sales on Repeat-Transaction House Price Indexes, Federal Housing Finance Agency, Research Paper**.**

Lin, Z., Rosenblatt, E., Yao V. W., 2009. Spillover Effects of Foreclosure on Neighborhood Property Values, *Journal of Real Estate Finance and Economics* 38(4), *f*orthcoming.

Pope, J. C., 2008. Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries, *Journal of Urban Economics* 64:601-614.

Rosen, S., 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition, *Journal of Political Economy* 82: 34-55.

Schwartz, A., Ellen, I., Voicu, I., Schill, M.,. 2003. Estimated External Effects of Subsidized Housing Investment on Property Values. Lincoln Institute of Land Policy. Working Paper WP03AS1.

Shlay, A., Whitman, G., 2004. Research for Democracy: Linking Community Organizing and Research to Leverage Blight Policy, *City and Community* 5(2): entire monograph.

Turnbull, G., Dombrow, J., 2006. Spatial Competition and Shopping Externalities: Evidence from the Housing Market, *Journal of Real Estate Finance and Economics* 32:391-408.

Wheelock, D., 2008. The Federal Response to Home Mortgage Distress: Lessons from the Great Depression, *Federal Reserve Bank of St. Louis Review.* 90(3) 133-148.

Table 1
Repeat Sales Observations: Distribution by State and MSA

	State Totals				7-MSA Samples		
State	**Number of Repeat Sales**	**Percent of Total Sample**	**Number of Zip Codes**	**# of MSAs**	**MSA**	**Number of Repeat Sales**	**Number of Zip Codes**
CA	42,521	6.80%	5	5	Los Angeles	7,767	1
GA	190,514	30.30%	30	2	Atlanta	186,655	29
IN	25,111	4.00%	14	7	--	--	--
MO	25,065	4.00%	7	2	--	--	--
NC	64,022	10.20%	15	6	St. Louis	19,594	4
NV	27,895	4.40%	4	1	Charlotte	46,219	10
OH	192,852	30.70%	51	8	Las Vegas	27,895	4
SC	5,194	0.80%	3	3	Columbus	84,751	18
TN	49,331	7.90%	8	3	--	--	--
UT	2,023	0.30%	1	1	Memphis	32,802	6
WA	2,237	0.40%	1	1	--	--	--
WY	1,766	0.30%	1	1	--	--	--
Total	628,531	100%	140	40		405,683	72

The repeat sales sample was drawn from the FHFA (previously OFHEO) joint GSE mortgage loan files, augmented with transaction data purchased from private vendors describing transactions not financed by a GSE.
The repeat sales were drawn from 140 zip codes for which we have a nearly complete record of foreclosures and a sufficent volume of regular sales transactions large enough to estimate an accurate repeat sales index.

Table 2
Summary Statistics for Foreclousre Sample
(Foreclosures from 1989 through 2007)

	Total Sample	Atlanta	Charlotte	Columbus	Las Veg.	LA	Memphis	St. Louis
Number (total)	60,708	24,334	8,711	11,858	3,303	2,887	6,087	3,528
% (of all foreclsures)	100.0%	40.1%	14.3%	19.5%	5.4%	4.8%	10.0%	5.8%
Average Time from F to S (months)	9.89	9.86	9.89	10.01	9.43	9.46	10.15	9.97
Foreclosures by Year								
1989	79	61	1	5	-	1	9	2
1990	127	87	1	4	-	22	9	4
1991	252	119	-	10	-	106	10	7
1992	287	83	4	6	1	173	14	6
1993	355	58	4	12	11	248	20	2
1994	369	50	8	13	7	251	29	11
1995	325	45	8	10	19	221	16	6
1996	813	189	7	28	31	352	136	70
1997	2,126	987	133	217	56	385	178	170
1998	1,961	645	136	297	157	275	221	230
1999	1,865	501	220	291	138	173	258	284
2000	2,172	535	312	473	159	110	287	296
2001	3,221	1,059	502	556	197	74	466	367
2002	4,700	1,688	859	937	283	59	541	333
2003	7,009	2,943	1,319	1,525	233	21	648	320
2004	7,548	3,144	1,470	1,865	33	10	695	331
2005	8,271	3,915	1,374	1,859	68	7	735	313
2006	10,881	4,927	1,423	2,438	615	93	970	415
2007	8,156	3,142	926	1,302	1,295	305	834	352

Mortgage Foreclosure Started (%): US Total and 7 States

	U.S.	GA	NC	OH	NV	CA	TN	MO
2000	0.62	1.48	1.43	2.18	2.18	1.28	1.63	1.14
2003	0.79	2.25	2.33	2.87	2.87	0.74	2.31	1.78
2005	0.72	2.27	2.02	3.36	3.36	0.59	2.20	1.84
2007	1.30	3.23	2.12	4.37	4.37	3.26	2.62	2.61

Notes:
1. The foreclosures described in Table 2 represent the combination of foreclosures identified in the GSE mortgage database and foreclosures identified from purchased transaction data
2. All foreclosures reported in Table 2 are drawn from the 72 zip codes identified in table 1.
Each selected zip code met the criteria needed to assure better than eighty percent coverage of foreclosures described in the text.
3. The foreclosaure data for 2007 are incomplete because the complete information on sale date and REO date are ofetn reported with a lag and as a result were excluded from the inventory of foreclosures because of incomplete information.
3. The state foreclosure rates are from Mortgage Banker Association (MBA) and may not be indicative of the foreclosure rate in the corresponding MSA.

Table 3
Descriptive Statistics for the Repeat sales Observations
(standard deviations in parentheses)

Panel A	All Seven MSAs	Atlanta	Charlotte	Col-umbus	Las Vegas	Los Angeles	Memphis	St. Louis
Number of Repeat Sales Pairs	405,631	186,626	46,205	84,743	27,895	7,767	32,801	19,594
% of Total	100	46.01	11.39	20.89	6.88	1.91	8.09	4.83
Purchase Price ($)	140,606	142,097	142,759	130,929	180,224	194,537	135,612	93,752
	(84,120)	(83,329)	(85,673)	(75,356)	(102,691)	(113,378)	(80,062)	(39,849)
Sale Price ($)	171,383	171,829	163,185	154,460	258,605	261,675	156,733	124,225
	(102,143)	(97,375)	(104,730)	(84,970)	(139,027)	(129,458)	(91,153)	(49,735)
Holding Period (yrs)	4.64	4.59	4.78	4.90	3.40	4.39	4.70	5.39
	(3.2)	(3.3)	(3.1)	(3.2)	(2.7)	(3.8)	(3.2)	(3.6)
Holding Period Return								
Total (%)	19.8	19.7	12.9	17.7	35.1	30.7	15.2	28.5
	(19.8)	(18.6)	(14.7)	(16.4)	(27.8)	(37.7)	(15.5)	(22.5)
Per Year (%)	4.0	4.0	2.6	3.4	9.2	6.3	3.1	4.8
	(5.7)	(5.3)	(4.5)	(4.9)	(9.6)	(8.8)	(4.7)	(5.9)
House Price Appreciation (OFHEO)								
1990 -2007	4.47%	4.14%	4.06%	4.19%	5.82%	5.46%	3.29%	4.36%
Number of Distinct Properties	281,063	127,930	32,236	59,024	19,569	5,504	22,076	14,724
Percent of Properties with one or more repeat sales								
1	67.76	65.79	67.73	66.87	67.66	68.7	64.56	73.04
2	23.94	24.95	23.48	24.67	24.24	23.4	25.2	21.62
3	6.58	7.25	6.89	6.78	6.35	6.3	7.85	4.61
4	1.42	1.67	1.56	1.41	1.43	1.34	1.92	0.63
5	0.25	0.29	0.3	0.23	0.25	0.18	0.41	0.07
6	0.04	0.05	0.03	0.03	0.06	0.04	0.04	0.01
7 or more	< .01	< .01	< .01	< .01	< .01	< .01	< .01	< .01

Panel B

Timing of Repeat Sales Transactions

	Initial Purchase		Resale	
Year	**N**	**%**	**N**	**%**
1990	22,721	5.60	383	0.09
1991	23,845	5.88	1,419	0.35
1992	28,044	6.91	4,095	1.01
1993	29,700	7.32	6,982	1.72
1994	28,179	6.95	9,241	2.28
1995	27,151	6.69	11,539	2.84
1996	31,524	7.77	15,999	3.94
1997	29,439	7.26	18,085	4.46
1998	32,773	8.08	24,440	6.03
1999	32,342	7.97	28,657	7.06
2000	28,061	6.92	28,140	6.94
2001	27,408	6.76	33,338	8.22
2002	21,615	5.33	33,482	8.25
2003	18,499	4.56	37,214	9.17
2004	13,669	3.37	39,903	9.84
2005	7,379	1.82	43,788	10.80
2006	2,787	0.69	39,515	9.74
2007	495	0.12	29,411	7.25
Sum	405,631	100	405,631	100

Table 4
Estimated Contagion Effects --Ring 1
(coefficients above, t-statistics below in parentheses)

	Atlanta	**Charlotte**	**Columbus**	**Las Vegas**	**Los Angeles**	**Memphis**	**St. Louis**	**Avg of All MSAs**
Phase of Foreclosure								
{F-12 to F-9}	0.04	-0.68	-1.11	-0.23	1.68	-0.74	0.00	-0.15
	(0.32)	-(3.05)	-(5.68)	-(1.23)	(3.79)	-(2.81)	(0.01)	-(1.39)
{F-9 to F-6}	0.15	-0.86	-0.77	0.58	0.22	0.00	-0.67	-0.19
	(1.07)	-(3.86)	-(3.89)	(2.88)	(0.48)	-(0.01)	-(1.44)	-(1.78)
{F-6 to F-3}	-0.27	-0.83	-1.22	0.17	0.23	-0.59	-0.50	-0.43
	-(1.82)	-(3.62)	-(6.10)	(0.84)	(0.44)	-(2.08)	-(1.09)	-(3.55)
{F-3 to F}	-0.01	-1.06	-1.30	0.25	-3.47	-0.93	-1.02	-1.08
	-(0.09)	-(4.68)	-(6.40)	(1.22)	-(6.84)	-(3.32)	-(2.17)	-(8.99)
{F to F+3}	-0.67	-1.67	-1.12	0.33	-1.08	-0.74	-0.86	-0.83
	-(4.34)	-(7.41)	-(5.43)	(1.70)	-(1.94)	-(2.58)	-(1.76)	-(6.55)
{F+ 3 to F+6}	-0.79	-1.75	-1.08	-0.52	-1.56	-0.93	-0.12	-0.96
	-(5.23)	-(7.83)	-(5.16)	-(2.85)	-(2.99)	-(3.17)	-(0.26)	-(7.95)
{F+6 to F+9}	-0.32	-1.21	-0.81	-0.24	-0.73	-0.15	-1.40	-0.69
	-(2.05)	-(5.23)	-(3.84)	-(1.19)	-(1.37)	-(0.51)	-(2.97)	-(5.59)
{F+9 to F+12}	-0.77	-1.73	-0.96	-0.40	-1.57	-0.05	-0.21	-0.81
	-(3.43)	-(5.47)	-(3.30)	-(1.17)	-(1.77)	-(0.14)	-(0.34)	-(4.43)
{> F+12}	-0.75	-0.51	-0.33	-0.17	5.06	-0.17	2.65	0.83
	-(1.81)	-(0.75)	-(0.51)	-(0.13)	(1.52)	-(0.20)	(1.77)	(1.41)
{S to S+3}	-0.62	-2.41	-1.08	-0.24	-1.03	-0.77	-0.64	-0.97
	-(3.66)	-(10.20)	-(4.97)	-(1.08)	-(1.68)	-(2.44)	-(1.26)	-(7.10)
{S+3 to S+6}	-0.96	-1.99	-1.46	-0.23	-0.58	-1.34	-0.24	-0.97
	-(5.50)	-(8.12)	-(6.41)	-(0.97)	-(0.97)	-(4.11)	-(0.47)	-(7.08)
{S+6 to S+9}	-0.56	-1.60	-1.37	-0.30	-1.22	-1.32	0.54	-0.83
	-(3.18)	-(6.59)	-(5.83)	-(1.23)	-(2.09)	-(3.92)	(1.06)	-(6.08)
{S+9 to S+12}	-0.67	-2.29	-1.54	-1.12	-1.93	-1.02	1.23	-1.05
	-(3.56)	-(9.17)	-(6.34)	-(4.81)	-(3.51)	-(3.00)	(2.29)	-(7.66)
Average Discounts								
{F-12 through F}	-0.02	-0.86	-1.10	0.19	-0.34	-0.57	-0.55	-0.46
Joint F-Test	0.09	64.4***	131.98***	4.14**	1.96	16.79***	5.52**	
{F through F+12}	-0.64	-1.59	-0.99	-0.21	-1.24	-0.47	-0.65	-0.83
Joint F-Test	54.14***	171.21***	76.87***	3.12*	15.11***	8.79***	6.47**	
{S through S+12}	-0.70	-2.07	-1.36	-0.47	-1.19	-1.11	0.22	-0.96
Joint F-Test	64.81***	323.85***	149.04***	17.51***	18.01***	46.27***	0.78	

Notes: 1. Table 5 presents estimates of the contagion effect for a single nearby distressed property. The estimates reported here are for the effect of distressed properties less than 300 feet from the subject.
2. The rows of the table show how the estimated effect varies with the phase of foreclosure.
3. "F" denotes the foreclosure sale and "S" the REO sale by the lender.
4. As soon as a property is sold by the lender (REO sale), the phase is defined as being post REO sale. Consequently, not all properties proceed through each time bucket following F and the number of observations in each post F bucket declines.
5. The F-statistics reported for the Average Discounts are based test that the sum of four coefficients equals zero.
6. The t-statistics reported for the Average of All MSAs are calculated assuming each of the seven MSA estimates is independent

Table 5
Estimated Contagion Effects --Ring 2
(coefficients above, t-statistics below in parentheses)

	Atlanta	Charlotte	Columbus	Las Vegas	Los Angeles	Memphis	St. Louis	Avg of All MSAs
Phase of Foreclosure								
{F-12 to F-9}	0.62	-0.32	-0.94	0.36	0.87	-0.27	-1.30	-0.14
	(4.76)	-(1.59)	-(5.63)	(2.33)	(2.71)	-(1.22)	-(3.22)	-(1.49)
{F-9 to F-6}	0.40	-0.46	-0.52	0.31	-0.93	0.34	-0.50	-0.19
	(2.96)	-(2.31)	-(3.07)	(1.94)	-(2.42)	(1.48)	-(1.27)	-(1.99)
{F-6 to F-3}	0.33	-0.44	-0.40	0.16	0.19	-0.27	-0.71	-0.16
	(2.46)	-(2.20)	-(2.35)	(0.95)	(0.47)	-(1.11)	-(1.81)	-(1.60)
{F-3 to F}	0.14	-0.69	-0.23	0.11	0.16	-0.22	-0.48	-0.17
	(0.99)	-(3.41)	-(1.34)	(0.61)	(0.38)	-(1.00)	-(1.19)	-(1.69)
{F to F+3}	-0.08	-0.90	-0.37	0.40	0.71	-0.51	-0.26	-0.15
	-(0.60)	-(4.38)	-(2.10)	(2.36)	(1.74)	-(2.11)	-(0.62)	-(1.42)
{F+ 3 to F+6}	-0.04	-0.78	-0.98	0.23	0.63	-0.45	0.21	-0.17
	-(0.29)	-(3.92)	-(5.52)	(1.33)	(1.48)	-(1.78)	(0.53)	-(1.63)
{F+6 to F+9}	0.06	-0.77	-0.89	0.06	-0.96	-0.70	-0.46	-0.52
	(0.38)	-(3.71)	-(5.07)	(0.35)	-(2.08)	-(2.73)	-(1.12)	-(4.83)
{F+9 to F+12}	-0.25	-0.28	-0.46	-0.43	-0.59	-0.57	0.42	-0.31
	-(1.16)	-(1.00)	-(1.90)	-(1.67)	-(0.80)	-(1.75)	(0.76)	-(1.97)
{> F+12}	-0.71	0.77	-0.12	-1.26	-10.05	-1.75	1.14	-1.71
	-(1.85)	(1.17)	-(0.22)	-(1.10)	-(3.18)	-(2.65)	(0.95)	-(3.19)
{S to S+3}	-0.18	-1.40	-0.66	-0.46	-1.80	-0.68	-0.51	-0.81
	-(1.15)	-(6.55)	-(3.55)	-(2.52)	-(3.67)	-(2.58)	-(1.19)	-(7.15)
{S+3 to S+6}	-0.22	-1.23	-0.88	-0.44	-0.69	-0.23	0.13	-0.51
	-(1.41)	-(5.54)	-(4.56)	-(2.24)	-(1.51)	-(0.82)	(0.29)	-(4.51)
{S+6 to S+9}	-0.05	-1.32	-0.68	-0.31	-0.64	-0.17	-0.17	-0.48
	-(0.29)	-(5.97)	-(3.41)	-(1.61)	-(1.26)	-(0.61)	-(0.39)	-(4.04)
{S+9 to S+12}	-0.12	-1.12	-0.88	-0.29	-0.45	0.32	1.53	-0.14
	-(0.71)	-(4.92)	-(4.27)	-(1.45)	-(0.94)	(1.21)	(3.34)	-(1.22)
Average Discounts								
{F-12 through F}	0.37	-0.48	-0.52	0.23	0.08	-0.10	-0.75	-0.17
Joint F-Test	31.19***	25.27***	40.96***	8.53***	0.16	0.83	14.16***	
{F through F+12}	-0.08	-0.69	-0.67	0.07	-0.05	-0.56	-0.02	-0.29
Joint F-Test	0.95	40.16***	50.85***	0.49	0.04	16.96***	0.01	
{S through S+12}	-0.14	-1.27	-0.78	-0.38	-0.90	-0.19	0.24	-0.49
Joint F-Test	3.2*	147.61***	68.14***	15.47***	14.24***	2.00	1.22	

Notes: 1. Table 5 presents estimates of the contagion effect for a single nearby distressed property. The estimates reported here are for the effect of distressed properties less than 300 feet from the subject.
2. The rows of the table show how the estimated effect varies with the phase of foreclosure.
3. "F" denotes the foreclosure sale and "S" the REO sale by the lender.
4. As soon as a property is sold by the lender (REO sale), the phase is defined as being post REO sale. Consequently, not all properties proceed through each time bucket following F and the number of observations in each post F bucket declines.
5. The F-statistics reported for the Average Discounts are based test that the sum of four coefficients equals zero.
6. The t-statistics reported for the Average of All MSAs are calculated assuming each of the seven MSA estimates is independent

Table 6
The Effect of Multiple Foreclosures
Estimated Coefficients (with T-statistics in parentheses below)

Panel A One Indicator per Ring -- Identifies the Presence of One or More Foreclosures in the Ring

	Indicator	Atlanta	Charlotte	Columbus	Las Vegas	Los Angeles	Memphis	St. Louis	Average
Ring 1	1 or more	-0.77	-3.04	-2.38	-0.48	-1.01	-2.21	-0.40	-1.47
		-(10.08)	-(24.74)	-(21.96)	-(3.85)	-(3.26)	-(14.48)	-(1.63)	-(21.59)
Ring 2	1 or more	-0.24	-2.57	-1.79	-0.23	0.04	-1.65	-0.23	-0.95
		-(3.23)	-(21.19)	-(17.47)	-(1.89)	(0.12)	-(11.54)	-(0.98)	-(14.50)
Ring 3	1 or more	-0.69	-1.98	-1.32	0.25	-1.71	-2.15	-0.90	-1.21
		-(11.07)	-(17.80)	-(14.30)	(1.81)	-(5.50)	-(16.06)	-(4.13)	-(18.76)
Ring 4	1 or more	-1.04	-0.63	-1.23	2.30	-0.13	-1.42	-2.03	-0.60
		-(16.59)	-(5.44)	-(13.12)	(13.08)	-(0.35)	-(9.47)	-(7.93)	-(7.84)

Panel B Indicators for Exactly One, Exactly Two and Three or More Foreclosures in the Ring

		Atlanta	Charlotte	Columbus	Las Vegas	Los Angeles	Memphis	St. Louis	Average
	Exactly 1	-0.77	-1.64	-1.49	-0.41	-0.34	-1.43	-0.49	-0.94
		(5.99)	-(2.17)	-(0.52)	(0.72)	(0.99)	(1.50)	(4.40)	-(12.65)
Ring 1	Exactly 2	-0.71	-3.56	-2.58	-0.70	-1.12	-1.79	0.23	-1.46
		-(4.64)	-(15.97)	-(12.20)	-(3.32)	-(2.09)	-(6.44)	(0.49)	-(11.78)
	3 or more	-0.89	-5.99	-4.84	-0.45	-4.97	-2.96	-0.53	-2.95
		-(4.14)	-(22.22)	-(18.52)	-(1.77)	-(7.65)	-(7.96)	-(0.79)	-(18.41)
	Exactly 1	-0.29	-1.40	-0.95	-0.30	0.24	-0.72	-0.51	-0.56
		-(3.59)	-(10.47)	-(8.26)	-(2.23)	(0.72)	-(4.64)	-(1.97)	-(7.75)
Ring 2	Exactly 2	-0.05	-2.65	-2.00	0.25	0.17	-1.89	0.78	-0.77
		-(0.33)	-(12.75)	-(10.61)	(1.29)	(0.33)	-(7.58)	(1.86)	-(6.21)
	3 or more	0.36	-4.12	-3.81	-0.20	-0.34	-2.33	1.02	-1.34
		(1.88)	-(17.01)	-(17.21)	-(0.94)	-(0.62)	-(7.75)	(1.91)	-(10.11)
	Exactly 1	-0.60	-0.95	-1.05	0.28	-1.30	-1.09	-0.51	-0.75
		-(8.77)	-(7.70)	-(10.10)	(1.76)	-(3.75)	-(7.45)	-(2.08)	-(10.28)
Ring 3	Exactly 2	-0.82	-1.96	-1.02	0.44	-3.23	-2.18	-1.55	-1.47
		-(8.30)	-(11.81)	-(7.14)	(2.30)	-(7.23)	-(11.26)	-(4.92)	-(15.71)
	3 or more	-0.52	-3.54	-1.99	-0.25	-1.96	-4.31	-0.05	-1.80
		-(4.92)	-(21.54)	-(13.83)	-(1.42)	-(4.63)	-(21.63)	-(0.15)	-(19.71)
	Exactly 1	-0.85	-0.17	-1.10	2.18	-0.81	-0.68	-1.51	-0.42
		-(12.31)	-(1.28)	-(10.30)	(10.48)	-(1.86)	-(4.11)	-(5.27)	-(4.79)
Ring 4	Exactly 2	-1.12	-0.55	-1.46	2.05	0.19	-1.36	-1.70	-0.56
		-(12.63)	-(3.36)	-(10.73)	(8.67)	(0.41)	-(6.82)	-(4.94)	-(5.70)
	3 or more	-1.56	-2.06	-1.50	2.62	0.95	-3.85	-3.27	-1.24
		-(17.45)	-(13.13)	-(11.77)	(12.73)	(2.04)	-(19.84)	-(10.17)	-(12.90)

Panel C Quadratic Specification for the Number of Foreclsoures in the Ring

		Atlanta	Charlotte	Columbus	Las Vegas	Los Angeles	Memphis	St. Louis	Average
Ring 1	a_d	-0.71	-1.57	-1.29	-0.19	-0.89	-1.16	-0.88	-0.96
		-(10.68)	-(17.88)	-(15.36)	-(2.50)	-(5.65)	-(9.26)	-(4.47)	-(20.72)
	b_d	0.10	-0.03	-0.01	0.01	0.03	0.05	0.27	0.06
		(5.99)	-(2.17)	-(0.52)	(0.72)	(0.99)	(1.50)	(4.40)	(5.07)
Ring 2	a_d	-0.36	-1.25	-0.97	0.10	-0.25	-1.09	-0.50	-0.62
		-(6.07)	-(15.26)	-(13.60)	(1.45)	-(1.99)	-(10.25)	-(2.92)	-(15.62)
	b_d	0.11	0.02	0.03	-0.02	0.01	0.11	0.19	0.06
		(9.19)	(1.78)	(2.28)	-(1.89)	(0.30)	(5.15)	(4.22)	(7.41)
Ring 3	a_d	-0.28	-0.86	-0.67	0.10	-0.20	-1.05	-0.53	-0.50
		-(8.91)	-(17.20)	-(19.11)	(2.27)	-(3.01)	-(17.00)	-(4.85)	-(21.41)
	b_d	0.02	0.04	0.02	-0.01	0.00	0.05	0.06	0.03
		(7.15)	(8.54)	(10.68)	-(3.37)	(1.18)	(10.22)	(5.86)	(13.25)
Ring 4	a_d	-0.43	-0.25	-0.13	0.13	-0.03	-0.58	-0.63	-0.28
		-(23.40)	-(8.69)	-(7.76)	(4.66)	-(0.72)	-(16.45)	-(11.52)	-(21.38)
	b_d	0.02	0.01	0.00	0.00	0.00	0.01	0.01	0.01
		(21.23)	(4.56)	(6.86)	-(3.96)	-(0.28)	(10.34)	(8.29)	(16.02)

Table 7 Alternative Screens

	Short Term Holding Period		Long Term Holding Period		Total Sample Size	
Screen	Years	Quarterly Return Threshold	Years	Quarterly Return Threshold	Number of Observations	% of Base
Base	≤ 2	>10%	>2	>8%	405,631	--
Screen 2	≤ 2	>7.5%	>2	>6%	395,535	97.51%
Screen 3	≤ 1	>10%	>1	>8%	398,727	98.30%
Screen 4	≤ 1	>7.5%	>1	>6%	394,273	97.20%
Screen 5	≤ 1.5	>7.5%	>1.5	>5%	392,456	96.75%
Screen 6	<=.5	all pairs with holding period < .5 year excluded	>.5	>8%	374,558	92.34%

Notes:

1. Table 7 defines the Base Filter and Alternative Filters used to screen the data to exclude unusual observations where it is likely that the property or neighborhood characteristics have changed
2. All screens (except Screen 6) apply different limits based on the holding period: a higher threshold for shorter holding periods and a lower threshold for longer holding periods. See text discussion for the rationale.
3. The column labelled "Years" defines the holding period for each screen. For example the Base screen excludes all observations with a holding period of two years or less and a holding period return that exceeds 10% per quarter. The Base Long Term screen excludes any obseravtion with a holding period greater than two years and a quarterly holding period return in excess of 8%.
4. The alternative screens are made more restrictive (i.e., exlcude more observations) either by lowering the thresholds (e.g., Screen 2) or by loweirng the definition of the short term holding period.
5. Screen 6 excludes all repeat sales pairs where the holding period is less than .5 year and retains the same return threshold for the pairs with holding periods greater than .5 year.

Figure 1
Foreclosure Process

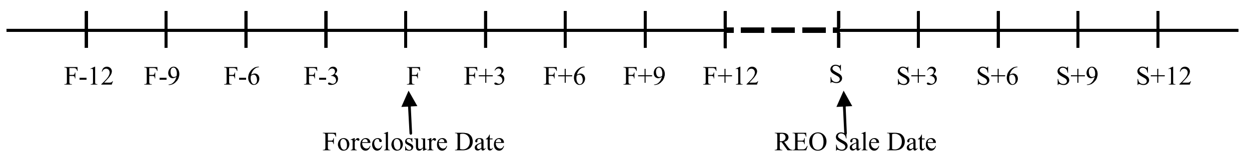
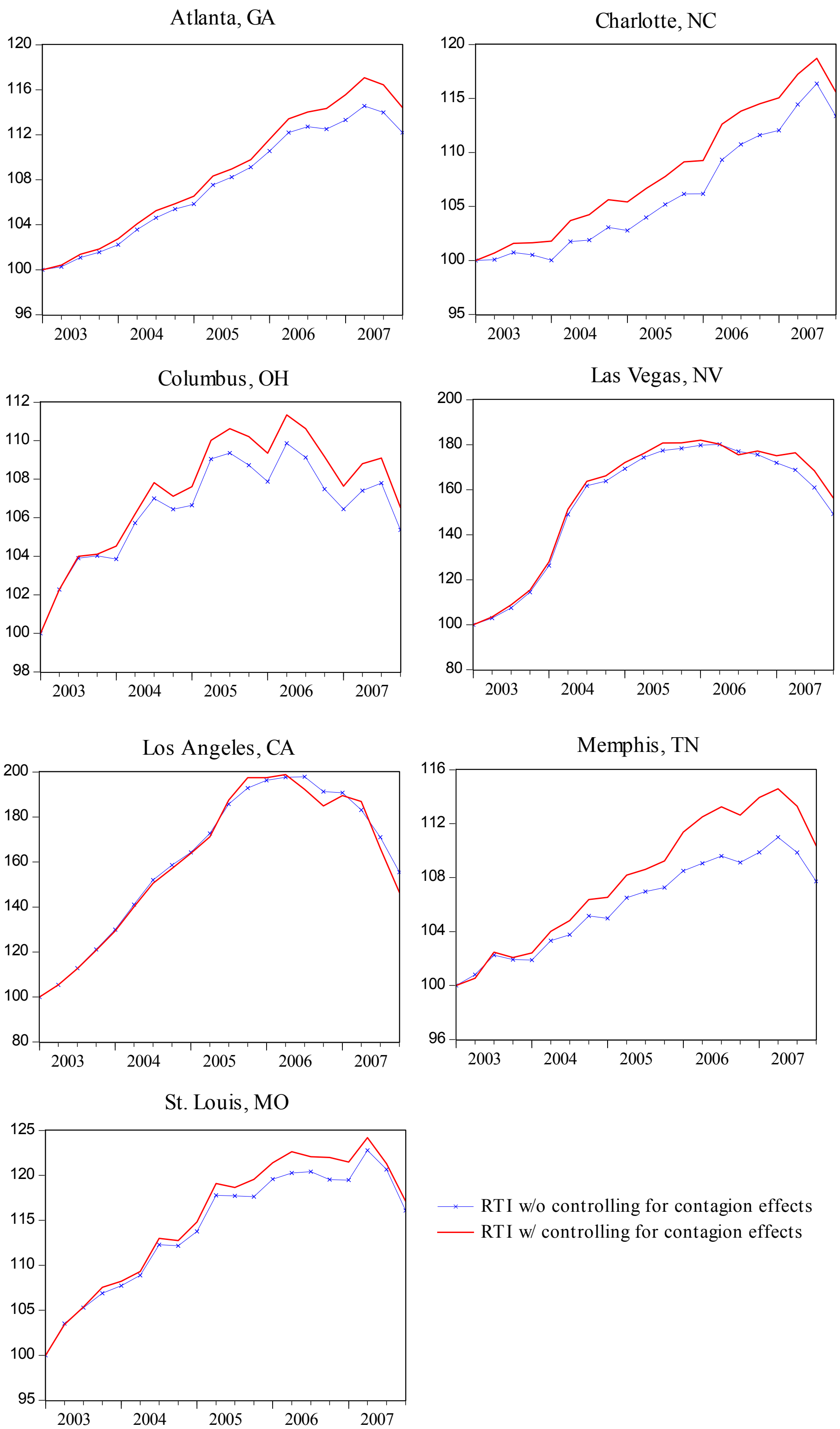


Figure 2 shows the thirteen different phases of the foreclosure process used in the paper. The two key reference dates are the foreclosure date (F) and the REO sale date (S). We classify a property as being in the foreclosure process from twelve months before the foreclosure sale date until twelve months after the REO sale date. Under our classification scheme, as soon as a property is sold by the lender, the property is classified as being post-REO sale. Therefore, not all properties pass through all five post-foreclosure sale windows and the number of observations in each post-foreclosure window declines.

Figure 2
Repeat Transaction Indices w/ and w/o Controlling Nearby Foreclosures



Note. Figure 2 compares the House Price Index estimated with and without controlling for the contagion effect The scales for each MSA vary because the house price appreciation rates vary.

Figure 3

Average Contagion Effect

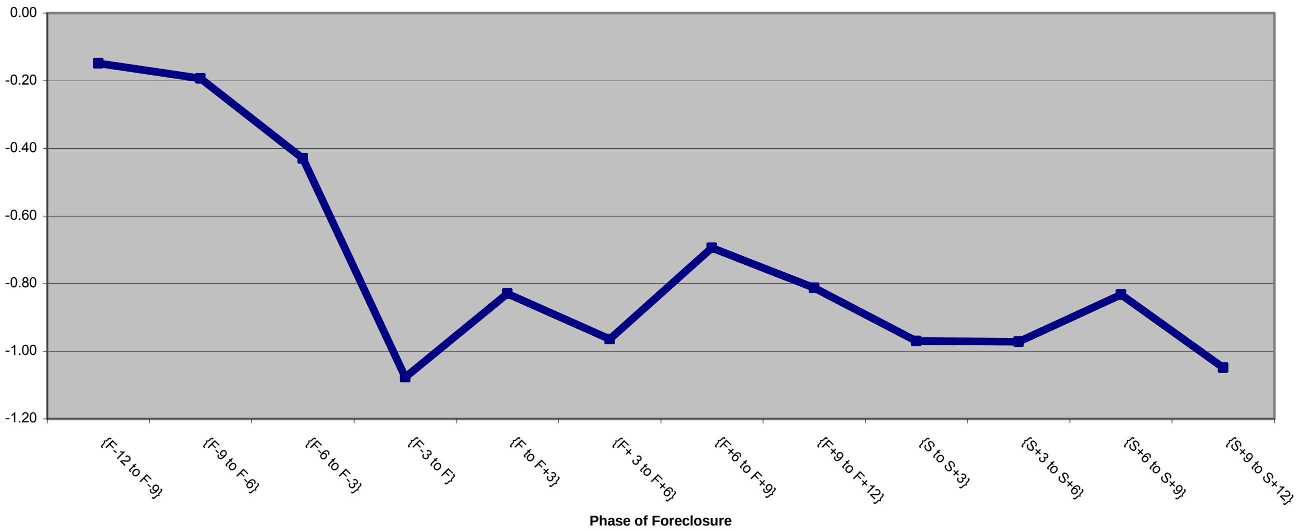


Figure 3 displays the estimated foreclosure discounts resulting from foreclosures within three hundred feet (Ring 1) of a non-distressed sale. The discount varies with the phase of the foreclosure, ranging from twelve months prior to the foreclosure sale until twelve months after the REO sale.

Figure 4

Contagion Effect by Phase of Foreclosure

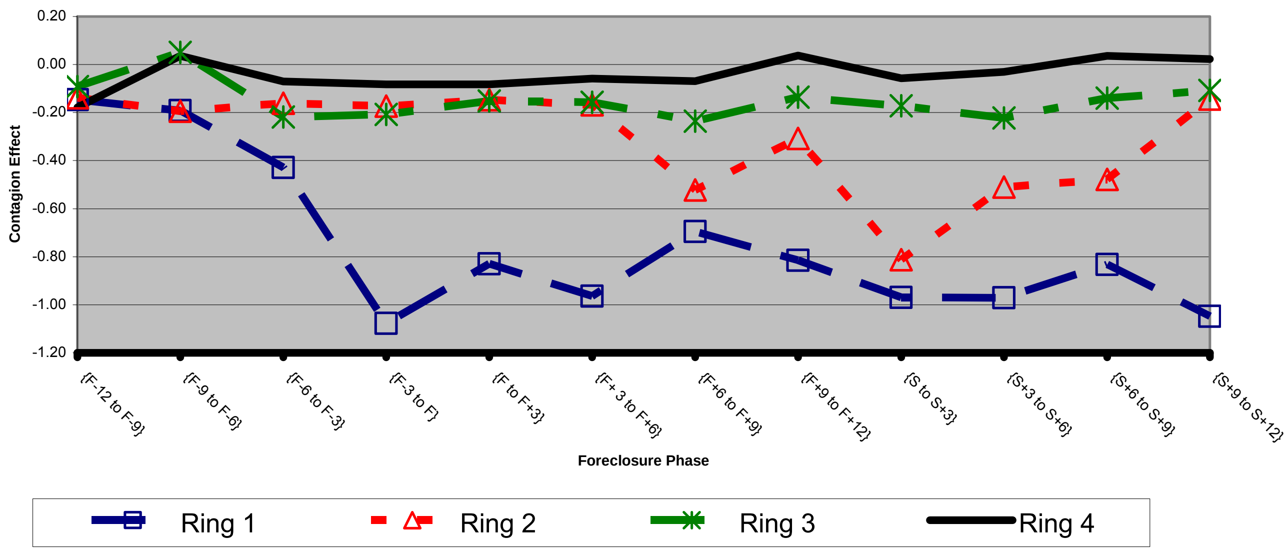
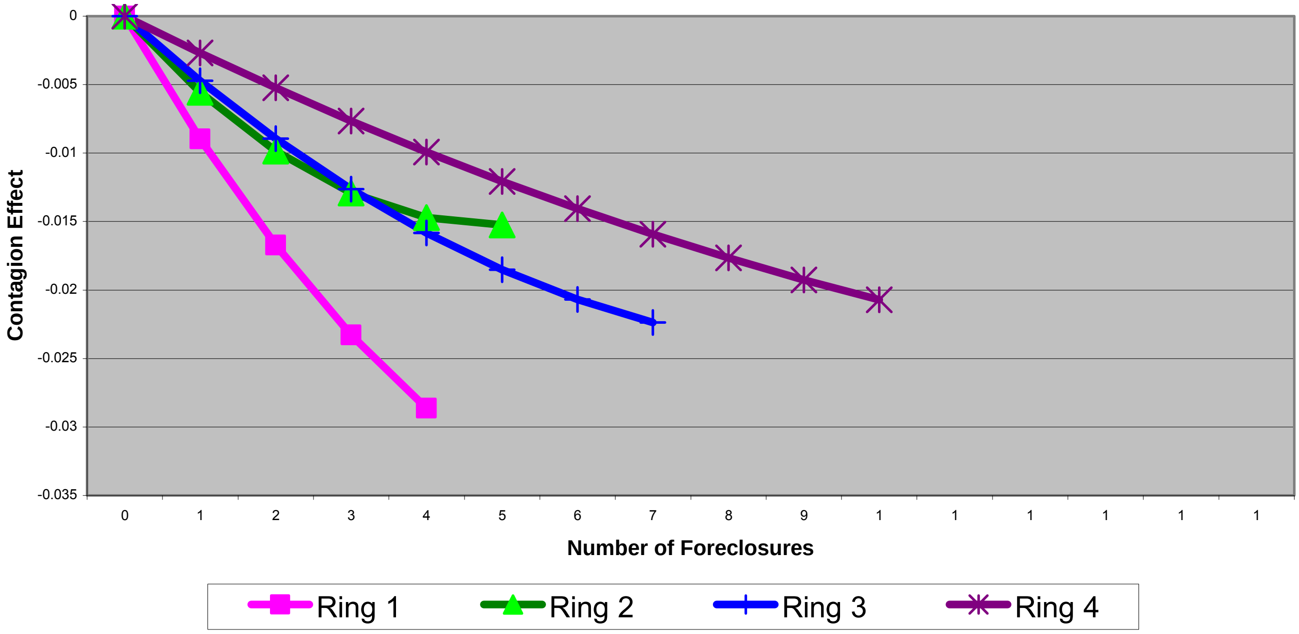


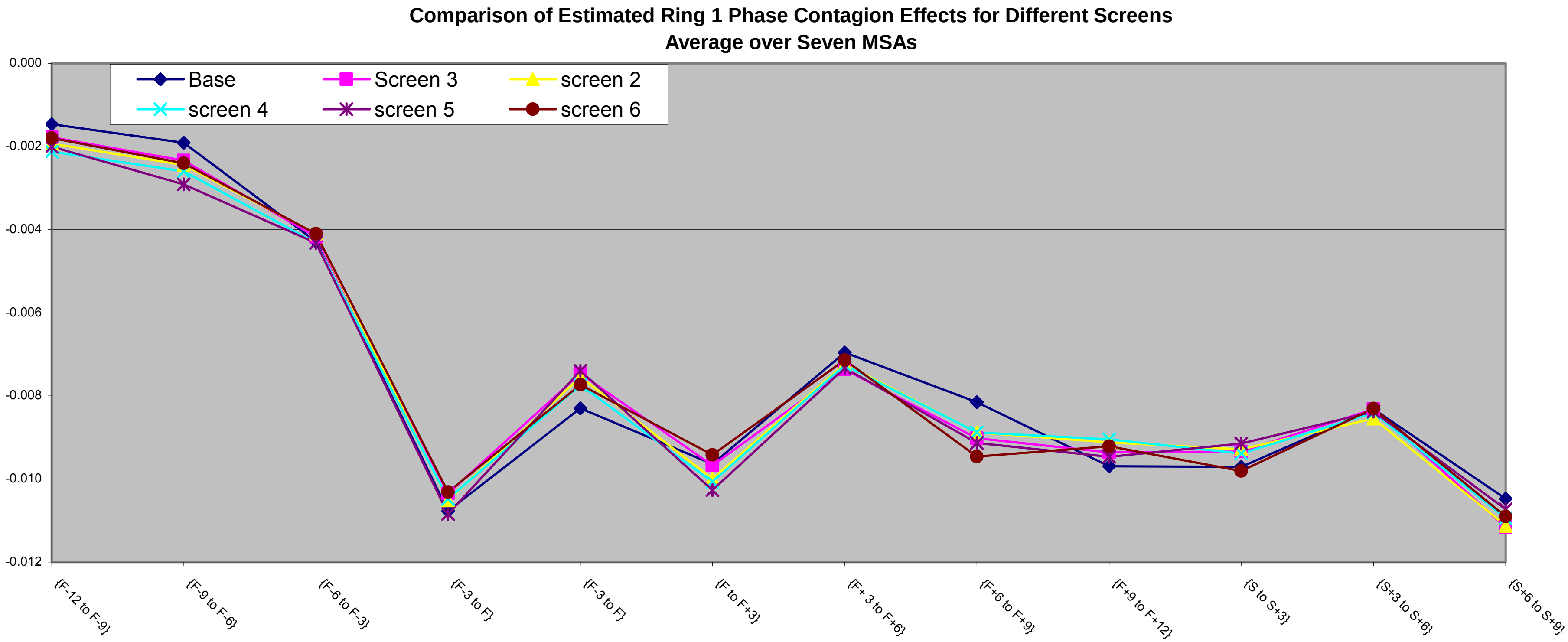
Figure 4 compares the estimated contagion effect by phase of foreclosure for all four Rings. Ring 1 contains all properties within three hundred feet of the non-distressed sale. Ring 2 contains all properties greater than three hundred feet and less than five hundred feet from the non-distressed sale. Ring 3 includes properties between five hundred feet and one thousand feet and Ring 4 contains properties from one thousand feet to two thousand feet. The plotted phase effects represent the average estimated effect over the seven different MSAs. The individual MSA effects vary and are reported in Tables 4 and 5 for Rings 1 and 2.

Figure 5
Effect of Multiple Foreclosures by Ring
Model Specification Estimates a Quadratic Effect



Note: Each line in Figure 5 shows how the estimated contagion discount varies with the number of nearby foreclosed properties within each of the specified rings around the subject property. The lines for all r are truncated to avoid extrapolating the effect beyond the range of the data used to estimate the models. Ring 1 includes all foreclosures less than 300 feet from the subject property. Ring 2 includes foreclosures that are 300 to 500 feet from the subject. Ring 3 includes foreclosures that are between 500 and 1000 feet from the subject, while ring 4 includes foreclosures that are between 1000 and 200 feet from the subject property.

Figure 6



Notes:
Figure 6 plots the average estimated Ring 1 phase effect from twelve months before the foreclosure sale to twelve months after the REO sale date. Ring 1 includes all properties within three hundred feet of the non-distressed property sale. The estimated effects attributable to properties that take longer than twelve months after the foreclosure sale to be sold to a third party are excluded because the sample sizes are small for that phase window and the estimates are not significant. The Base screen refers to the standard screen applied to repeat sales pairs used throughout most of the paper. The various screens are described in Table 7. Each screen is more restrictive (i.e., excludes more observations) than the Base screen. Each line in the figure represents the average estimated effect of all seven MSAs, where each model was estimated on a sample of repeat sales pairs that passed the indicated screen.