THE IMPACT OF MORTGAGE FORECLOSURES ON EXISTING HOME PRICES

IN HOUSING BOOM AND BUST CYCLES:

A CASE STUDY OF PHOENIX, AZ

A Dissertation

by

SANG HYUN LEE

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2011

Major Subject: Urban and Regional Planning

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ABSTRACT

The Impact of Mortgage Foreclosures on Existing Home Prices in Housing Boom and Bust Cycles: A Case Study of Phoenix, AZ. (May 2011)

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Many communities around the country have already been dealing with the problems of increasing and concentrated foreclosures for several years. Thus, the evidence of the social costs of foreclosures will guide policy makers in deciding what policies should be put in place in many communities that are plagued by foreclosures. The objective of this research is to quantify the price-depressing foreclosure effects on existing home sale prices as one of the major social costs for communities. The first methodological goal is to quantify simultaneously the magnitude of the direct and the spillover effects of foreclosures on existing home prices. The second is to provide usefulness concerning spatial econometric models in measuring the impact of foreclosures on housing prices.

This study was estimated with traditional hedonic and spatial hedonic models specified during two different housing cycles, a strong housing market when prices were up (2005) and a weak housing market with falling prices (2008) in Phoenix, Arizona.

However, ordinary least squares models statistically do not correct spatial autocorrelation and endogeneity that exist in a cross section of housing prices. They tend to overestimate the absolute values of the coefficients. As alternatives, the maximum likelihood spatial lag or error model corrects spatial autocorrelation, but it still causes computation obstacles for large data sets and heteroskedasticity in error terms. Thus, the preferred specification is a generalized method of moment approach which requires weak assumptions, and has a flexible form for large datasets. As a joint analysis, the most appropriate specification is the general spatial two-stage least-squares method with a HAC (spatial heteroskedasticity and autocorrelation consistent) variance estimator.

These findings provide further evidence that foreclosures had negative effects (direct and indirect foreclosure discounts) on existing housing prices, depending on housing types and cycles. With regard to the spillover effect of nearby foreclosures on existing home prices, both foreclosures of single family homes and condos were statistically significant and negatively impact each type of housing price. However, the cumulative effects of neighborhood foreclosures were much greater with nonlinear effects in a housing bust year than a housing boom year. Furthermore, this study emphasizes the price-depressing effects of pre-foreclosures and the importance of early intervention at the beginning of the foreclosure process.

DEDICATION

To my wife, daughter,

and

my parents

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1. INTRODUCTION

1.1 Background and Statement of the Problem

Americans have had one of the longest periods of housing market booms in history, driving an imbalance in supply and demand. Low mortgage interest rates, low down payment requirements, various financing alternatives, and relaxed lending standards have lowered the barriers to home ownership. However, a growing credit risk has been stretched to an excessive level with this achievement. The explosive growth in mortgage lending between 2000 and 2005 led to a mortgage crisis beginning in 2007. Such collapse in the values of mortgages brought a substantial increase in foreclosures and large declines in house prices, especially in Sun Belt states like Arizona, California, Florida, and Nevada, and Rust Belt states like Michigan and Ohio.[1]

Some real estate experts reported that 14-20 million U.S. homeowners (approximately 20-27% of all homeowners with mortgages) had a negative equity or were in an underwater position in which debt obligations exceeded the home's current market value at the end of the first quarter of 2009.[2] As a result, a number of residential foreclosures have been recorded in many parts of the United States, with about 3.2 million identified in some stage (default notices, auction notices, or bank repossessions) of the foreclosure process during the 2008, up more than 2.3 million from 2007

This dissertation follows the style of *Journal of the American Planning Association*.

[1] Sun Belt states (or sand states) are well known as bubble states characterized by a relaxed lending market and overbuilding. Rust Belt states are experiencing a weak economy because of the collapse of the U.S. manufacturing industry.

[2] Deutsche Bank estimated that approximately 14 million U.S. homeowners had negative equity, or approximately 27% of all homeowners with mortgages at the end of the first quarter of 2009. Real estate Website Zillow.com estimated that approximately 20 million homeowners had negative equity at the end of the first quarter 2009. Economy.com estimated that approximately 15 million homeowners had negative equity at the end of the first quarter of 2009 (Weaver and Shen, 2009).

(RealtyTrac, 2009). It was also reported that cities in the four Sun Belt states accounted for all of the top 20 foreclosure rates in 2009 (RealtyTrac, 2010). These foreclosures tend to be spatially concentrated within metropolitan areas, particularly stressing housing markets in neighborhoods where subprime and other exotic mortgages are more prevalent (Ding and Quercia, 2010; Gramlich, 2007; Immergluck, 2008a; Sanders, 2008). Many communities around the country have already been dealing with the problems of increasing and concentrated foreclosures for several years.

The impacts of foreclosures are devastating on a number of levels. For borrowers, foreclosures cause significant costs and hardships, involving not only the loss of home equity but also potentially limiting access to stable credit. For communities, the rapid rise in mortgage delinquencies and foreclosures has significant negative spillover effects: foreclosed and abandoned properties in a neighborhood can lead to a rise in violent crime, vandalism, and neighborhood deterioration.[3] These problems, in turn, can lead to increased costs for services and decreased revenues for local governments as well as population loss in the communities. In such neighborhoods, real estate values are either stagnant or declining due to the presence of distressed homes, which can lead to housing market instability, thereby adversely affecting new homeowners' interest in purchasing a house. Existing homeowners in such markets might not have any incentive to invest in

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[3] As representative examples, see Baxter, V., & Lauria, M., (2000), Residential Mortgage Foreclosure and Neighborhood Change, *Housing Policy Debate*, *11*(3), 675-699.; Apgar, W. C., Duda, M., & Gorey, R. N., (2005), *The Municipal Cost of Foreclosures: A Chicago Case Study*, Minneapolis, MN: Homeownership Preservation Foundation.; Immergluck, D., & Smith, G., (2006a), The External Costs of Foreclosure: The Impact of Single-family Mortgage Foreclosures on Property Values, *Housing Policy Debate, 17*(1), 57-79.; Immergluck, D., & Smith, G., (2006b), The Impact of Single-family Mortgage Foreclosures on Neighborhood Crime, *Housing Studies, 21*(6), 851-866.; Kingsley, G. T., Smith, R., & Price, D., (2009), *The Impacts of Foreclosures on Families and Communities*, Washington, DC: The Urban Institute.

basic maintenance and upgrades to their homes.

Ultimately, the direct price-depressing effects on property itself as well as the spillover effects due to rising foreclosures and falling house prices will likely impact the wellbeing of a community and individuals. In the absence of further policy actions and our interest in overcoming the mortgage crisis, an additional several million families may default or foreclosure on their mortgages in the next few years and lose their homes to foreclosure. Therefore, the foreclosure issue has currently attracted considerable attention from the media, homeowners or home buyers, policymakers, lenders, real estate specialists, economic analysts, as well as academic scholars. This background supports this research on dealing with the relationship between foreclosure issues and property values.

1.2 Objective of the Research

Based on the background and statement of the problem, the evidence of the social costs of foreclosures will guide policy makers in deciding what policies should be put in place in many communities that are plagued by foreclosures around the country. Thus, the objective of this research is to quantify the price-depressing foreclosure effects on existing housing values as one of the social costs for communities. The research will address questions regarding direct discounts on property under foreclosure and the extent of foreclosure spillover effects, which are capitalized into property values in surrounding areas.

The first methodological goal is to estimate simultaneously the magnitude of direct and spillover effects of foreclosures on existing home prices in a single model. This analysis will test in two ways. First is to separate this estimate into a part of the direct price-depressing effect due to foreclosure on property and a part of the spillover effect caused by surrounding foreclosures on existing home prices. To measure the foreclosure spillover effect, another methodological strategy is to separately estimate the effects of the same types of home foreclosures and the effects of different types of home foreclosures on nearby home prices. This estimation will also be examined and interpreted in different housing cycles.

The second is to provide usefulness concerning spatial econometric models in measuring the impact of foreclosures on existing home prices. It is to suggest estimation procedures for spatial hedonic models, which control for spatial dependence in real estate data and correct problems dealing with the heteroskedasticity of error terms when using cross-sectional data. Thus, the measurement resulting from this approach will provide not only the precise impact of foreclosures on existing home prices, but also distinguish between foreclosure effects and any spatial influence on existing home prices occurring in cross-sectional housing data.

1.3 Significance of the Research

As housing markets unexpectedly change and the pace of change quickens, planners and policymakers need to examine more responsive indicators for detecting housing market changes. Public sectors such as local or urban planners and policy makers are likely to be most interested in ideas about how to address the crisis and respond more effectively under the current housing and financial crisis. The answers to these questions are enough to attract the attention of home owners and policy makers as well as other practitioners such as lenders and real estate experts. It has also become of practical and scholarly interest for analysts and researchers.

The objective of current government efforts such as the Home Affordable Modification Program (HAMP) and the Neighborhood Stabilization Program (NSP) are not only to minimize the negative impacts of foreclosure on borrowers and neighborhoods, but also to help promote local economic recovery and growth. However, rising mortgage foreclosures are still oppressing the housing market, increasing unemployment, and ultimately recession, as well as lowering consumption and production. They may eventually influence the behavior of current mortgage borrowers. They are also signaling additional challenges to the government's efforts to stabilize the housing market crisis.

Therefore, this research may contribute to significant policy implications concerning how the government sector can forecast the negative externality costs of foreclosure and budget the limited funds that originated from taxpayers to effectively help distressed homeowners or communities hit by the foreclosure crisis. Most of all, it is critical to know what strategies are effective in stabilizing communities in the wake of foreclosures and how they should be targeted to the greatest need as soon as possible. Therefore, this study will examine empirical evidence to emphasize the importance of neighboring properties including home price trends, foreclosure trends, and foreclosure effects on housing prices. The empirical evidence associated with foreclosure issues is essential in designing a strategy that fits local conditions and motivates local decision makers to provide adequate support for the greatest need.

Another contribution is that this study uses spatial econometric models to incorporate spatial effects. The characteristic coefficients can be estimated more precisely because this approach has the advantage of addressing the spatial dependence of sale prices in neighborhoods and eliminating the omitted variable bias. Thus, this study will contribute to the accuracy of measurement techniques in property valuations.

1.4 Structure of the Research

The study is divided into six sections. Section 1 is designed to provide background information, to define the problem, and to state the objective and importance of the research. Section 2 details the literature that is available on the subject. It is drawn from a wide body of research that includes topics such as foreclosure trends, theory, government responses to the foreclosure crisis at both the federal and state level, previous studies regarding direct and indirect foreclosure effects on property values, and major issues regarding research methodologies.

Section 3 provides the conceptual framework, a visual representation of the foreclosure effects on home values and lists the ten hypotheses that will be tested. Section 4 describes the study area, the data preparation, and the methodology that was employed in this research. Section 5 includes detailed information on the econometric methods, the descriptive statistics, and data analysis as well as results. These methods include both traditional hedonic modeling and spatial hedonic modeling for single family homes and condos in different housing cycles. Section 6 addresses the findings and discusses the hypotheses tested and provides summaries as well as conclusions of the research. It also includes policy recommendations, study limitations, and future studies.

2. LITERATURE REVIEW

2.1 The Context of Mortgage Foreclosures

2.1.1 Type of Foreclosure and the Foreclosure Process

Foreclosure is a process that allows a lender to recover the amount owed on a defaulted loan by selling or taking ownership (repossession) of the property by foreclosing the mortgage (Frumkin, 2000). The foreclosure begins when a borrower/home owner defaults on loan payments and the mortgage originators or the lender files a public default notice, called a “Notice of Default” in a judicial foreclosure or “Lis Pendens” in a non-judicial foreclosure (Cutts and Merrill, 2008; Pennington-Cross, 2006).

The judicial process starts with a foreclosure filing in the local court. The lender files a suit in the local court, and the borrower will receive a notice in the mail demanding payment. The borrower then has only 30 days to respond with a payment in order to avoid foreclosure. If the borrower fails to make payments consistent with the loan agreement after a certain time period, the mortgaged property is then sold to the highest bidder through an auction in a local court or sheriff's office. However, a mortgage deed does not have a power of sale clause.

On the other hand, a non-judicial foreclosure, also known as a statutory foreclosure, is allowed by many states if the mortgage includes a power of sale clause. After a homeowner has defaulted on mortgage payments, the lender sends out a notice of foreclosure (also called a notice of default) to the borrowers directly demanding payment. Once a 20 day grace period has passed and the borrower cannot repay the loan, the mortgage company rather than local courts or sheriff's office carries out a public auction (Cutts and Merrill, 2008). Non-judicial foreclosures typically are less costly to the lender than judicial foreclosures. The judicial foreclosure takes five months longer, on average, and imposes additional transactions costs (Pence, 2003). Many states in the U.S. allow both judicial and non-judicial processes.

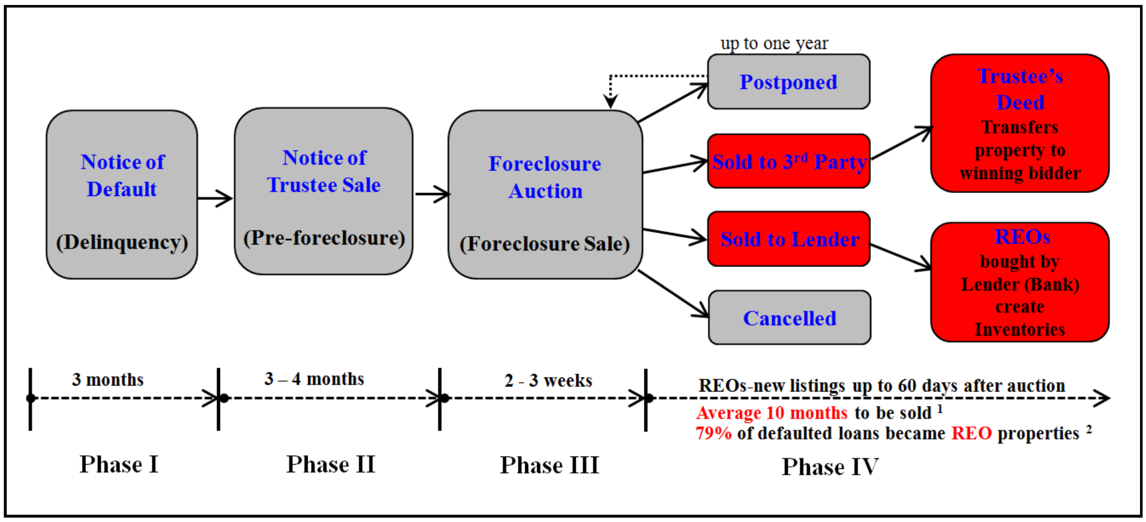

Figure 2.1. Foreclosure Process of Non-judicial Case.
Source: Cutts and Merrill; 2008.

The foreclosure begins when a borrower/owner defaults on loan payments and the lender files a public default notice, called a “Notice of Default” or “Lis Pendens” as shown in Figure 2.1 (Cutts and Merrill, 2008; Pennington-Cross, 2006). The foreclosure process can end one of four ways. First, the borrower/owner reinstates the loan by paying off the default amount during a grace period determined by state law. This grace period is also known as pre-foreclosure. Second, the borrower/owner can sell the property to a third party during the pre-foreclosure period. The sale allows the borrower/owner to pay off the loan and avoid having a foreclosure on his or her credit history. Third, a third party buys the property at a public auction at the end of the pre-foreclosure period. It is known as a foreclosure sale. Last, the lender takes ownership of the property, usually with the intent to resell it on the open market. The lender can take ownership either through an agreement with the borrower/owner during pre-foreclosure, by a short sale foreclosure, or by buying back the property at the public auction. Properties repossessed by the lender are also known as bank owned or REO (Real Estate Owned by the lender) properties.

2.1.2 Default Theory and Alternatives to Foreclosure

2.1.2.1 Default Theory

One theory for explaining default and subsequent foreclosure is insufficient equity or negative equity in the property. When the value of the property drops below the value of the mortgage, borrowers may default based on a pure wealth-maximizing motive. Such defaults are often termed “ruthless defaults” (Foster and Van Order, 1984, 1985). Rather than examining borrower-related factors, this theory examines the amount of equity in the home.

Empirical evidence found a strong relationship between negative equity and default (Clauretie and Sirmans, 2003; Foster and Van Order, 1984, 1985; Quigley and Van Order, 1991). These studies have included economic factors in borrowers’ decisions to pay their mortgages. This theory asserts that home equity and loan-to-value ratios have a primary influence on the decision to default and no borrower with substantial equity would default.

The second theory, known as ability to pay, suggests that unexpected events affect the homeowner's ability to meet the monthly payments on their mortgage (Clauretie & Sirmans, 2003). These difficulties are typically referred to as trigger events and usually involve employment and family structure shocks. Such trigger events and constrained liquidity hamper a borrowers' ability to pay were significant in determining the risk of default.

Quercia and Stegman (1992), Vandell (1995), and Elmer and Seelig (1998) suggest that mortgage defaults are explained by the ability-to-pay theory. They propose that "non-ruthless events" or "trigger events" such as the death of a family member, divorce, health problems, and unemployment increase the likelihood that a borrower will default.

In reality, it seems to be the intersection between trigger events and a negative equity position in the current economic conditions. In an equity-theoretic view, a lack of home equity is an important determinant, but foreclosures are most commonly triggered by some other unforeseen event that causes borrowers to be not able to meet their mortgage obligations.

Recently, Foote, Gerardi, and Willen (2010) suggest that foreclosures are associated with two "triggers"—falling house prices and rising unemployment rates. The double-trigger theory asserts that the potential for a foreclosure is highest when a homeowner has an underwater mortgage, which means the price of the house has fallen below the outstanding mortgage balance so that the owner cannot sell or pull equity from the house; and suddenly the homeowner experiences a significant disruption to income, such as unemployment, a health problem or divorce. When a borrower is in underwater position and experiences an adverse life event, foreclosures generally result. The current foreclosure crisis seems to have all the characteristics of three theories.

2.1.2.2 Alternatives for Foreclosure

There are several alternatives to foreclosure for borrowers in financial distress.[4] These options are divided into two major groups: retention workout options and non-retention options. Retention workout options allow a borrower to work directly with their loan servicer to retain possession of the home. Alternatively, non-retention options result in the borrower relinquishing the home, but avoiding the expense of the foreclosure process.

Retention workout options

In forbearance, borrowers can pay reduced or suspended payments for a short period, usually not to exceed three months, but are expected to cure the delinquency by the end of the forbearance period. Forbearance is financed solely by the servicer of the mortgage and does not change the terms of the underlying loan. A lender expects that during the moratorium period the borrower can solve the problems be securing a new job,

[4] The literature review on alternatives to foreclosure is based on the studies of Hatcher (2006) and Frumkin (2007).

selling the property, or finding some other acceptable solution.

A repayment plan is when past due amounts are divided and added to the regular monthly payments for an extended amount of time to bring the mortgage loan current. Repayment plans provide some relief for borrowers with short-term financial problems. They typically last 6 months or less, but may extend to more than 18 months. Loan modifications involve changes to the mortgage loan documents to reduce the interest rate or extend the loan term, similar to a refinance.

Prior to a foreclosure sale, borrowers have the right to reinstate a delinquent loan. The reinstatement option gives homeowners the opportunity to make up back payments plus any incidental charges incurred by the bank such as filing fees, trustee fees and legal expenses. Paying off the reinstatement amount will cancel the foreclosure and enable the homeowner to continue to live in the home as if no default occurred.

If the borrower can make the payments on the loan, but does not have enough money to bring the account current or cannot afford the total amount of the current payment, a loan is modified in a written agreement between a borrower and servicer that permanently changes one or more of its original loan terms. Loan modifications involve increasing the principal balance by adding the past due amount (principal, interest, taxes and insurance) to the existing principal balance, extending the term of the loan, or reducing the interest rate. For FHA loans, the loan must be at least 12 months old, and the first lien position must be maintained. For nonprime loans, most investors require the borrower to have made at least 12 monthly payments to be considered for modification.

A short refinance allows borrowers with negative equity to refinance their property for a reduced value and the lender writes off the balance not refinanced. A short refinance forgives some of the debt and refinances the rest into a new loan, usually resulting in lower financial loss to the lender than foreclosing.

Non-retention options

A short sale is when borrowers sell their home prior to foreclosure (a pre-foreclosure sale) even though the proceeds may be less than the amount owed on the mortgage but the lender agrees to forgive the portion of the debt not covered by the sale price. This option preserves the owner's equity and credit score. The lender can assist in the marketing and sale of the home and writes off any loss at the time of settlement. The advantage to the lender is that costly foreclosure proceedings are avoided.

A deed-in-lieu of foreclosure is a transfer of title from a borrower to the lender without going through the foreclosure process, avoiding costs and reducing the harm to the borrowers' credit standing. This prevents long-term foreclosure proceedings for those who cannot afford to keep the home. With this option, borrowers voluntarily give back his or her property to the mortgage company. Homeowners won't save their houses, but do avoid the trauma of foreclosure and reduce the negative impact on their credit.

Therefore, the important question for policymakers is how to prevent the largest share of foreclosure. They need to extend additional financial assistance to borrowers suffering negative equity and negative shocks in the current foreclosure crisis.

2.1.3 Foreclosure Trends

While many communities have been struggling with high rates of foreclosure for some time, this crisis is most pronounced in the Sun Belt states and in the states of the Rust Belt as shown in Figure 2.2. States have been divided into six groups based on changes in the foreclosure start rate between 2005 and 2008 (U.S. Department of Housing and Urban Development, 2010). Four states that have experienced the sharpest rise in foreclosures from 2005 to 2008 have been referred to as the "sand states" which are Arizona, California, Florida, and Nevada.

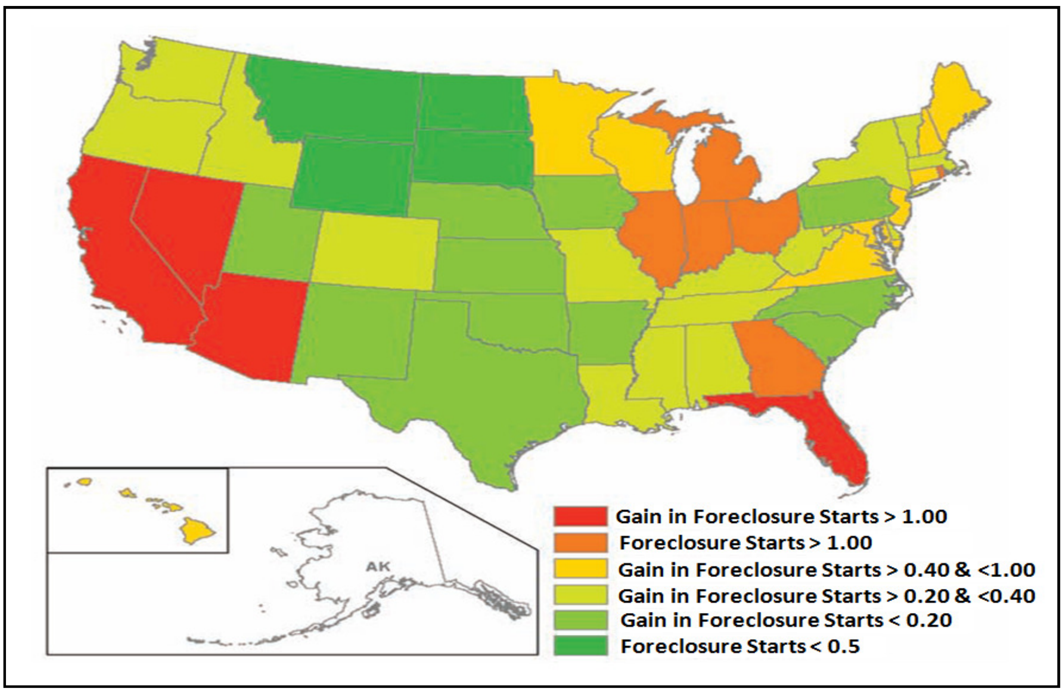

Figure 2.2. State-Level Trends in Foreclosure Start Rates between 2005 and 2008.
Source: U.S. Department of Housing and Urban Development, 2010.

According to the second quarter 2008 U.S. Foreclosure Market Report released by RealtyTrac.com, forty-eight of the 50 states and 95 of the nation's 100 largest metro areas experienced year-over-year increases in foreclosure activity in the second quarter of 2008 (RealtyTrac, 2008). These accelerated the national level foreclosure rates since 2007, as shown in Figure 2.3.

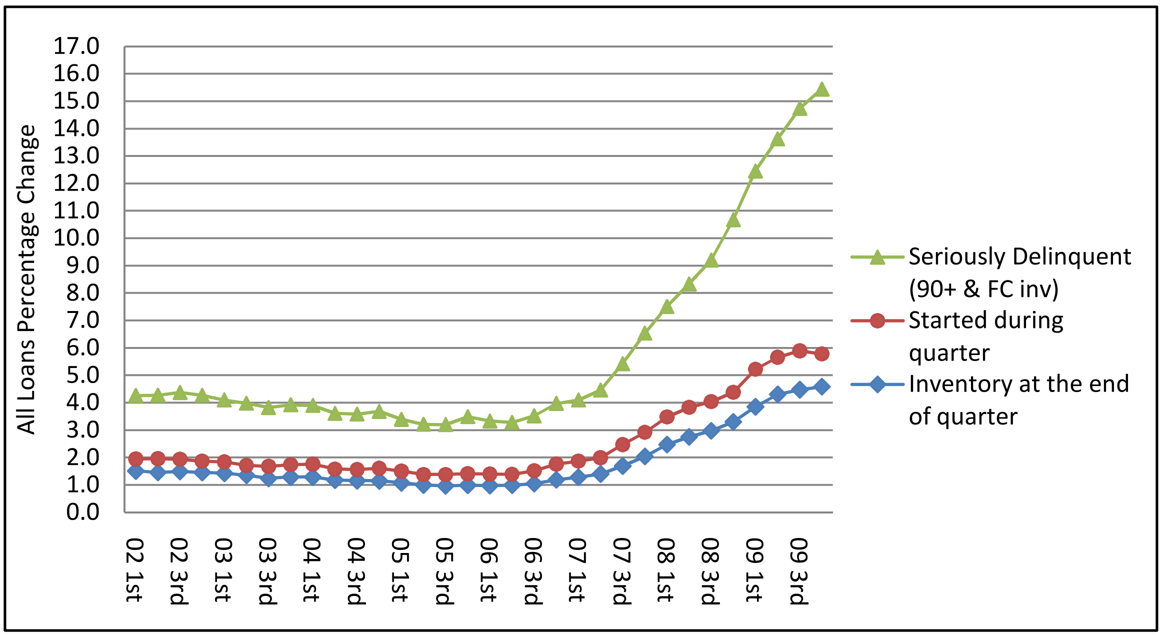

Figure 2.3. 90-Day Delinquency and Foreclosure Start Rates.
Source: Mortgage Bankers Association, National Delinquency Survey, 1Q 2010.

The sand states had house price increases that were well in excess of the national level through the end of 2005. House price increases slowed substantially in 2006 and stared to decline at the beginning of 2007. The sharp rise in foreclosure starts for these states mirrors this dramatic fall in house prices. These states not only had the highest rates of foreclosure starts in 2008, they also experienced the highest increase in foreclosure starts since 2005. In contrast, the Rust Belt states (the industrial Midwest) had the lowest rates of housing price appreciation prior to 2006 and have also experienced fairly significant declines in house prices since 2006.

2.2 Policy Responses to the Foreclosure Crisis

The foreclosure crisis calls for significant federal and local government intervention to keep families in their homes and prevent further deterioration in the housing market. Regional economic downturns, dramatic changing home prices, and unfair and deceptive mortgage lending practices have combined to create the foreclosure storm in America. While the truth of what actually occurred is likely some combination of all of these explanations, one of the most frequently expressed arguments against helping homeowners facing foreclosure is concern over the moral hazard, encouraging unduly risky borrowing and lending in the future. To be sure, the bottom line is that some of these families would not own their current homes if risks had been recognized fully during the past several years. Thus, this background supports justification for government intervention for mortgage market and lending regulations.

The following two parts will describe the causes of this foreclosure crisis and government actions and current programs to correct the foreclosure problems.

2.2.1 Causes of Current Mortgage Foreclosure Crisis[5]

There have been a number of prominent reviews of the fundamental causes of the sharp rise in mortgage delinquencies and foreclosures since 2006. However, the combination of three broad causes has been consistently linked to the current foreclosure crisis. The first is subprime rates have been one of main causes of the foreclosure crisis. The second is the mortgage lending industry increase using subprime lending and alternative mortgage products, and with substantial growth in the volume of risky loans. The third is the widespread slowdown in house price growth followed by actual declines in prices in most areas of the country. This part presents a review of the literature that supports these conclusions.

First, subprime rates have been treated as one of main causes of the foreclosure crisis. The share of subprime mortgages substantially increased before the crisis. Subprime lenders lowered their standards to meet the insatiable demand for mortgages. Subprime home loans made to borrowers with impaired credit have substantially higher rates of foreclosure than prime mortgages.

Research has documented that subprime mortgage originations increased substantially in the years before the crisis and are inherently associated with higher delinquency and foreclosure rates than prime loans (Gerardi, Shapiro, and Willen, 2008; Schloemer, Li, Ernst, and Keest, 2006). As summarized by Immergluck (2008b), subprime loans of all types generally foreclose at rates between 10 and 20 times the rate of prime loans.

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[5] For a detailed discussion, see the report to congress on the root causes of the foreclosure crisis, U.S Department of Housing and Urban Development (2010).

Second, large numbers of new mortgages were nontraditional. Nontraditional loans often include features that increase the risk of foreclosure. Immergluck (2008b) indicated that changes in mortgage markets and increases in foreclosures have been concentrated in neighborhoods where borrowers were given high-risk products, subprime mortgages, and exotic mortgages. Such features include adjustable interest rates, balloon payments, prepayment penalties, and loans with limited documentation of borrowers' loan qualifications.[6]

Foreclosure rates for adjustable-rate mortgages (ARMs) have increased considerably, especially in the subprime sector. Millions of these were ARMs, whose low introductory interest rates were beginning to reset too much higher rates. Finally, high loan-to-value originations in recent years, coupled with stagnant or falling home prices, have left many people with insufficient equity to sell or refinance their homes.

Substantial growth in risky loans and risky borrowers has been a result of lax underwriting standards. There is significant evidence that lenders' loose underwriting through weakening qualification standards of borrowers who experienced a more rapid house price growth than expected, was associated with the high volume of risky loans (Dell'ARiccia, Igan, and Laeven, 2008; Mian and Sufi, 2008; Reeder and Comeau, 2008).

Third, rapid house price growth caused a surge in the use of nontraditional risky

[6] In addition to adjustable-rate features, other characteristics of subprime and Alt-A loans that have an independent association with higher default risk include the following: prepayment penalties (Danis and Pennington-Cross, 2005; Demyanyk and Van Hemert, 2008; Pennington-Cross and Ho, 2006; Quercia, Stegman, and Davis, 2005); low or no documentation of income or savings (Danis and Pennington-Cross, 2005; Demyanyk and Van Hemert, 2008; Pennington-Cross and Ho, 2006); balloon terms (Danis and Pennington-Cross, 2005; Demyanyk and Van Hemert, 2008; Quercia, Stegman, and Davis, 2005).

mortgages, extending more credit to borrowers under looser underwriting. Thus, declining home prices meant that a large majority of borrowers who obtained larger mortgages than they could afford were no longer able to avoid higher mortgage payments by selling their homes or by refinancing a new mortgage.

Several studies by researchers (Doms, Furlong, and Krainer, 2007; Gerardi, Shapiro, and Willen, 2008; Demyanyk and Hemert, 2008) argue that the slowdown and then decline in house price appreciation plays an important factor in producing the mortgage crisis.

The combination of these factors led to a sharp increase in foreclosure rates, and the foreclosures, in turn caused the inevitable decline in house prices.

2.2.2 Government Actions to the Foreclosure Crisis

A variety of voluntary private and government-administered or supported programs were implemented during 2007-2009 to assist distressed homeowners with mortgage delinquency and foreclosure. Examples include the Federal Housing Administration (FHA) Secure Program, the Housing and Economic Recovery Act, and Homeowners Affordability and Stability Plan.

One early prominent national effort is the Hope Now Alliance, formed in 2007, with $180 million, an ongoing collaborative effort between the U.S. government and private industry to help certain subprime borrowers (Hope Now Alliance, 2008). Hope Now Alliance assisted distressed borrowers in keeping their homes through either a repayment plan or voluntary loan modifications and additional counseling. As another action through Hope Now Alliance, former President George W. Bush announced a plan to voluntarily and temporarily freeze the mortgages of a limited number of borrowers holding adjustable-rate mortgages (ARMs). The Alliance reported that during the second half of 2007, it had helped 545,000 subprime borrowers with shaky credit, or 7.7% of the 7.1 million subprime loans outstanding as of September 2007 (Hope Now Alliance, 2008).

Critics have argued that the case-by-case loan modification method is ineffective in addressing the increasing problem of foreclosures. 70% of subprime mortgage holders are not getting the help they need. Nearly two-thirds of loan workouts require more than six weeks completing under the current case-by-case method of review (Christie, 2008).

HUD's Federal Housing Administration (FHA) also launched the FHA Secure program in late 2007. It was intended to use the Federal Housing Administration's mortgage insurance to provide relief by fixed-rate, long-term financing to financially distressed homeowners with risky subprime and high-cost loans, including those that became delinquent due to a payment reset However, one limitation of this program was the selective eligibility criteria that prevented participation for many borrowers (U.S. Department of Housing and Urban Development, 2010).

In July 2008 Congress authorized the FHA under the Housing and Economic Recovery Act (HERA) to insure up to $300 billion in loans via a new program: Hope for Homeowners. The Hope for Homeowners program supported refinancing loans for borrowers who are at risk of foreclosure. The program assisted homeowners who could not afford to refinance into mortgages in the government sponsored enterprises (GSEs) of Fannie Mae and Freddie Mac. This program required existing lenders to accept as payment in full of the original first lien mortgage an amount equal to no more than 90 percent of the current appraised value of the property to reduce mortgage principal. However, homeowners must meet a number of criteria including purchasing the home before 2008, the mortgage payments should be no more than 31% of their monthly income, and the property must be their primary residence (U.S. Department of Housing and Urban Development, 2008). As of late 2008 the program had insured only one loan.

Accordingly, results of these workout plans have been modest. A study by the Center for Responsible Lending (2008) estimated that only 20% of this loss mitigation to help some 2.7 million borrowers through October 2008, including 1.6 million subprime borrowers, actually resulted in lower monthly mortgage payments (Garrison, Rogers, and Moore, 2008). Furthermore, the comptroller of the currency reported that more than half of the owners who modified loans in hope of stabilizing their mortgage during the first half of 2008 ended up in default again within six months (Office of the Comptroller of the Currency and the Office of Thrift Supervision, 2008).

In response to the rise in mortgage foreclosures, the numerous programs for correcting foreclosure problem are divided into two main major categories: prevention efforts, extended programs aimed at keeping families in their homes and households who are compelled to leave their homes due to foreclosure, and mitigation of neighborhood and community impacts and recovery (Immergluck, 2008a). Among prominent government interventions, the U.S Treasury's Home Affordability Modification Program (HAMP) provided alternative financial options such as loan modification and refinancing. In addition, Neighborhood Stabilization Program (NSP) grants were distributed to states and some local governments through the U.S. Department of Housing to prevent social costs, or externalities, associated with foreclosures (U.S. Department of Housing and Urban Development, 2008).

In February 2009, the Obama administration announced the Homeowner Affordability and Stability Plan of 2009 to help homeowners to refinance at a lower cost and prevent foreclosures. It provided $75 billion in federal funding to help homeowners struggling to make their payments and was intended to assist as many as 7 to 9 million homeowners (U.S. Department of Housing and Urban Development, 2009).

In May 2009, President Obama signed into law the Helping Families Save Their Homes Act. This act modifies Hope for Homeowners with the goal of helping additional families. Until recently, loss-mitigation efforts offered limited relief due to onerous requirements. Based on the May 2010 update from the federal government, approximately 340,000 modifications among the 7 million seriously delinquent homeowners had been converted into permanent status (Nickerson, 2010).

The magnitude of the current foreclosure crisis has resulted in large and spatially concentrated increases in vacant homes in many metropolitan areas. The negative effects of the foreclosure crisis are not limited to the well-being of millions of at-risk households that may lose their homes, but also spillover into neighborhoods where foreclosed properties are located.

One approach in addressing the spillover effects of foreclosures is the Neighborhood Stabilization Program. As part of the Housing and Economic Recovery

Act of 2008, Congress allocated $3.9 billion in community development block grant (CDBG) funds to state and local governments to purchase a growing number of foreclosed homes and vacant residential properties and mitigate the adverse impacts of foreclosures. These funds from Neighborhood Stabilization Program (now often referred to as NSP I) were intended to stabilize neighborhoods that were hardest hit by the foreclosure crisis. The U.S. Department of Housing and Urban Development (HUD) has recently released these funds to states and local governments by formula allocations based on the magnitude of the foreclosure problems faced (U.S. Department of Housing and Urban Development, 2008).

According to HUD, NSP I funds was specifically focused on recovery and redevelopment of vacant, abandoned foreclosed homes. NSP I funds have three purposes: to stabilize neighborhoods impacted by foreclosure, to remove significant blight from neighborhoods, and to provide housing for low- to moderate-income households. Because of the anticipated condition of the properties, the acquisition price for land or property must be at a discount (at least five percent) below the appraised value (U.S. Department of Housing and Urban Development, 2008). The NSP I program allowed flexibility with use of the funds for rehabilitation, redevelopment, demolition, reconstruction, and land banking of vacant foreclosed properties to complement larger redevelopment efforts, and to make a significant impact on distressed areas.

For example, the city of Phoenix government divided its neighborhoods into three tiers for targeting the use of NSP I funds. The three-tiered system was consistent with the community development goals of the consolidated plan. The city of Phoenix and Maricopa County governments are stabilizing communities through programs that support owner-occupancy of foreclosed properties and through direct acquisition and rehabilitation of foreclosed properties. They have received more than $121 million in NSP funding since March 2009 and supported the purchase of 162 Fannie Mae properties through down-payment assistance for owner-occupants and acquisition and rehabilitation programs (Sheldon, Bush, Kearsley, and Gass, 2009).

However, Mallach (2009) has criticized the NSP I program stating that the 18-month timeline for the program was too short to develop well-designed local recovery or rehabilitation property reclamation efforts. The author argues that formula risk indicators of foreclosure based on universal data on either delinquency or foreclosure does not represent the complete set necessary to pinpoint the problems with foreclosed or vacant properties, and that the NSP formula based funding allocations at similar levels to all states do not incorporate a local market's strengths, challenges, or assets.

There is also the concern that most local governments are not able to spend them effectively and many jurisdictions have different administrative capacities to implement effective target programs in relation to market differences (Kingsley, Smith, and Price, 2009).

The American Reinvestment and Recovery Act (ARRA) of 2009 included an additional $2 billion for what has been called NSP II (H.R. 1, the American Economic Recovery and Reinvestment Act, passed in February 2009). This is part of the large $787 billion American Recovery and Reinvestment Act that served as a large stimulus package to many sectors of the economy. ARRA also changed some of the rules of the NSP I program. Unlike the existing NSP I program, the new NSP II funds are to be allocated through a competitive process (U.S. Department of Housing and Urban Development, 2009).

However, as Immergluck (2009) indicated, while NSP I had allowed redevelopment for uses other than housing, one change that has less flexibility in the NSP II program restricts redevelopment to housing uses only and may constraint larger scale redevelopment proposals.

Although aggressive loan modification programs can help many borrowers remain in their homes and neighborhood stabilization plans like NSP can prevent spillover effects, foreclosures in many areas were unavoidable and many policies were not able to appreciably stop the rising tide of foreclosures in U.S. housing markets. For example, RealtyTrac reported in its 2009 Metropolitan Foreclosure Market Report that 1 in 45 housing units received at least one foreclosure filing and recorded 2.8 million U.S. properties with foreclosure filings in 2009. It amounted to approximately 3.1 million foreclosure filings in U.S. (RealtyTrac, 2010).

One study by the National Low Income Housing Coalition (2008) suggests that government funds for distressed borrowers such as loan modification and repayment are wasteful in formerly hot markets like Los Angeles or Boston since refinanced or modified loan mortgages are two to three times that of renting a comparable unit (Baker, Pelletiere, and Rho, 2008).

While workouts such as loan modifications and repayments can help some households meet their mortgage payment obligations, it seems clear that the decline in house prices has increased the number of foreclosures and the increase in foreclosures has further exacerbated the decline in house prices in today's housing market. These workouts do not make sense for those mortgage borrowers in an "underwater" position, namely a situation where the amount of their outstanding mortgage debt and deferred payment is more than the value of the property securing the mortgage. Indeed, with home prices falling rapidly in many market areas, a growing number of delinquent owners or underwater homeowners are apt to accept the consequences of entering into foreclosure (U.S. Department of Housing and Urban Development, 2010).

Thus, efforts to reduce the flood of foreclosed properties are critical in stabilizing home prices, preventing the loss of housing wealth. This research tries to recommend appropriate policies based on the evidence to alleviate the negative impact of foreclosures on housing prices.

2.3 Social Costs of Foreclosures

The recent increase in mortgage delinquencies and foreclosures has brought significant attention to the costs of foreclosures to homeowners, the mortgage industry, local governments, and communities.

For borrowers, a 1998 study by the Minnesota Family Fund estimated the cost of foreclosure on a household resulted in $7,200 in administrative charges to the borrower, taking into account the costs of moving, legal fees associated with the foreclosure process, loss of equity upon transfer of the home, and long term higher costs of borrowing due to poor credit rating.

A foreclosure results not only in the loss of a stable living place and significant portion of wealth, but also has a severe adverse impact on future access as a result of diminished credit quality, creating barriers to future home purchases. Intangible costs include the emotional and physical stress of managing the foreclosure process, disruption to household stability, and negative effects on children in households forced to move as a result of foreclosure (Kingsley, Smith, and Price, 2009).

For mortgage lenders, lenders also bear substantial foreclosure related costs, putting significant financial pressure on the residential mortgage industry in the recent increase in mortgage delinquencies and foreclosures. A study reported that lenders alone could lose over $58,000 per foreclosed home or as much as 30 to 60 percent of the outstanding loan balance, even before the 2006 foreclosure spike (Cutts and Green, 2003).

Direct costs tied up in the foreclosure process often entails incurring maintenance and tax obligations, transaction costs associated with liquidating the property, reduction in the value of assets held by mortgage investors, and mortgage losses due to unpaid mortgage and the reduction of the sale price.

Similarly, there are many indirect costs, including weaker pricing on subsequent bond issues, increased monitoring costs in originations, as well as contagion that may weaken the performance of other loans in their portfolio (Apgar, Duda, and Gorey, 2005).

For local government, foreclosures can also impact cities and neighborhoods, particularly if concentrated, by putting downward pressure on neighboring housing prices and raising costs for local governments. An early study by Moreno (1995) estimated an average of $27,000 as the potential municipal costs associated with foreclosures and vacancies, and neighborhood costs of $10,000 in examining FHA foreclosures.

A more recent case study for Chicago (Apgar, Duda, and Gorey, 2005) found that the direct municipal costs of foreclosures to local government agencies ranged from $430 for a vacant and secured property to more than $34,000 for an abandoned property damaged by fire. City governments bear the costs of municipal services (code enforcement, boarding, demolition, maintenance, and police and fire) associated with addressing vacant and abandoned properties.

If foreclosure densities go up, there will be additional expenses to address increased vandalism and crime in the area and worse physical condition such as abandoned and blighted properties. Recently, the Community Research Partners documented the magnitude and cost of the vacant and abandoned properties problem in eight Ohio cities. The research found 25,000 vacant and abandoned properties due to foreclosure. These costs to local jurisdictions address the problems related to vacant and abandoned properties and to provide essential city services conservatively identified was nearly $64 million across the eight study cities. This included nearly $15 million in city service costs and over $49 million in lost tax revenues from demolitions and tax delinquencies (Garber, Kim, Sullivan, and Dowell, 2008).

For neighboring homeowners and community, foreclosures have a significant impact in the community in which the foreclosed homes are located. One of the main concerns of communities suffering from large numbers of foreclosures, especially in an overall weak housing market, is negative spillover effects of foreclosures. Many studies have found that neighborhoods can become blighted by foreclosed properties and pose substantial threat to neighborhood stability and quality of life (Baxter and Lauria, 2000; Immergluck and Smith, 2006b; Lauria and Baxter, 1999). These problems, in turn, can lead to increased costs and decreased revenues for local governments (Apgar, Duda, and Gorey, 2005; Mallach, 2008).

Most of all, the presence of distressed homes due to foreclosure may raise direct and indirect costs to neighborhoods through a negative impact on local property values and price trends, adding to the supply of for-sale homes (Mallach, 2008). The following section will deal with the detailed literature associated with direct and indirect effects of foreclosure on property values in neighborhoods.

2.4 Previous Studies for Direct Foreclosure Effects on Property Values

The literature on the effects of foreclosures on real estate prices may be divided into two general categories. The first category involves foreclosed property valuation concepts and methods. Most of the literatures reviewed in these categories are largely based on case studies. Nine prior empirical studies on foreclosure discount were identified in this review of literature.

Shilling, Benjamin, and Sirmans (1990) conducted research in 1985 to empirically estimate the magnitude of the foreclosure discount on condominium units that were foreclosed and sold by the lender in Baton Rouge, Louisiana. The authors used a hedonic model to examine 62 condominium sales. The regression analysis indicated that the discount on distressed real estate was roughly 24% of market value, not controlling for property physical condition.

Forgey, Rutherford, and VanBuskirk (1994) estimated the discount on foreclosed single-family properties in Arlington, Texas, from 1991 to 1993. They found a foreclosure discount of 23% for residential sales in Arlington, Texas, between July 1991 and January 1993. Of their sample of 2,482 properties, 280 were foreclosure sales. They found that property prices were reduced by 16% when purchased for cash and discovered that additional closing costs and removing uncertainty by cash sales results in a lower selling price.

In related studies, Hardin and Wolverton (1996) estimated the discount on foreclosed apartment complexes sold in the Phoenix, Arizona, area in 1993 and 1994. They analyzed 9 foreclosed properties of a total of 90 apartment sales in Phoenix. They included variables representing the income potential of the properties (rent, vacancies, etc.). They found that foreclosed properties sold with the discount at 22% less than comparable non-foreclosed properties.

These first three studies provided similar estimates of the discount using a hedonic model. The studies used different property types: condominiums, single family homes, and apartments. They indicated estimates of the foreclosure discount between 22% and 24%.

Springer (1996) used data on 2,317 single-family homes sold between May 1991 and June 1993 in Arlington, Texas. The author focused primarily on estimating the effect of marketing time as well as other motivation variables such as relocation of the seller and property vacancy. He found that, after controlling for other types of seller motivations, foreclosed homes were sold more quickly with about a 4 to 6% discount. Springer found a much smaller foreclosure effect for single-family properties in Arlington, Texas during the period from 1989-1993 than was reported in the three previous studies.

In contrast, Carroll, Clauretie, and Neill (1997) found no discount associated with selling a foreclosed property. They analyzed data on Housing and Urban Development (HUD) sales of foreclosed properties in Las Vegas, Nevada. Authors used a sample of 1,974 single-family properties between 1990 and 1993 and found that, without properly controlling for neighborhood effects, a foreclosure discount of 12% to 14% emerges from the data. After controlling for neighborhood (ZIP codes entered as dummy variables), the authors found that the price discount on HUD foreclosed homes was negligible (approximately 2%) and statistically insignificant. However, this finding is questionable because HUD as the part of the federal government is not a typical seller of foreclosed properties.

Pennington-Cross (2006) evaluated the price of 12,280 foreclosed single-family properties sold nationwide for which the mortgages originated from 1995 through 1999. Unlike these previous studies, Pennington-Cross (2006) used a repeat sales method as opposed to a hedonic model in examining the discount associated with REO sales or foreclosure sales. The author found that overall the actual prices of foreclosed properties were 22% less than other properties in the surrounding market, comparing the change in original purchase price of REO sales and a nationwide sample of foreclosed homes using the metro area house price index. The author also found that the discount was higher in locations that had seen a decrease in overall prices and on properties that were held by lenders for a longer time.

Campbell, Giglio, and Pathak (2009) examined 1.8 million home sales in the Greater Boston Massachusetts market during the period from 1987 through 2008. They identified forced sales using public records related to death, bankruptcy and foreclosure and linked that data to the transaction data. Using a standard hedonic specification, they estimated a 28% foreclosure discount, controlling for physical and neighborhood characteristics including zip code dummies. In comparison, other types of forced sales lowered home prices by smaller amounts. When a house was sold after the death of an owner, they found, the price dropped 5% to 7% on average. When an owner declared bankruptcy, the value sank to 3%. The presence of a foreclosed house in a neighbourhood reduces the value of the homes around it. In their estimation, the value of a home dropped by 1.1% controlling for the average level of recent unforced sale prices in the neighbourhood if it was within roughly 250 feet of a foreclosed home. Foreclosure tends to be endogenous to house prices because homeowners are more likely to default if they have negative equity, which is more likely as house prices fall. However, they have not been able to find such as instrument to control for the endogeneity. Instead, they compared the effects of foreclosure before and after each transaction, and the effects of close foreclosure (0.1 mile) with those of that occur further away the 0.25 mile radius.

As another recent study, Sumell (2009) included indicators of observable subjective quality and found that foreclosed homes of poor quality had larger than average foreclosure discounts. The author estimated REO sale discounts using a hedonic analysis of residential sales from Cuyahoga County, Ohio. This analysis included 9,906 typical sale transactions of single-family homes and 1,837 REO sales (18.5%) from Cleveland in Cuyahoga County, Ohio, occurring during 2004-2006. The coefficient on REO sales indicated that, all else constant, foreclosed homes sold for approximately 50% less than their estimated market. The overall magnitude of the foreclosure discount was larger in the lower income sub-sample (54%) compared to the higher income sub-sample (41%), suggesting that their impact on the foreclosure discount were driven primarily by foreclosed homes in low-income communities. However, this was a substantially larger discount level than previous hedonic studies have estimated. The author pointed out that Cuyahoga County had an extraordinarily weak housing market during the sample periods (2004-2005). As a result, the magnitude of the estimated discount level was larger than previous hedonic studies estimated. The results also indicated that there was a negative relationship between the number of foreclosures in the community and property values. The sale price of a home was lowered by approximately 2.5% for every percentage increase in foreclosures in the same census tract, other factors constant.

Clauretie and Daneshvary (2009) addressed many of the shortcomings of earlier papers in estimating the foreclosure discount. Using data from the Las Vegas, they built a sample of 1,302 foreclosed property sales and 8,498 non-distressed sales from November 2004 through November 2007. They argue that many of these previous estimates may be downwardly biased because they failed to control for property condition, spatial effects, and marketing time. They found that the foreclosure status reduced price by about 10% in the OLS cross-sectional hedonic model. To control for the local trend in prices, the authors extended their specification to include the spatially weighted prices of neighboring properties; correcting endogeneity and autocorrelation by generalized spatial two-stage least-squares (GS2SLS) models and accounting for property condition. They estimated that the foreclosure discount, based on a single MSA, was approximately 7.5% after controlling for property condition, spatial effects, and marketing time. These results indicated that the discount caused by foreclosure in this study was about one third of foreclosure discount (22% - 28%) reported by previous studies. They also found that as much as one-third of the negative effects of foreclosure (2.5% of 10% discount in OLS) could be attributed to associated characteristics that also negatively affect prices. A less-than-excellent property condition, renter occupancy and a cash transaction all had a more negative impact on prices.

Table 2.1 summarizes the key findings from the previous works on foreclosure discount. Nine previous works have documented a foreclosure discount on distressed residential sales prices. Many of these studies found significant sale discounts in the range of 20%s for foreclosed property or even 50%s for REO sales in the worst case. After controlling for property conditions, spatial effects, and marketing time, the result was about less than one-third of the discount caused by foreclosures found in previous studies.

Two early studies (Shilling, Benjamin, and Sirmans, 1990; Hardin and Wolverton, 1996) based on small sample sizes were limited in the reliability of the statistical techniques in a multiple regression analysis because the underlying assumptions should be satisfied with normally distributed errors with a zero mean and constant variance (Epley, 1997).

Table 2.1. Literature Review Summary: Direct Foreclosure Effects on Home Values.

Author	Study Area(s)	Study Period	Property Type	Sample Size (All/Foreclosures)	Empirical Test	Estimated Foreclosure Discount
Shilling et al. (1990)	Baton Rouge, LA	1985	Condos	62/?	Hedonic Model (OLS)	-24%
Forgey et al. (1994)	Arlington, TX	1991-1993	Single-Family Homes	2,482/280	Hedonic Model (OLS)	-23%
Hardin & Wolverton (1996)	Phoenix, AZ	1993-1994	Apartments	90/9	Hedonic Model (OLS)	-22%
Springer (1996)	Arlington TX	1989-1993	Single-Family Homes	2,317/270	Hedonic Model (OLS)	-4 to -6%
Carroll et al. (1997)	Las Vegas, NV	1990-1993	Single-Family Homes	1,974/404	Hedonic Model (OLS)	insignificant
Pennington-Cross (2006)	U.S.	1995-1999	Single-Family Homes	12,280 foreclosures	Hedonic Model (OLS)	-22%
Campbell et al. (2009)	Boston, MA	1987-2008	Single-Family Homes & Condos	1,800,000/ 55,200	Hedonic Model (OLS)	-28%
Sumell (2009)	Cuyahoga County, OH	2004-2006	Single-Family Homes	9,906/1,837	Hedonic Model (OLS)	-41% to -54%
Clauretie & Daneshvary (2009)	Las Vegas, NV	2004-2007	Single-Family Homes	10,000/1,302	Hedonic & Spatial Hedonic Model (OLS & GS2SLS)	-7.5%

Carroll, Clauretie, and Neill (1997) found foreclosure discounts of 12% to 14% for foreclosed homes. However, the generality of this finding is questionable since HUD is not a typical seller of foreclosed properties because it is part of the federal government. The seller is not likely to feel pressure to dispose of its inventory of foreclosed properties too quickly.

Sumell (2009) found that REO sold property was approximately 50% less than the estimated market value in Cleveland, Cuyahoga County, Ohio, during the years 2004-2006. This study was limited to one location during a bad housing market and might suffer from sample selection bias.

Furthermore, eight previous studies related to foreclosure utilized a single-equation ordinary least squares (OLS) test. They defined a foreclosure discount as the difference between foreclosure sales and non-foreclosure sales as a stigma effect (Lee, 2010). However, they rarely discussed limitations of a traditional hedonic model even though the estimation methodology is questionable in generalizing the results.

One recent study (Clauretie and Daneshvary, 2009) controlled for property conditions or use instrumental variables to address the potential omitted variable problem. This study attempted to disentangle spatial effects such as endogeneity of time of marketing and spatial autocorrelation from the effects of the variables mentioned in earlier studies. Their empirical model also controlled for the property condition, occupancy status, and cash transaction. However, it’s not clear how the effects of these variables are different for foreclosed properties and non-foreclosed properties on their specifications.

Properties sold through a cash transaction or renter occupied home are expected to lower the quality of the property and potentially impact transaction prices in purchasing foreclosed properties as investments. Thus, one suggestion would use interactive terms to independently distinguish the effects of renter occupancy status and cash transaction on distressed property, which is absent in previous studies.

In addition, although the endogenous relationship between price and foreclosure and spatial autocorrelation that might exist using a cross-section of house prices are theoretically important and empirically recognized by the most recent study, none of the previous studies of foreclosure have corrected for both effects in a single-equation model.

Finally, these early studies generally showed evidence that foreclosed properties sold at lower prices than non-distressed properties, but each of the analyses underscored the differences of foreclosure discounts, depending on property types and housing market conditions. Thus, it highlights the need for additional research on the impacts of direct foreclosure on real estate prices with different property types and housing cycles.

2.5 Previous Studies for Spillover Effects of Neighboring Foreclosures on Property Values

The second literature category presents empirical studies on negative externalities of foreclosures on nearby real estate prices. Studies in this category mainly deal with the negative effects of foreclosures on nearby real estate prices. The relatively few empirical analyses assessing the effects of foreclosure on surrounding properties are partly due to data restraints. More importantly, the impacts of foreclosures on nearby property values have recently received a great deal of attention by scholars because weaker housing prices began with the mortgage crisis.

Immergluck and Smith (2006a) set forth the first conceptual framework for estimating foreclosure impacts on property values. They analyzed the relationship between foreclosures and property values through use of a hedonic model and created a database with 3,800 foreclosures that occurred in 1997 and 1998 and over 9,600 single-family property transactions in Chicago in 1999. After controlling for property and neighborhood characteristics based on census tract boundaries, conventional single-family foreclosures had a statistically and economically significant effect on nearby property values. For each conventional foreclosure within an eighth of a mile of a home, single-family home values decreased by 0.9%; a single foreclosure causes home values to decrease even more in low- to moderate-income communities by 1.4 percent. In the distance range between a one-eighth and one-quarter of a mile, the result was a 0.33% decline in prices with only modest spillover effects. Making an estimate based on the number of foreclosures in Chicago from 1997 to 1998, property values in Chicago were lowered by more than $600 million or $159,000 per foreclosure. These estimates were conservative, as they included only the effects of foreclosures on single-family property values, not the values of condominiums, larger multifamily rental properties, and commercial buildings.

Shlay and Whitman's (2006) study of Philadelphia analyzed 14,526 residential sales in Philadelphia that were greater than $1,000 in 2000 and 2000-2001 abandoned property data, a common result of foreclosed properties, to assess the impact on property values. This research measured each property's distance from an abandoned residential structure in 150 feet increments using four binary variables to denote a property's distance from an abandoned unit. They estimated that the presence of one abandoned property located within 150 feet decreased the value by $7,500 or more than -12% of the market value with effects diminishing as distance increases. When the distance was extended to 150 to 300 feet, the discount shrank to a little less than $7,000. Housing within 300 to 500 feet of an abandoned property experienced a net decrease in sale price of $3,500. Beyond 450 feet, any effect was negligible. In terms of density of abandoned property, one abandoned property on a block decreased the sale price by $6,500. As abandoned properties increase on a block, sale prices decrease by about $10,000.

The approach used in the study by Schuetz, Been, and Ellen (2008) was similar to those estimated by Immergluck and Smith (2006a). The researchers examined the impact of pre-foreclosures on existing property values. They used residential (single and multi family) property sales and foreclosure notices in New York City between 2000 and 2005. This study analyzed house prices before and after foreclosure to control for differences of pre-existing prices across neighborhoods to minimize selection bias and included dummy variables for zip code to control for characteristics of neighborhoods.

They found evidence that properties in close proximity to foreclosures sold at a discount and the magnitude of the price discount increased with the number of nearby foreclosure notices, but with some diminishing marginal impacts. Their results indicated that the impact size of foreclosure decreased as distance increased for pre-foreclosures within less than 18 months prior to sale, ranging from -2.2% for pre-foreclosures within

250 feet to -1.2% for pre-foreclosures within 500-1000 feet. Adding to pre-foreclosures more than 18 months prior to sale decreased the magnitude of the 0-18 month time interval, and all coefficients on the 18+ month variables were negative and statistically significant in three distances. The coefficients on all three post-sale variables were negative and strongly significant; suggesting that the occurrence of future foreclosure starts was correlated with current conditions and property values.

To test for the possibility of nonlinear marginal effects of foreclosures due to density levels of foreclosures, they also used a set of dummy variables to capture foreclosure activity. In the 250-500 foot ring, they found no significant effect of 1-2 pre-foreclosures in the 18 months prior to sale, but they found that three or more pre-foreclosures during this time period and within this distance were associated with lower property values. Prices appear still less sensitive to small numbers of pre-foreclosures within the 500-1000 foot ring. Properties within that range of 1-5 pre-foreclosures in the 18 months prior to sale did not show a significant price discount, but proximity to six or more pre-foreclosures was associated with a 2.8% lower sale price.

Mikelbank (2008) examined the effect of foreclosure and vacant properties on 9,046 single-family home transactions using 6,083 foreclosure filings and 4,152 properties identified as vacant and abandoned in 2006 in Columbus, Ohio. After correcting spatial errors, which measured how neighborhood characteristics influenced nearby home prices through maximum likelihood spatial analysis, the results found that the negative impact of vacant and abandoned properties on nearby home sale prices were more severe than that of pre-foreclosures' properties. The results indicated that a vacant and abandoned property within 250 feet of a property, on average, could decrease the sale price by -3.6%, holding other conditions constant, but such impact was reduced to -2.1% for a pre-foreclosed property. The vacant and abandoned property impact was more severe than pre-foreclosure within the first 250 foot ring. Nonetheless, the negative impact of a vacant and abandoned property drastically decreased to merely -0.6% at 250-500 foot ring, while a pre-foreclosure's negative impact diminished to -1.6% at the same distance.

Harding, Rosenblatt, and Yao (2009) used a repeat sales approach based on a 1989 to 2007 data set of over 400,000 repeat housing sales in seven MSAs, holding the house and neighborhood characteristics constant. The repeat sales methodology provided joint estimates of the local trend in house prices based on a house price index and nearby foreclosure activity using differentiated spatial distances (0-300 feet; 300-500 feet; 500-1000 feet; and 1000-2000 feet) and time intervals (any stage in the foreclosure process). They found that property sales located within 300 feet of a foreclosed property fell to about a 1% discount per foreclosure and 0.5% discount per foreclosure within 300-500 feet. Beyond 500 feet (0.1 mile), negative effects were negligible. The size of the discount continued to fall as the distance increased and the effect of a foreclosed property located within 300-500 feet from the subject property sales was roughly half compared to that within 300 feet.

With respect to the phase of foreclosure, results found that the peak discount occurred at the time of the foreclosure sale before the REO sale within 300 feet. They also used an alternative specification that allowed a nonlinear effect, using quadratic terms of the number of nearby foreclosures. These negative external effects existed in up to a year after the foreclosure sale.

Lin, Rosenblatt, and Yao (2009) explored property sales data for the Chicago in 2003 and 2006 (14,427 property transactions in 2006 and 11,000 properties sold in 2003), controlling for the housing cycles and using zip code dummies to control for neighborhood characteristics. They found that spillover effects for foreclosures were significant within a radius of 0.9 km, or approximately 2,700 feet (physical distance) and up to five years (temporal distance). The spillover effect decreased as distance in time and space between the foreclosure and the subject property increased. The price-depressing effects was most severe within 2 years of a foreclosure and created an 8.7% discount in a housing bust year (2006), which gradually diminished to as low as -1.7% at about 0.9 km (2700 feet) away. However, the estimated intensity of spillover effects was milder during a housing boom year (2003) than a housing bust year (2006) and was reduced by half.

Leonard and Murdoch (2009) studied 23,218 sales of single-family homes in Dallas County, Texas, during 2006. Their hedonic price analysis contained a large number of properties and neighborhood characteristics, including recent house price trends. The authors identified the number of foreclosures at four spatial distances: within 250 feet, 250-500 feet, 500-1000 feet, and 1000-1500 feet. They implemented the generalized method of moments (GMM) estimator that allowed for a heteroskedastic error structure. The GMM estimated that foreclosures had a smaller impact less than half of the OLS results. This suggested that the standard errors in the OLS models were biased downward. The authors found that each foreclosure within 250 feet had an effect of about -0.5% on sale prices, but it was not statistically significant within 250-500 feet. They indicated that price-depressing effects diminished at modest levels (-0.1%) within 500 - 1000 feet and 1000 - 1500 feet. The magnitude of the effect of a foreclosure was five times greater in the inner ring (250 feet) than those of beyond 250 feet.

Rogers and Winter (2009) explored the spatial-temporal effects of foreclosure. The dataset included 98,828 single-family home sales for the years 2000 through 2007, and 23,334 single-family home foreclosures and liquidations for 1998 through 2007 in Saint Louis County, Missouri. Rogers and Winter (2009) included GMM (generalized methods of moments) as a spatial statistical technique that further reduced statistical problems associated with spatial dependent data and controlled for unobserved neighborhood characteristics. They found that foreclosures in St. Louis County had a negative impact, but the marginal impact of foreclosures on neighboring house sale prices declined as foreclosures increased, depending on the spatial-temporal dimensions. For a foreclosure within the last six months and 200 yards (600 feet), the results indicated a price decline of almost 2% in the years 2000 through 2005 or about $4,000 off the sales price of an otherwise $200,000 unit, while the results indicated a decline of about 0.6% or $1,200 in 2006 and 2007 at a stable but beginning time period of the housing crisis. These results were robust to a variety of neighborhood control variables and spatial econometric techniques without controlling for the quality of foreclosure events (i.e. the foreclosed properties physical condition or vacancy status).

Despite the fact that these studies covered different areas and different time periods, using different methodologies, seven studies identified a negative relationship between foreclosures in a neighborhood and the value of surrounding homes, utilizing single family home sale transactions. Only one research by Harding, Rosenblatt, and Yao (2009) exclusively examined the relationship between foreclosures and neighborhood property values, using repeat sales price index. The results are summarized in Table 2.2.

Eight empirical studies suggest that these negative externalities (spillovers) of foreclosures in neighborhoods are partially capitalized into the value of surrounding properties, and that this capitalization even begins to occur during the pre-foreclosure stage. Five studies utilized a regression model (in particular a hedonic price function) to determine the price impact of surrounding foreclosures in identified distances. Another three most recent studies allowed for spatial effects that might exist using a cross-section of house prices through spatial hedonic models.

The critical variables in these studies are the distance to the foreclosures and frequency of foreclosures. Their results suggest that the frequency of foreclosures and proximity to foreclosures can be associated with a modest decrease in the sale prices of single-family homes. Their results indicate that the price-depressing impact increase as the frequency of foreclosures increases, but it decreases as distance from neighboring foreclosures increases.

Table 2.2. Summary of Literature Review: Spillover Effects of Neighboring Residential Foreclosures on Home Values.

Authors (Pub. Year)	Data Sets and Study Area(s)	Empirical Test	Focus Variables & Measurements	Findings: Marginal Impacts of Neighboring Residential Foreclosures on Home Sale Prices
Immergluck and Smith (2006a)	9,600 Single Family Home Sales (1999) Chicago, IL	Hedonic Model (OLS regressions)	# of residential foreclosures (1997&1998) 2 buffers (1/8 and 1/4 mile)	# Foreclosure of conventional mortgage within 1/8 mile (660 feet) → 0.9%-1.1% sale price↓*** # Foreclosure of conventional mortgage between 1/8 and 1/4 mile (660 feet and 1320 feet)→ 0.27 %-0.33% sale price↓*** ****a* =.01 significant level (R^2 = .76)
Shlay and Whitman (2006)	14,526 Single Family Home Sales (2000) Philadelphia, PA	Hedonic Model (OLS regressions)	Dummy- foreclosed and abandon properties (2000) 4 buffers (150; 300; 450; 600 feet)	# Foreclosed Abandoned Unit within 150 ft → 10% sale price↓($7,627/75,520)** # FAs, 150-300 ft → 9.0% sale price↓** # FAs, 300-450 ft → 4.7% sale price↓** # FAs, 450-600 ft → 1.8% sale price↓ ***a* =.05 significant level (R^2 = .50)
Schuetz, Been, and Ellen (2008)	89,814 Residential (1_4 family buildings, multi-family or mixed residential-commercial buildings) sales (1980-1999) New York, NY	Hedonic Model (OLS regressions)	# of pre-foreclosures (Lis Pendens) (2000-2005) 3 buffers (250; 500; 1000 feet) with 3 time lines	# LPs, any time, 250 ft → 0.43% sale price↓*** # LPs, any time, 250_500 ft → 0.11% sale price↓*** # LPs, any time, 500_1000 ft → 0.04% sale price↓*** 1+ LPs, 0_18 months, 250 ft → 0.54% sale price↓* 1+ LPs, 18+ months, 250_500 ft → 1.44% sale price↓*** 1+ LPs, any time, 500_1000 ft → 1.81% sale price↓*** 6+ LPs, any time, 250 ft → 3.87% sale price↓*** 6+ LPs, 0_18 months, 250_500 ft → 2.58% sale price↓*** 6+ LPs, 18+ months, 500_1000 ft → 1.56% sale price↓*** **a* =.1, ***a* =.05, *** *a* =.01 significant level (R^2=.69)
Mikelbank (2008)	9,049 Single Family Home Sales (2006) Cleveland, OH	Hedonic model (OLS regressions) and ML Spatial Hedonic model (Error model)	# of foreclosure filings and vacant / abandoned properties 4 buffers (250; 500; 750; 1000 feet)	# FFs, within 250 feet → 2.1% sale price↓*** # FFs, 251_500 feet → 1.6% sale price↓*** # FFs, 501_750 feet → 1.3% sale price↓*** # FFs, 751_1000 feet → 1.1% sale price↓*** # V/As, within 250 feet → 3.6% sale price↓*** # V/As, 251_500 feet → 0.06% sale price↓** ***a* =.05, *** *a* =.01 significant level of confidence

Table 2.2. Continued.

Authors	Data Sets and Study Area(s)	Empirical Test	Focus Variable & Measurements	Findings: Impacts of Neighboring Residential Foreclosures on Sales Prices
Harding, Rosenblatt, and Yao (2009)	628,531 Residential repeat sales including 405,683 repeat sales in MAS (1989-2007) 12 states + 7 metropolitan areas	Log-linear Hedonic model (OLS regressions)	# of nearby REO properties (1989-2007) 4 buffers (300; 500; 1000; 2000 feet) & phases of foreclosure	Three or more foreclosed properties within 300 feet → average 1.0% sales price↓ 300-500 ft → average 0.62% sale price↓ 500-1000 ft → average 0.46% sale price↓ 1000-2000 ft → average 0.45% sale price↓ *a* =.1, .05, and .01 significant level of confidence
Lin, Rosenblatt, and Yao (2009)	14,427 Single Family Home Sales (2006) and 11,000 Sales (2003) Chicago, IL	Hedonic Model (OLS regressions)	# of foreclosure including REOs (1990-2006) Distance (0.9 km ≈2950 feet) & three time intervals (0_2 yrs, 2_5 yrs, and 5_10 yrs)	Within a 0.9km (2700 feet or 10 blocks) radius, The most severe impact is an 8.7% discount on neighborhood property values, which gradually drops to anywhere between −1.7 to −4.7% for foreclosures liquidated within the past 5 years. *a* =.05 significant level of confidence
Leonard and Murdoch (2009)	23,218 Single Family Home Sales (2006) Dallas County, TX	Hedonic model (OLS regressions) and Spatial Hedonic Model (Error & GMM)	# of foreclosures including pre-foreclosures, auctions, and REOs (end of 2005-2Q of 2007) 4 buffers (250; 500; 1000; 1500 feet)	# FCs, 250 ft → 0.7% sale price↓**(ML spatial error model) # FCs, 500 ft → 0.3% sale price↓**(ML spatial error model) ***a* =.05 significant level of confidence (R^2 = .95) # FCs, 250 ft → 0.5% sale price↓***(GMM) # FCs, 1000 ft → 0.1% sale price↓**(GMM) # FCs, 1500 ft → 0.1% sale price↓*(GMM) **a* =.1, ***a* =.05, *** *a* =.01 significant level of confidence
Rogers and Winter (2009)	98,828 Single Family Home Sales (2000-2007) St. Louis County, MO	Hedonic model (OLS regressions) and Spatial Hedonic model via GMM	# of pre-foreclosures (2000-2007) 3 buffers (200; 400; 600 yard) with 4 time lines 200 yard = 600 feet	# FCs, 0_6 months, 200 y → 0.53% (06_07) price↓** # FCs, 7-12 months, 200 y → 0 .51% (06_07) price↓** # FCs, 18_24 months, 201_400 y → 0.35% (03_05) price↓** # FCs, 0-6 months, 401_600 y → 0 .30% (03_05) price↓** vs. 0.57% (06_07) price↓** # FCs, 12_18 months, 401_600 y → 0.34% (03_05) price↓ ***a* =.05 significant level of confidence

All previous empirical analyses employ geographically detailed data through geographic information system (GIS). Geographic Information System techniques allow researchers to analyze the effects of proximity to foreclosures. Variables of foreclosure frequency and distance measured through GIS are generated to examine the spatial decay of foreclosures on nearby property values, which enables researcher to understand the geographic limits of the foreclosure effect. Most studies generally divide the frequency of foreclosures into three or four proximity rings and estimate separate equations for each ring. For the existing foreclosure, the results indicated that this spillover effect was diminished as distance from the foreclosure and property sold increased.

Although these studies provide valuable methodological frameworks for examining spillover effects of neighboring foreclosures on neighborhood property values, some methodological issues remain. The limitations of previous studies and main issues of methodology will be explained in more detail in the next section.

Last, either traditional hedonic modeling or spatial hedonic modeling has been used extensively in analyzing single family home properties and in estimating the effects of neighboring foreclosures on single family home prices. There have been no attempts to model for condo properties in a spatial hedonic framework. The application of this technique to condo properties is limited by the difficulty of assembling a sufficiently large number of transactions on relatively homogenous properties. Thus, there is a need for additional research on condo prices to highlight whether or not these spillover effects of foreclosures change by housing market conditions (housing booms versus housing busts) and housing types (single family home versus condo).

2.6 Major Issues of Measuring Foreclosure Effects on Property Values

2.6.1 Spatial Dependence

Recently, empirical econometric works have started to take into consideration the potential bias and loss of efficiency that can result when spatial effects such as spatial autocorrelation and spatial heterogeneity are ignored in the estimation process. Spatial dependence results from the fact that properties in close proximity to each other often share similar environmental, accessibility, and neighborhood characteristics. Spatial dependencies affect hedonic studies from either structural relationship among the observations (lagged dependency) or among the error terms (Anselin, 1988).

Thus, the existence of spatial dependence may affect the validity and accuracy of the traditional hedonic model (Can, 1992; Dubin, 1998). The OLS model tends to overestimate the importance of structural and neighborhood attributes on housing values (Anselin, 1988). Spatial econometric methods, which incorporate the spatial dependence in cross-sectional data into model specifications, estimation and testing, have become fairly commonplace in empirical studies of housing and real estate, leading to so called spatial hedonic models (Anselin, 2006).

For the previous studies of foreclosure effects on property values, two important recent methodological developments are provided to control for spatial autocorrelation. The first is the maximum likelihood (ML) spatial hedonic model (Leonard and Murdoch, 2009; Mikelbank, 2008) and the second is the spatial hedonic model via the general method of moments (GMM) as the alternative of maximum likelihood (ML) spatial hedonic model (Rogers and Winter, 2009; Leonard and Murdoch, 2009). When the spatial hedonic models control for spatial effects through spatial lags or errors, the previous empirical results revealed that the coefficients of foreclosure variables in spatial hedonic models were less than ones found in OLS. This means that the foreclosure effect on property values measured in the OLS model are overestimated or biased.

2.6.2 Selection Bias and Endogeneity

Another methodological issue is related to the sample selection bias. In order to make inferences about the entire stock of housing, it is necessary to assume that the houses sold are a representative sample, or sample selection bias would occur in analyzing housing sale samples.

Immergluck and Smith (2006a) found that foreclosures of single family homes significantly impacted property values within an eighth of mile, with a conservative estimate of each foreclosure resulting in a decline of 0.9% on single family property sales in 1999. However, Lin, Rosenblatt, and Yao (2009) analyzed the same Chicago market, but focused on 2003 and 2006. Their contribution to the literature was a more flexible estimation of the neighboring foreclosure effect. Lin, Rosenblatt, and Yao (2009) found that foreclosures had a significant negative marginal impact of -8.7% on neighborhood property values within 100 meters and five years from the foreclosure. Foreclosures further away in space had a much smaller, but still quite large effect: about a -4% negative marginal impact on neighboring sales within 400 meters. Lin, Rosenblatt, and Yao (2009) found that the marginal foreclosure impact was larger in bad market (2006) when they estimated a model using sales data from 2003 and compared the results to the 2006 samples.

However, it is difficult to identify the difference in results from the two previous studies. They both analyzed the same market area but in different time periods, different data sources, and used only slightly different methodologies. As Schuetz, Been, and Ellen (2008) point out, both only use cross-sectional data, which may introduce neighborhood bias as housing sales near foreclosures are more likely to be in poor neighborhoods. Thus, Lin, Rosenblatt, and Yao (2009) used a simple two-step procedure to test, and they corrected sample bias with instrument. The authors used variables describing the characteristics of the loan and financial situation of borrowers.

An attempt to control for sample bias was made through use of a probit analysis using a sale as the binary dependent variable.[7] Therefore, sample rules resulted in a specification error in the regression. Heckman (1979) offered a solution to this problem through a two stage estimator. First, a probit analysis of the full sample was performed to estimate the probability that an observation will have a value for the dependent variable. This is then used as a regressor in the subsequent hedonic regression to eliminate the specification error. This rule would identify what types of houses are more likely to have changed and would use variables that would not properly enter the hedonic index, that is, the sample selection rule says nothing about the value of the houses, just their probability of having a sale during the time period. Moreover, these results indicate that

[7] Such a procedure is described by Heckman (1979). The logic of this approach is that the regression error *e* is not independent of the sample selection rule.

even though the housing which is sold is a biased sample of the total stock, represents strong pressure on neither the demand side or on the supply side (Rothenberg, Galster, Butler, and Pitkin, 1991).

Lin, Rosenblatt, and Yao (2009) found that the price-depressing effect was most severe within 2 years of a foreclosure and created an -8.7% discount in housing bust year (2006), which gradually diminished to as low as -1.7% at about 0.9 km (2700 feet) away. When correcting sample selection bias, the change in magnitude of spillovers was quite small and was approximately within a -1% reduction compared to the spatial-temporal effects of foreclosures, which has not been corrected for sample selection bias.

Another potential estimation problem is endogeneity. Discussion on endogeneity (reverse causation) is either very limited or weakly controlled in previous studies. The causal relationship between home prices and foreclosures is two-directional: high foreclosure activity can both cause and be caused by home price declines. Falling property values may lead to an increase in foreclosures by decreasing the equity that homeowners have in their properties. Mortgagors are much more likely to default on their loans if they owe more than the house is worth. Declines in home prices will increase the frequency with which homeowners find themselves with no equity and thus may be motivated to walk away from the property and the mortgage. Home foreclosures contribute to weakening prices by introducing additional supply to the inventory of unsold homes. As a result, they may be willing to sell for lower prices than resident homeowners. Under the ruthless option theory, it is clear that the default indicator will be negatively correlated with the house price error.

Lower neighborhood prices will also increase the chances of future foreclosures, so the process is to some degree endogenous, with foreclosures potentially causing lower neighborhood prices and then lower neighborhood prices causing more foreclosures. The critical question is whether foreclosures are the cause of the decline in values of nearby properties or merely a symptom of general decline in house prices (Harding, Rosenblatt, and Yao, 2009).

Endogeneity has remained an open problem in the literature. Endogeneity is a problem of spurious correlation between a regressor and the error term. The error term consists in part of omitted variables. Spatial statistics helps control for the influence of omitted variables, thus alleviating the need to instrument for endogenous variables (Brasington, 2001).

The following two recent studies control for endogeneity with instrument variable. First, Clauretie and Daneshvary (2009) addressed many of the shortcomings of earlier papers while estimating the foreclosure discount. Using data from the Las Vegas MLS, they built a sample of 1,302 foreclosed property sales and 8,498 non-distressed sales from November 2004 through November 2007. The authors extended their specification to include the spatially weighted prices of neighboring properties. In this specification, the resulting specification was a nonlinear model involving two endogenous variables (marketing on time and spatially lagged dependent variable) with spatially correlated disturbances. The authors estimated this model using generalized spatial two-stage least-squares (GS2SLS), developed by Kelejian and Prucha (1998, 1999). They estimated that the foreclosure discount, based on a single MSA, was approximately -7.5% after controlling for property conditions, spatial effects, and marketing time. These results indicated that estimates of true discount caused by foreclosure were reduced by about one-third of foreclosure discount reported by previous studies (-22% ~ -28%).

Second, Ding and Quercia (2010) found that a higher level of subprime activity caused a decline in neighborhood property values and increased the price volatility. Because of the declined property value, the default risk of Community Advantage Program (CAP) loans in the same neighborhoods increased significantly. Overall, this study provided new evidence concerning the negative impacts of the concentration of subprime lending in certain neighborhoods. They used a two-stage least-squares (2SLS) analysis. In the first stage of the analysis, the neighborhood housing price change was regressed on MSA house price changes, neighborhood subprime activities, local economic conditions, and other explanatory variables in the model. It is assumed that area house price changes, subprime activities, and other neighborhood controls are uncorrelated with unobserved determinants of the CAP loan default behavior and that these instruments only influence the troublesome neighborhood house price change, controlling for the other covariates. In the second stage of the analysis, the CAP loan default was regressed on the predicted value of neighborhood house price changes, as well as other controls of individual borrower credit risk. The instruments, such as neighborhood subprime activities, were not included as regressors in the second stage, assuming they did not influence the default behavior directly.

As Cambell, Giglio, and Pathak (2009) pointed out, foreclosure status may be endogenous to house prices but proper instruments for foreclosures are hard to find. Specifically, foreclosures are likely to be more common in neighborhoods where property values are lower, raising the concern of endogeneity (Leonard and Murdoch, 2009). However, it is difficult to tell whether value changes are a cause of foreclosures, and foreclosures are a cause of value change. The non-recursive inferring of causality thus requires very careful structuring of data sets as well as solving some technical issues associated with the regression models. Thus, further study needs to address methodological challenges to overcome the causality problem between housing price and foreclosures.

2.6.3 Marginal Impacts and Nonlinear Effects of Neighboring Foreclosures in Different Housing Cycles

Despite the role in refining the mathematical models to quantify spillover effects in previous studies (see tables on pages 46-47 [Table 2.2]), discussion on the nonlinearity of their marginal effects is very limited. In general, these studies provide some evidence that properties in close proximity to foreclosures sell at a discount. The magnitude of the price discount increases with the number of neighboring foreclosures, although not in a direct linear relationship, suggesting some diminishing marginal impacts. Many previous simulation results were based on a linear model of the relationship between foreclosure growth and housing price change. A few recent studies (Lin, Rosenblatt, and Yao, 2008; Rogers and Winter, 2009; Schuetz, Been, and Ellen, 2008) considered nonlinear relationships between the number of foreclosures and property values.

Schuetz, Been, and Ellen's study (2008) was one of the few that attempt to assess the nonlinearity of foreclosures' marginal effects when the number of pre-foreclosures increases. Their research on New York City indicated that additional pre-foreclosures had diminishing marginal spillover effects. This study played a pioneering role in refining the mathematical models using dummies to measure the nonlinearity of multiple foreclosures. This study did not directly quantify the marginal impact of additional pre-foreclosures, but rather it aggregated the spillover effects of a neighborhood's foreclosure exposures and the number of foreclosure petitions in the area. Their findings suggest the importance of preventing early foreclosures from happening in the first place since they tend to have bigger price-depressing effects on nearby properties. However, a dummy approach to measure nonlinearity of multiple foreclosures was subject to methodological limitations in the mathematical model. In the presence of clustered foreclosures, using dummy variables to refine the effect of multiple foreclosures around property values will arbitrarily estimate the effects of approximately grouped foreclosure counts rather than exactly measure the effects of cumulative foreclosures around objective property values.

Rogers and Winter (2009) addressed one of these methodological problems in their study of the impact of foreclosures and enhanced measurement of the nonlinear effects of foreclosure on neighboring property prices, using quadratic terms of foreclosures in the GMM spatial hedonic model. However, to date no study has measured exactly the extent of cumulative (incremental) impacts of nearby foreclosures on home prices. In other words, how much foreclosure density (or frequencies) in a specific distance affects the extent of nearby housing value changes? One would expect a threshold effect that might be caused by the foreclosure density.

If a household owns a house that rapidly appreciates, it may be better able to overcome the down payment constraint, move, and generate a house sale. Frequent sales will tend to be observed in rapidly appreciating neighborhoods. Another possibility is that in a declining market, the mortgage default or foreclosure rate is highest for houses with rapid price depreciation. The potential bias may be largest during economic downturns when few houses sell (Haurin and Hendershott, 1991).

The studies of direct foreclosure impact on property values generally indicate that the effects include reductions in sale prices. However, areas and time periods that have a weaker market demand may be impacted by foreclosure to a greater degree than areas and time periods with stronger market demand. The foreclosure impact on property values appears to be temporary. There is, however, a limited amount of evidence to date on this point. It is unclear how spillover effects of foreclosure on property values may change due to market conditions or cycles.

For the single family property type, Lin, Rosenblatt, Yao (2009) find reductions in property value by nearby foreclosures and importantly suggest that bad market conditions tend to augment the adverse effects of neighboring foreclosures on property values. Rogers and Winter (2009) found a similar implication for market conditions in their foreclosure study. However, they argued that weaker market conditions mitigated the price impact of foreclosure.

While Rogers and Winter (2009) findings that the price effects of existing foreclosures do diminish over time seems to be inconsistent with those of Lin, Rosenblatt, Yao (2009), the effect of housing cycles on foreclosure impact is a critical factor in their research framework. Their framework focuses on changes in the housing price impact by nearby foreclosures over time corresponding to changes in housing market cycles.

Therefore, further study needs to be done to analyze cyclical housing markets such as the cities in the Sun Belt states in which housing prices are rapidly declining and rising. It needs to utilize sample data in different years, such as housing boom and bust periods, to capture how the external effects of foreclosures on neighborhood property values may vary over the housing market cycles.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

3.1 Introduction

This section begins with the conceptual framework for the research. It provides a brief outline for foreclosure timelines and then presents overall conceptual models. Following the section of conceptual framework, ten hypotheses will be proposed. The question to be addressed in this dissertation is the impact of foreclosure on existing home prices. The objective of this research is to examine questions regarding direct foreclosure effects capitalized into property itself and the resulting negative effects generated by foreclosed properties on the value of nearby existing homes. These questions will drive adequate hypotheses and suitable analysis.

3.2 Conceptual Framework

Foreclosure is the legal procedure that a mortgage lender must follow to take possession of a home whose owner has not satisfied the requirements of a mortgage contract. In most states, foreclosure is generally a four-phase process that begins when a homeowner misses three consecutive scheduled loan payments. In the first phase of foreclosure, the lender may file a legal intent (“Notice of Trustee’s Sale” in non-judicial approach and “Notice of Lis Pendens” in non-judicial approach) to foreclose upon the mortgage after such default (Cutts and Merrill, 2008; Pennington-Cross, 2006). In the second phase of foreclosure, the mortgage lender can negotiate the possibility of either a restructured loan or a short sale by which the property is sold for less than the amount owed on the mortgage. If these negotiations fail, the property goes to the third phase of foreclosure, which is an auction requiring a minimum bid set to cover the distressed mortgage's loan balance and fees. If the minimum is not met, in the fourth phase of the foreclosure process the property reverts to the lender and it is considered real estate (or lender) owned (REO) property. Capozza and Thomson (2006) found that 79% of defaulted loans (90 days or more delinquent) became REO properties and the remaining 21% cured or prepaid.

There is a range of possible outcomes for any given foreclosure, pre-foreclosure sale (or short sale), foreclosure sales at auction, bank owned sales, and vacant or abandoned properties because time to reach those outcomes would likely vary across properties. Thus, it is difficult to forecast exactly how long it would take the process after foreclosure to affect surrounding property values (see Figure 3.1).

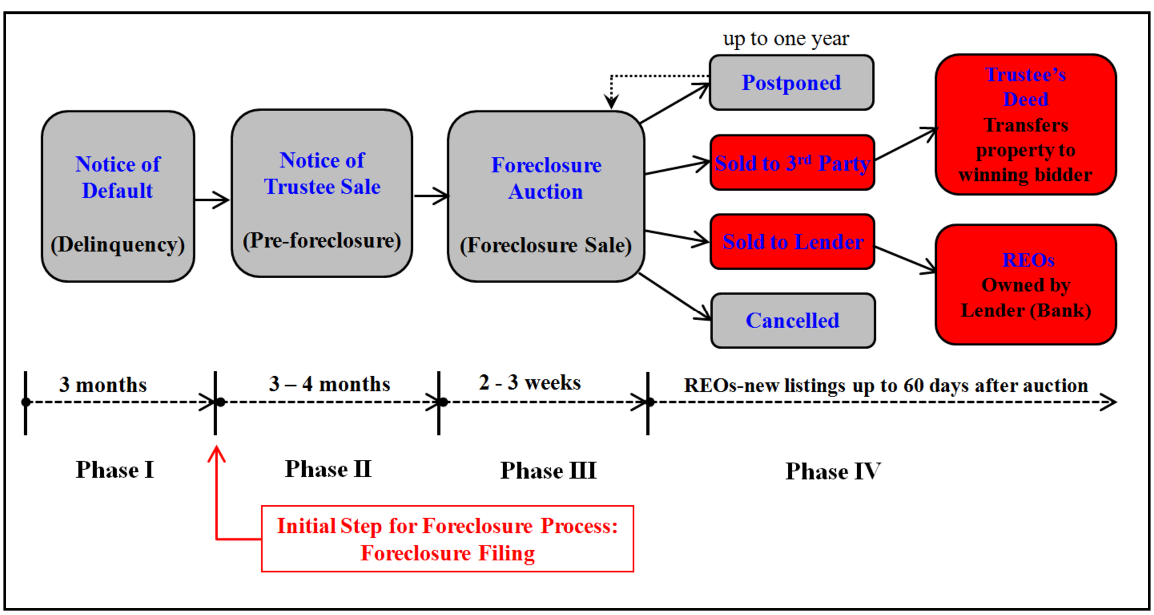

Figure 3.1. Foreclosure Timeline.
Source: Cutts and Merrill, 2008.

As discussed in section 2, empirical evidence shows that mortgage foreclosure has not only a direct influence on the sale price of a home under foreclosure status but also an indirect influence on nearby home prices. Based on the previous contributions, the following description will illustrate a mechanism to clarify the relationship between foreclosure and housing values for the study focus.

As summarized by Lee (2008), foreclosures could negatively impact nearby housing values through three channels: increased supply, discounting, and the neighborhood spillover effect. In the first channel, additional inventory comes on the market when homes are foreclosed, exacerbating the mismatch between demand and supply. Foreclosure is usually a forced act and thus unnaturally raises the supply of homes in a neighborhood.

Since prospective homebuyers usually shop around neighborhoods before making a transaction, the increase in distressed homes lowers the prospective selling price of all homes in a neighborhood due to the expansion of available choices. Thus, a large number of short sales or foreclosed properties in a neighborhood, by raising the supply of properties for sale, would likely reduce nearby home prices.

Once the downturn begins, both short sales and a rising tide of foreclosed and REOs add to the downward pressure on prices, exacerbating the problem. In addition, a high concentration of foreclosed properties and REOs can create an additional supply in the inventory of unsold homes, thereby lowering the values of nearby homes.

In the second channel, short sales or properties which have a foreclosure notice may sell at a lower price than the average sale price for the area. Typically, distressed sellers who have defaulted on loans will be more open to any offers and willing to sell the property below its appraised value since the home owner wants to pay off the mortgage in order to avoid the foreclosure sale, and to prevent damage to their personal credit rating. There will often be time pressures to complete the transaction before the foreclosure sale takes place, and homeowners then realize that they must lower their prices to sell their homes. Thus, the housing price in a neighborhood will affect or be affected by the housing prices in adjacent neighborhoods. Properties with distressed loans are likely to sell at a discount, affecting the price of comparable homes used to estimate neighboring property values.

However, when foreclosures are thought to negatively impact the values of nearby properties, timing on selling may influence nearby housing prices based on the concept of comparable property valuation. In general, foreclosure sales and distressed REOs occur at steep discounts, further undercutting market prices. Moreover, the distressed properties occupied by tenants would depreciate faster than owner occupied units since renter occupied units might lead to lower levels of maintenance after the bank pursued foreclosure (Galster, 1983, 1987; Gatzlaff, Green, and Ling, 1998; Shilling, Sirmans, and Dombrow, 1991).

In the last channel, if not sold quickly after the foreclosure auction, foreclosed properties stay unoccupied for extended periods of time, which attracts vandalism and crime, increasing the blight, making the neighborhood undesirable for potential homebuyers and pushing down home values in the immediate neighborhood (Kingsley, Smith, and Price, 2009). Bank owned homes are more likely to suffer physical neglect before and after repossession. Abandoned and vacant properties blighting a neighborhood make difficult for the remaining homeowners in the community to maintain their properties. These problems can lead to increased costs for fire, police, and other services and decreased revenues for local governments. Foreclosures, in turn, can lead to yet more foreclosures by deferred maintenance, disinvestment, and declining neighborhood stability. This negative externality could be attributable to the fact that homeowners facing foreclosure eliminate or reduce maintenance expenditures causing a decline in the value of normally maintained nearby homes. These results in lower property values for homeowners and a reduced tax base for communities. If foreclosures lead to a decline in neighborhood property values, the reverse may also be true. Falling property values may lead to an increase in foreclosures because, if house prices drop dramatically, the borrower may owe more than the house is worth, which could cause more borrowers to default on their mortgages. If both of these inferences are true, this would cause an undesirable feedback loop between property values and foreclosure.

Figure 3.2 illustrates the conceptual diagrams of the impacts of foreclosure on property values discussed above.

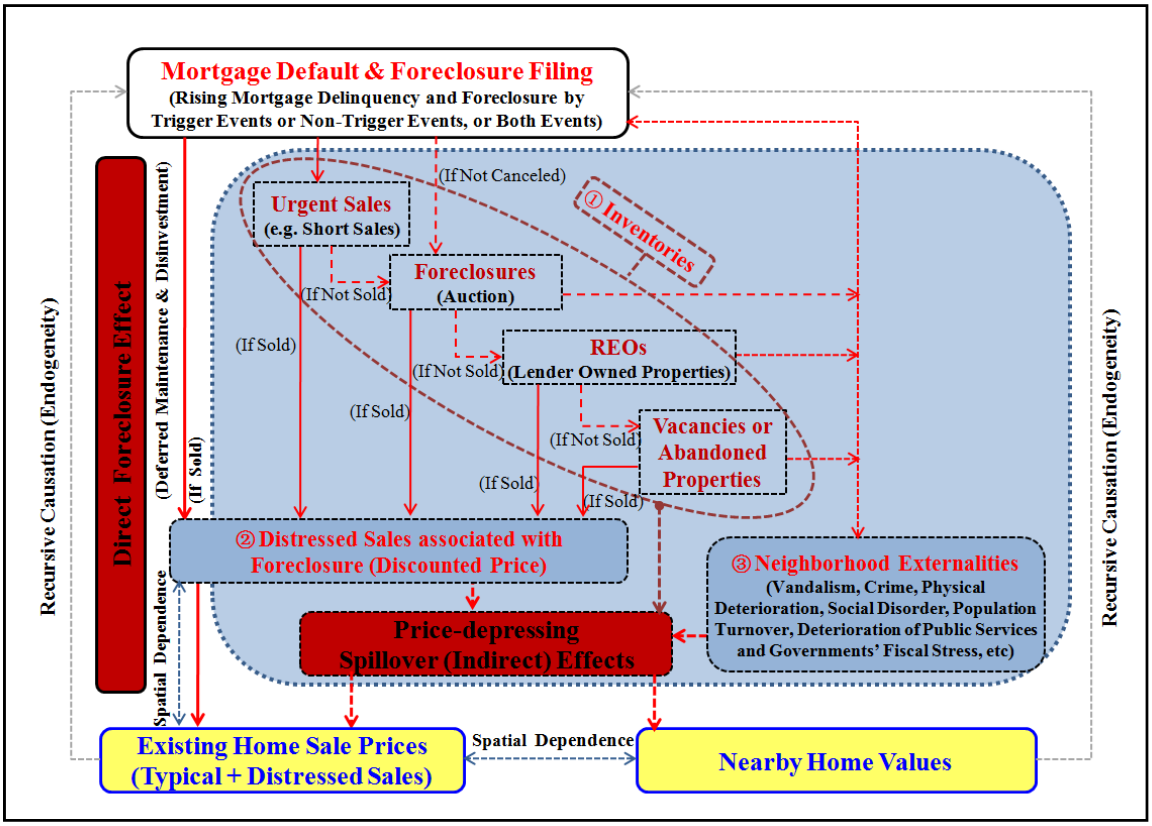

Figure 3.2. Conceptual Diagrams of Direct and Spillover Effects of Foreclosures on Existing Home Prices.

Home value depreciation would not arouse much attention in governmental sectors in strong market neighborhoods, even if there are some risks of foreclosure impacts. In neighborhoods where there is a low density foreclosure rate, the low cost of government interventions could be expected regardless of market strength. Thus, trends should be monitored in order to head off problems quickly if foreclosures start to increase. If risks increase substantially, there will be a need to act quickly to prevent actual foreclosures and then minimize vacancy in any properties where foreclosures do occur. Moreover, if the housing market is strong enough, the investors or owner occupants are more likely to invest the full costs to operate the property in an economically stable manner.

However, the current housing market condition is more likely to be a weak housing market with a high level of foreclosure impacts. Homeowners facing foreclosure are also more likely to defer maintenance leading up to the foreclosure regardless of whether or not the bank pursues foreclosure. From the public perspective, it represents a more difficult challenge in most cities since there is not likely to be sufficient funding for the costs of acquisition or rehabilitation.

Figure 3.3 illustrates the relationship between housing market conditions and foreclosure. The rows present housing market strength that the upper side indicates a good housing condition and the bottom side indicates a poor housing condition. The columns picture the foreclosure impact risk from low foreclosure density on the left to high foreclosure density on the right. This diagram shows how foreclosures destabilize neighborhoods and cause a decline in housing values.

As discussed above, mortgage foreclosure has a direct influence on the selling price of a home under foreclosure as well as an indirect influence on the nearby selling prices, depending on housing market conditions. Thus, searching for empirical evidence that foreclosure has both price-depressing effects on home values for homes in foreclosure and on nearby home values is the main question of this study.

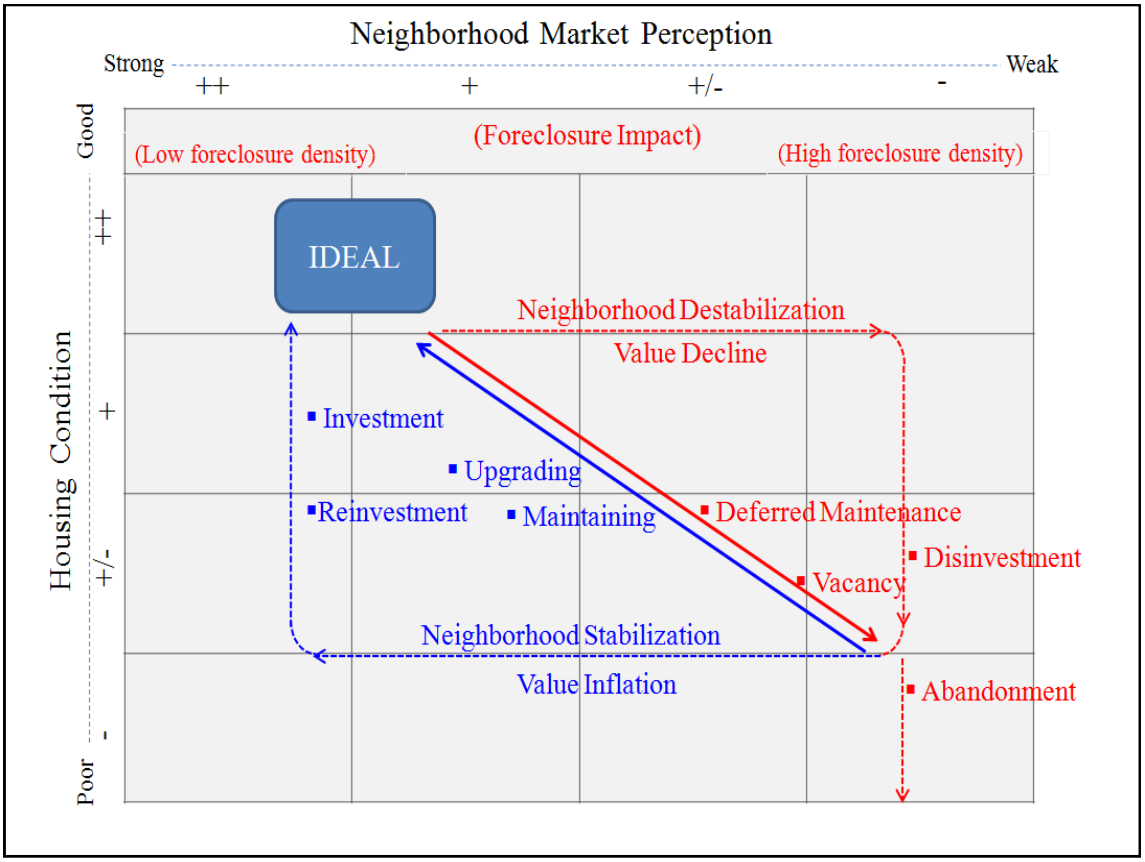

Figure 3.3. The Matrix of Housing Market Dynamics.
Source: Goetze, 1979.

To measure foreclosure impact on housing values, this study modified the standard appraisal practice, including (1) the variable for classifying distressed homes related to foreclosure and a typical arm's length transaction, (2) structural variables describing the physical characteristics of housing, (3) quarter variables representing market price trends, (4) selling characteristics associated with foreclosure status such as renter occupancy and cash transactions, and (5) neighboring residential foreclosures as s proximity externality (see Figure 3.4).

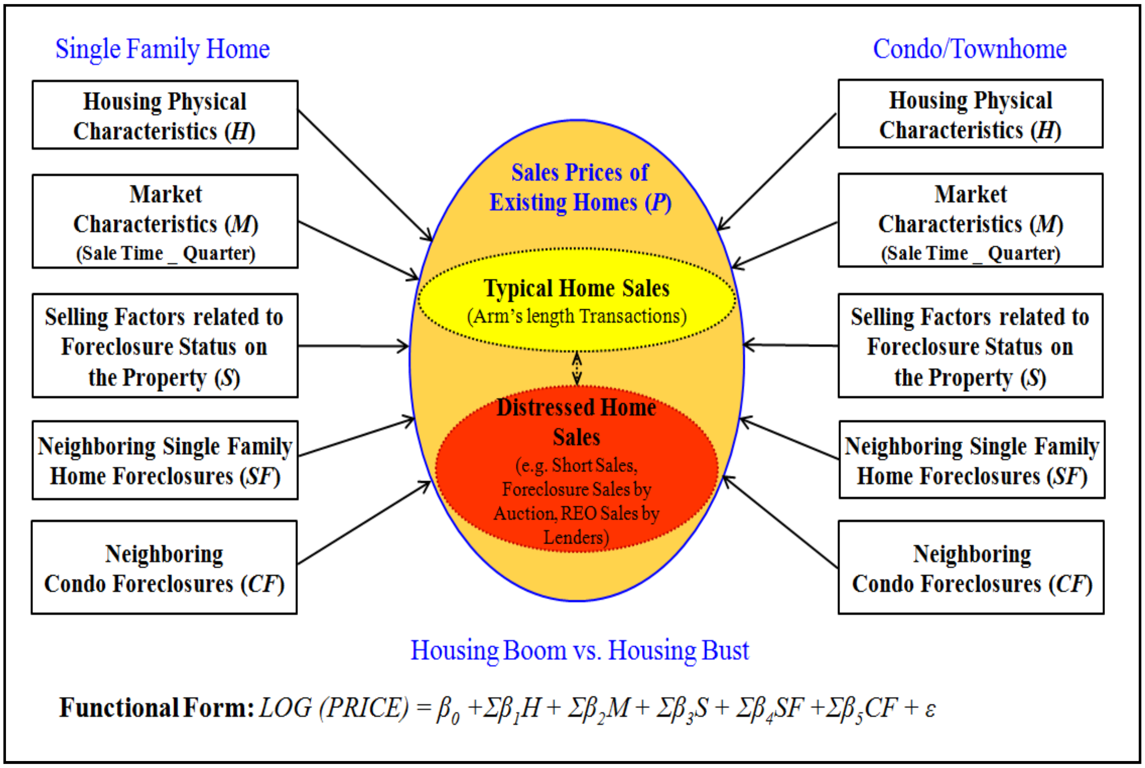

Figure 3.4. The Conceptual Framework for Measuring Existing Home Values and Foreclosure Effects.

In relation to the main question, this study will investigate whether foreclosures cause a significant reduction in neighborhood home values in housing booms and busts. In addition, this study will also investigate how foreclosure impacts on home values vary with housing type and foreclosure type, as well as how the home values vary with the foreclosure proximity and density in neighborhoods. The following section addresses ten hypotheses associated with foreclosure impacts on home prices, which will be examined through descriptive and analytical methods in the next section.

3.3 Research Questions and Hypotheses to be Tested

To achieve the research objectives, the following research questions and ten hypotheses will be investigated through the related literature review and conceptual models.

3.3.1 Spatial Dependence in Cross-Sectional Housing Sales Data

3.3.1.1 Hypothesis 1: Existence of Spatial Dependence on Housing Prices

Question 1: Does a spatial dependence or spatial autocorrelation exist among home sale prices?

The first null hypothesis is as follows: holding all else constant, spatial dependence (spatial autocorrelation) doesn't exist among home sale prices. The null hypothesis is denoted as H_{10}: $\beta_{Spatial\ Dependence} = 0$; the alternative hypothesis is denoted as H_{1A}: $|\beta_{Spatial\ Dependence}| > 0$. It is expected that there is the presence of spatial autocorrelation among home sale prices, and the expected sign will be positive, thus rejecting the null. It will be tested by using different housing types (single family home versus condo) and different housing cycles (a housing boom year versus a housing bust year).

It is well known that, when analyzing geographical and cross sectional data, geographic location plays an important role in the occurrence of spatial effects, including spatial autocorrelation. The literature on spatial econometrics focuses on two types of spatial effects; spatial dependence and unobserved spatial heterogeneity (LeSage, 1999). Spatial dependence is likely to exist in a situation where the dependent variable or error term at each location is correlated with observations of the dependent variable or values for the error term at other locations. Spatial dependence refers to the fact that one observation associated with a location depends on other observations in adjacent locations. For example, houses in locations near each other tend to have similar prices and characteristics in housing markets. Unobserved spatial heterogeneity refers to the error in the measurement of the externality caused by the presence of spatial externalities and missing variables. It will likely be similar for proximate houses, creating an error term of spatial dependence (Dubin, 1992). Realtors or property appraisers tend to evaluate houses by referring to similar housing values in nearby locations. Thus, the purpose of this hypothesis is to test spatial dependence that may exist using a cross-section of house price data.

3.3.2 Direct Foreclosure Effects

3.3.2.1 Hypothesis 2: Distressed Sale Associated with Foreclosure

Question 2: Is residential property that previously faced a foreclosure and sold later at a discount?

The null hypothesis is as follows: holding all else constant, there is no difference between the sale price of a home that previously faced foreclosure and the sale price of typical home. The null hypothesis is denoted as H_{20}: $\beta_{\textit{Distressed Sale Associated with Foreclosure}} = \beta_{\textit{Typical Sale}}$; the alternative hypothesis is denoted as H_{2A}: $\beta_{\textit{Distressed Sale Associated with Foreclosure}} < \beta_{\textit{Typical Sale.}}$ It is expected that there is a difference, and the expected sign will be negative, thus rejecting the null. It will be tested by using different housing types (single family home versus condo) and different housing cycles (a housing boom year versus a housing bust year).

The impacts of direct foreclosure effects are likely to differ according to the condition of the local housing market. In hot markets, market demand is more likely to absorb foreclosed properties or short sales. In doing so, foreclosed properties or foreclosure-scheduled properties are less likely to sell at a discount. However, distressed homes associated with a foreclosure status are likely to remain in inventories or later lay in a vacant and abandoned condition for long periods in a sluggish housing market. Thus, distressed properties are also less likely to resell rapidly through conventional channels without big discounts in a bad market condition.

Existing research on condo (Shilling, Benjamin, and Sirmans, 1990), single family home (Carroll, Clauretie, and Neill, 1997; Clauretie and Danenshvary, 2009; Forgey, Rutherford, and VanBurskirk, 1994; Pennington-Cross, 2006), and apartments (Hardin and Wolverton, 1996) have all confirmed a foreclosure discount in a specific housing market condition. All except two studies found a significant 20%s discount for foreclosed property. One case (Sumell, 2009) was at about a 50%s discount for REO property in Cuyahoga County. Recent results (Clauretie and Danenshvary, 2009) indicated that the direct discount caused by foreclosure was 7.5%, when corrected for spatial autocorrelation and accounting for the endogeneity of marketing time. The estimate of foreclosure discount reported in this study was about one-third of previous findings (22% - 28%).

3.3.2.2 Hypotheses 3 and 4: Renter Occupancy

Question 3: Does a renter occupied home have a discount compared to an owner occupied home when sold?

The third null hypothesis is as follows: holding all else constant, there is no difference between the sale price of renter occupied home and the sale price of owner occupied home. The null hypothesis is denoted as H_{30}: $\beta_{\text{Renter Occupied Home}} = \beta_{\text{Owner Occupied Home}}$; the alternative hypothesis is denoted as H_{3A}: $\beta_{\text{Renter Occupied Home}} < \beta_{\text{Owner Occupied Home.}}$ It is expected that there is a difference, and the expected sign will be negative, thus rejecting the null. It will be tested by using different housing types (single family home versus condo) and different housing cycles (a housing boom year versus a housing bust year).

The fourth null hypothesis is as follows: holding all else constant, there is no difference between the sale price of a renter occupied home that previously faced a foreclosure and the sale price of an owner occupied home that previously faced a foreclosures. The null hypothesis is denoted as H_{40}: $\beta_{\text{Foreclosure*Renter Occupied Home}} = \beta_{\text{Foreclosure *Owner Occupied Home}}$; the alternative hypothesis is denoted as H_{4A}: $\beta_{\text{Foreclosure*Renter Occupied Home}} < \beta_{\text{Foreclosure*Owner Occupied Home.}}$ It is expected that there is a difference, and the expected sign will be negative, thus rejecting the null. It will be tested by using different housing types (single family home versus condo) and housing cycles (a housing boom year versus a housing bust year).

Homeowners are likely to be more involved in local organizations and social activities. This involvement, again, may improve the quality of life in a community and raise property investment or values (DiPasaquale and Glaeser, 1999; Rohe, Van Zandt, and McCarthy, 2000). Moreover, economic research found that owner occupied units had higher values than renter occupied units (Coulson, Hwang, and Imai, 2003; Gatzlaff, Green, and Ling, 1998; Shilling, Sirmans, and Dombrow, 1991). One aspect that has not been fully examined in previous research would be the effects of occupancy status on housing prices depending on the existence of the foreclosure externality. Thus, these two hypotheses will investigate the effect of renter occupancy status on home in both a full sample and a distressed sample associated with foreclosure.

3.3.2.3 Hypotheses 5 and 6: Cash Transaction

Question 4: Does residential property sold in a cash transaction have a greater discount than financing transaction?

The fifth null hypothesis is as follows: holding all else constant, there is no difference between the sale price of a home sold in a cash transaction and the sale price of a home sold with a mortgage financing. The null hypothesis is denoted as H_{5O}: $\beta_{Cash} = \beta_{Financing}$; the alternative hypothesis is denoted as H_{5A}: $\beta_{Cash} < \beta_{Financing}$. It is expected that there is a difference, and the expected sign will be negative, thus rejecting the null. It will be tested by using different housing types (single family home versus condo) and different housing cycles (a housing boom year versus a housing bust year).

The sixth null hypothesis is as follows: holding all else constant, there is no difference between the sale price of a home sold by cash that previously had a foreclosure filing and the sale price of a home sold with a mortgage financing that previously faced a foreclosure. The null hypothesis is denoted as H_{60}: $\beta_{Foreclosure*Cash} = \beta_{Foreclosure*Mortgage\ Financing}$; the alternative hypothesis is denoted as H_{6A}: $\beta_{Foreclosure*Cash} < \beta_{Foreclosure*Mortgage\ Financing}$. It is expected that there is a difference, and the expected sign will be negative, thus rejecting the null. It will be tested by using different housing types (single family home versus condo) and housing cycles (a housing boom year versus a housing bust year).

Many investors specialize in purchasing foreclosed properties through a cash transaction. Properties sold in a cash transaction are more likely to sell at a discount. Forgey, Rutherford and VanBuskirk (1994) found that property prices were discounted by 16% when purchased by cash. Clauretie and Danenshvary (2009) found that renter occupancy or a cash transaction had a negative impact on typical home sale prices, not controlling for distressed home sales associated with foreclosure. Furthermore, this hypothesis will investigate the price effect of cash transactions and renter occupancy status on both a full sample and distressed sample, which has not been examined in previous research.

3.3.3 Spillover Effects of Neighboring Foreclosures

3.3.3.1 Hypotheses 7 and 8: Distance Effects of Neighboring Foreclosures

Question 5: Do distressed properties associated with foreclosure lower neighboring housing sales price? If neighboring foreclosures have negative effects on existing property prices, does the price impact vary with the distance between surrounding foreclosures and existing home sale prices surrounded by foreclosures?

The seventh hypothesis is as follows: holding all else constant, there is no difference among price impacts of neighboring foreclosures (single family home and condo) on existing single family home prices by distance. If H_7: $\beta_{\textit{Neighboring Foreclosure in Each Distance}} < 0$, the null hypothesis is denoted as H_{70}: $|\beta_{\textit{Neighboring Foreclosure in Distance 1}}| = |\beta_{\textit{Neighboring Foreclosure in Distance 2}}| = |\beta_{\textit{Neighboring Foreclosure in Distance 3}}|$; the alternative hypothesis is denoted as H_{7A}: $|\beta_{\textit{Neighboring Foreclosure in Distance 1}}| > |\beta_{\textit{Neighboring Foreclosure in Distance 2}}| > |\beta_{\textit{Neighboring Foreclosure in Distance 3}}|$. The expected sign will be negative and there is a difference, thus rejecting the null. It is expected that a neighboring foreclosure (single family home or condo) closer to the single family home sample has a larger negative price impact than a neighboring foreclosure further away. It will be tested in different housing cycles (a housing boom year versus a housing bust year).

The eighth hypothesis is as follows: holding all else constant, there is no difference among price impacts of neighboring foreclosures (single family home and condo) on existing condo prices by distance. If H_8: $\beta_{\textit{Neighboring Foreclosure in Each Distance}} < 0$, the null hypothesis is denoted as H_{80}: $|\beta_{\textit{Neighboring Foreclosure in Distance 1}}| = |\beta_{\textit{Neighboring Foreclosure in Distance2}}| = |\beta_{\textit{Neighboring Foreclosure in Distance 3}}|$; the alternative hypothesis is denoted as H_{8A}: $|\beta_{\textit{Neighboring Foreclosure in Distance 1}}| > |\beta_{\textit{Neighboring Foreclosure in Distance 2}}| > |\beta_{\textit{Neighboring Foreclosure in Distance 3}}|$. The expected sign will be negative and there is a difference, thus rejecting the null. It is expected that a neighboring foreclosure (single family home or condo) closer to the condo sample has a larger negative price impact than a neighboring foreclosure further away. It will be tested in housing cycles (a housing boom year versus a housing bust year).

These hypotheses will test whether foreclosures appear to have a measurable negative impact on the sale prices of existing residential properties in the neighborhood. The existing literatures (see tables on pages 46-47) support negative relationships between neighboring foreclosures and housing sale prices. These previous studies indicate that, after controlling for hedonic characteristics, prices of homes with foreclosures in the neighborhood tend to be lower than those without foreclosures in the neighborhood. These studies also verified the evidence that property values had more negative impact by neighboring foreclosures that occurred at closer geographic distance, and that the negative impacts increased with the number of neighboring foreclosures.

However, previous studies (see tables on pages 46-47) focused on the spillover effects of nearby foreclosures on non-distressed or typical prices of single family housing transactions, not including distressed sales associated with foreclosure. They find that neighboring foreclosed properties tend to depress typical neighboring home prices, even though the impact magnitude varies with the study area. However, the tests of seventh and eighth hypotheses will extend the contributions of previous studies, separating the effects of different foreclosure types that may create negative impacts on the different types of property sale prices. For instance, single family foreclosure effects on condo sale price and vice versus. Furthermore, as shown in two previous studies (Lin, Rosenblatt, and Yao, 2009; Rogers and Winter, 2009), the expected negative marginal impact size of foreclosure on nearby home values in a housing boom cycle is likely to be different in those in a housing bust cycle.

3.3.3.2 Hypotheses 9 and 10: Nonlinear and Incremental Effects of Clustered Neighboring Foreclosures on Existing Home Prices

Question 6: If neighboring foreclosure does have negative effects on existing home prices, does the price impact vary with the frequency (density) of neighboring foreclosures on existing home sale prices?

The ninth hypothesis is as follows: holding all else constant, there is no difference among price impact of neighboring foreclosures (single family home or condo) on existing single family home prices by foreclosure frequency (density). The null hypothesis is denoted as H_{90}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} = 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} = 0$; the alternative hypothesis is denoted as H_{9A}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} < 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} > 0$. The expected sign will be negative for the marginal impacts of neighboring foreclosures on existing single family home prices, but the marginal impacts will diminish for multiple neighboring foreclosures, which would show a positive sign thus rejecting the null. A larger number of clustered neighboring foreclosures have a greater negative effect than fewer clustered neighboring foreclosures, diminishing marginal impacts with nonlinear effects. It will be tested in different housing cycles (a housing boom year versus a housing bust year).

The tenth hypothesis is as follows: holding all else constant, there is no difference among price impacts of neighboring foreclosures (single family home or condo) on existing condo prices by density. The null hypothesis is denoted as H_{100}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} = 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} = 0$; the alternative hypothesis is denoted as H_{10A}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} < 0$ & $\beta_{\text{The Square}}$

$_{\textit{of Neighboring Foreclosure in Each Distance}} > 0$. The expected sign will be negative for the marginal impacts of neighboring foreclosures (single family home or condo) on existing condo home prices but will diminish the marginal impacts for multiple neighboring foreclosures, which would show a positive sign thus rejecting the null. More clustered neighboring foreclosures have a greater negative effect than fewer clustered neighboring condo foreclosures, diminishing the marginal impacts with nonlinearity. It will be tested in different housing cycles (a housing boom year versus a housing bust year).

The ninth and tenth hypotheses will test whether or not the negative impacts of foreclosure on nearby home values have nonlinear and incremental effects by neighboring foreclosure frequency, diminishing marginal impacts in different housing cycles. Some empirical evidences (Harding, Rosenblatt, and Yao, 2009; Rogers and Winter, 2009; Schuetz, Been, and Ellen, 2008) proved by different methodologies suggest that the marginal impact of neighboring foreclosures may not be continuous or linear, but rather are characterized by diminishing marginal effects. Thus, the findings of this research would show a predictable warning sign that a high density of foreclosures may create serious impacts on neighborhood values. Moreover, the findings of this research will support evidence for the importance of early intervention in foreclosures.

Table 3.1 summarizes the ten hypotheses and expected sign for focus variables with regard to the impacts of foreclosure on housing prices.

Table 3.1. Summary of Hypotheses and Expected Signs.

The Existence of Spatial Dependence (Neighborhood Level)				
These hypotheses are based on conceptual model that foreclosure has direct price-depressing effect on existing home prices	**Expected Signs of Impact**			
Hypotheses to be Tested	**Sample Housing Type**	**Spatial Test**	**Housing Booms**	**Housing Busts**
Hypo 1: Spatial Dependence of Housing Sale Prices $H_{10}: \beta_{\lvert Spatial\ Dependence \rvert} = 0$ $H_{1A}: \beta_{\lvert Spatial\ Dependence \rvert} > 0$	**Single Family Home Sale**	Moran's I	+	+
		Parameter _Rho	+	+
		Parameter _ Lambda	+	+
	Condo Sale	Moran's I	+	+
		Parameter _Rho	+	+
		Parameter _ Lambda	+	+
Direct Foreclosure Effects on Existing Home Prices (Property Level)				
Hypo 2: Discount of Distressed Sale Associated with Foreclosure $H_{20}: \beta_{Distressed\ Sale\ Associated\ with\ Foreclosure} = \beta_{Typical\ Sale}$ $H_{2A}: \beta_{Distressed\ Sale\ Associated\ with\ Foreclosure} < \beta_{Typical\ Sale}$	**Single Family Home Sale**		-	-
	Condo Sale		-	-
Hypo 3: Discount of Renter Occupancy Home in Full Sale Samples for Each Housing Type $H_{30}: \beta_{Renter\ Occupied\ Home} = \beta_{Owner\ Occupied\ Home}$ $H_{3A}: \beta_{Renter\ Occupied\ Home} < \beta_{Owner\ Occupied\ Home}$	**Single Family Home Sale**		-	-
	Condo Sale		-	-
Hypo 4: Discount of Renter Occupancy in Distressed Sale Samples Associated with Foreclosure $H_{40}: \beta_{Foreclosure*Renter\ Occupied\ Home} = \beta_{Foreclosure*Owner\ Occupied\ Home}$ $H_{4A}: \beta_{Foreclosure*Renter\ Occupied\ Home} < \beta_{Foreclosure*Owner\ Occupied\ Home}$	**Single Family Home Sale**		-	-
	Condo Sale		-	-
Hypo 5: Discount of Cash Transactions in Full Sale Samples for Each Housing Type $H_{50}: \beta_{Cash\ Sale} = \beta_{Mortgage\ Financing}$ $H_{5A}: \beta_{Cash\ Sale} < \beta_{Mortgage\ Financing}$	**Single Family Home Sale**		-	-
	Condo Sale		-	-
Hypo 6: Discount of Cash Transactions in Distressed Sale Samples Associated with Foreclosure $H_{60}: \beta_{Foreclosure*Cash\ Sale} = \beta_{Foreclosure*Mortgage\ Financing}$ $H_{6A}: \beta_{Foreclosure*Cash\ Sale} < \beta_{Foreclosure*Mortgage\ Financing}$	**Single Family Home Sale**		-	-
	Condo Sale		-	-

Table 3.1. Continued.

Spillover (Indirect) Effects of Neighboring Foreclosures on Existing Home Prices (Neighborhood Level)			
These hypotheses are based on conceptual model that foreclosures also have indirect price-depressing effects (spillover effects) on nearby existing home prices	**Expected Signs of Impact**		
Hypotheses to be Tested	**Sample Housing Type**	**Nearby FC Type**	**Housing Booms & Housing Busts**
Hypo 7: Marginal Impacts of Neighboring Foreclosures (SFH and Condo) on Existing Single Family Home Prices by Distance H_7: $\beta_{\text{Neighboring Foreclosure in Each Distance}} < 0$, H_{70}: $\lvert\beta_{\text{Neighboring Foreclosure in Dist.1}}\rvert = \lvert\beta_{\text{Neighboring Foreclosure in Dist.2}}\rvert = \lvert\beta_{\text{Neighboring Foreclosure in Dist.3}}\rvert$ H_{7A}: $\lvert\beta_{\text{Neighboring Foreclosure in Dist.1}}\rvert > \lvert\beta_{\text{Neighboring Foreclosure in Dist.2}}\rvert > \lvert\beta_{\text{Neighboring Foreclosure in Dist.3}}\rvert$	**Single Family Home Sale**	Nearby SFH Foreclosure	D1: - D2: - D3: - & $\lvert D1\rvert > \lvert D2\rvert > \lvert D3\rvert$
		Nearby Condo Foreclosure	D1: - D2: - D3: - & $\lvert D1\rvert > \lvert D2\rvert > \lvert D3\rvert$
Hypo 8: Marginal Impacts of Neighboring Foreclosures (SFH and Condo) on Existing Condo Prices by Distance H_8: $\beta_{\text{Neighboring Foreclosure in Each Distance}} < 0$, H_{80}: $\lvert\beta_{\text{Neighboring Foreclosure in Dist.1}}\rvert = \lvert\beta_{\text{Neighboring Foreclosure in Dist.2}}\rvert = \lvert\beta_{\text{Neighboring Foreclosure in Dist.3}}\rvert$ H_{8A}: $\lvert\beta_{\text{Neighboring Foreclosure in Dist.1}}\rvert > \lvert\beta_{\text{Neighboring Foreclosure in Dist.2}}\rvert > \lvert\beta_{\text{Neighboring Foreclosure in Dist.3}}\rvert$	**Condo Sale**	Nearby SFH Foreclosure	D1: - D2: - D3: - & $\lvert D1\rvert > \lvert D2\rvert > \lvert D3\rvert$
		Nearby Condo Foreclosure	D1: - D2: - D3: - & $\lvert D1\rvert > \lvert D2\rvert > \lvert D3\rvert$
Hypo 9: Nonlinear and Incremental Impacts of Clustered Neighboring Foreclosures (SFH and Condo) on Existing Single Family Home Prices H_{90}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} = 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} = 0$ H_{9A}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} < 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} > 0$	**Single Family Home Sale**	Nearby SFH Foreclosure	D1: - D2: - D3: - & $D1^2$: + $D2^2$: + $D3^{2:}$ +
		Nearby Condo Foreclosure	D1: - D2: - D3: - & $D1^2$: + $D2^2$: + $D3^{2:}$ +
Hypo 10: Nonlinear and Incremental Impacts of Clustered Neighboring Foreclosures (SFH and Condo) on Existing Condo Prices H_{90}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} = 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} = 0$ H_{9A}: $\beta_{\text{Neighboring Foreclosure in Each Distance}} < 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Distance}} > 0$	**Condo Sale**	Nearby SFH Foreclosure	D1: - D2: - D3: - & $D1^2$: + $D2^2$: + $D3^{2:}$ +
		Nearby Condo Foreclosure	D1: - D2: - D3: - & $D1^2$: + $D2^2$: + $D3^{2:}$ +
D denotes # Foreclosures in Specific Distance D^2 denotes the Square of # Foreclosures in Specific Distance			

4. RESEARCH DESIGN

4.1 Introduction of Research Design

This section describes the study area, the data preparation, and the methodology that will be employed in this research. The study area, Phoenix, might be a drastic example of residential housing markets since Phoenix’s residential home values have appreciated at a faster rate than comparable markets, resulting in more of a spike than a gradual increase and decrease. The data sets, which were purchased from the Maricopa County Assessor office, contain sale prices, property characteristics, and location information for single family homes and condos that sold during 2005 and 2008 in Phoenix, Maricopa County, Arizona. This study utilizes data in different years to capture how the effects of foreclosures on nearby property values may vary over the housing cycles.

This methodology incorporates the spatial nature of the housing market into the hedonic price model. The distinctive characteristic of the spatial pattern in the data is likely to have a number of measurement problems caused by spatial effects such as spatial autocorrelation and spatial heterogeneity. The existence of these measurement problems affects the validity of traditional statistical methods and therefore requires specialized techniques developed in spatial econometrics. These will be described in the following sections.

4.2 Study Area and Data Preparation

4.2.1 Descriptions for Study Area: Why Phoenix Needs Attention

Before the dramatic foreclosure increase, the national average for house prices in the U.S. rose between 93% and 137% between 1996 and 2006, according to the Standard & Poor’s index. Some markets, such as Los Angeles, Phoenix, and Las Vegas, had even stronger house price growth (see Figure 4.1). These three metro areas have given back, on average, more than 30% of the value of homes since October of 2007 through December of 2008. Phoenix remains the weakest market, reporting an annual decline of 32.7%, followed by Las Vegas, down 31.7%, and San Francisco, down 31.0%. Miami, Los Angeles, and San Diego were close behind with annual declines of 29.0%, 27.9%, and 26.7%, respectively (Standard & Poor's Financial Services, 2008).

Phoenix real estate values soared to record levels over a five year period from 2002 through 2006. Many macro economic factors, location, demand, job growth, and low interest rates, coupled with a lack of sound underwriting practices by lenders and the expectation of future profits by investors could have led to the property value rise. Consequently, new homes entered the supply with a considerable lag and after the economic cycle heightened the market risk. Housing markets under these circumstances became overbuilt. Overheated markets triggered escalations in house prices, homes sales, and sometimes production levels beyond those suggested by fundamentals like the rate of income growth and the sustainable demand for new primary and secondary residences (McCue and Belsky, 2007).

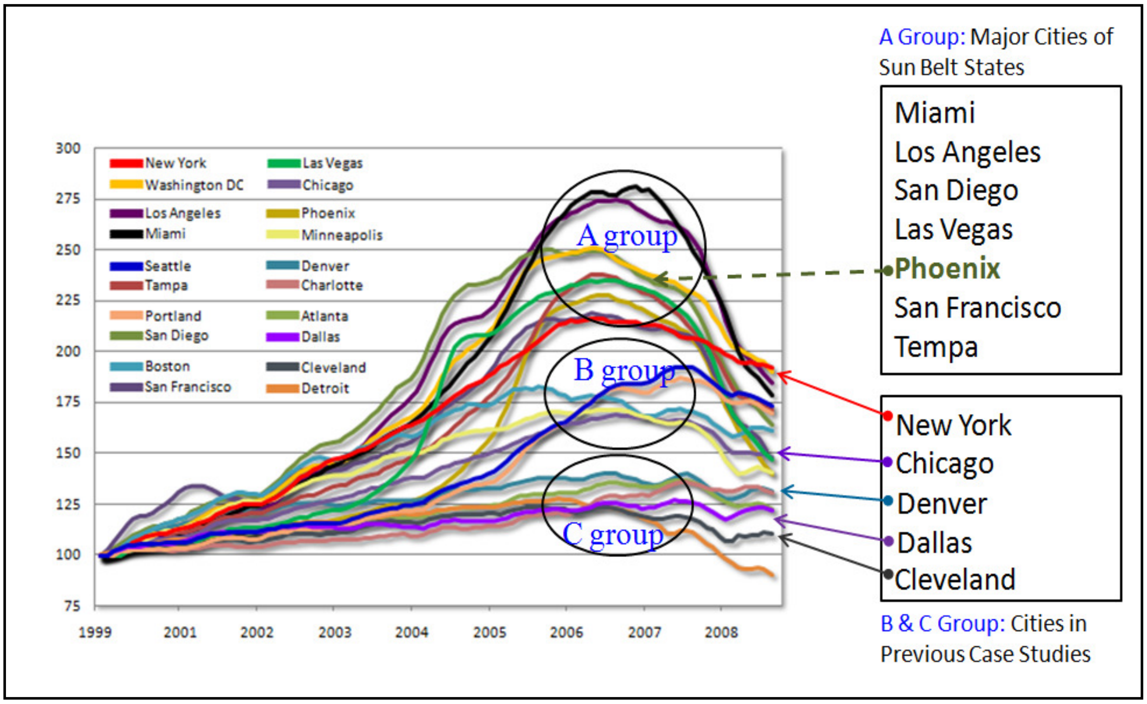

Figure 4.1. S&P/Case-Shiller Home Price Indices: Jan. 2000 – Sep. 2008.
Source: Standard & Poor's Financial Services, 4Q 2008.

Particularly, the rapid growth of sales activity and prices of the early 2000s in Phoenix has been largely due to the ever increasing involvement of investors in the market. Many buyers and investors who declined to pay the increased prices in California and Las Vegas rushed to Phoenix to live and invest, at a much lower cost. Out-of-state investors were eager to get into Phoenix residential investments including condos, in 2004 and 2005, but the market has declined since the middle of 2005. California investors were around 60% of the out-of-state investors in 2005, but were around 20% in 2008 (Rappaport, 2007). Thus, the slowdown in the investor market can be a relevant reason for the overall market slowdown and the increase in troubled properties.

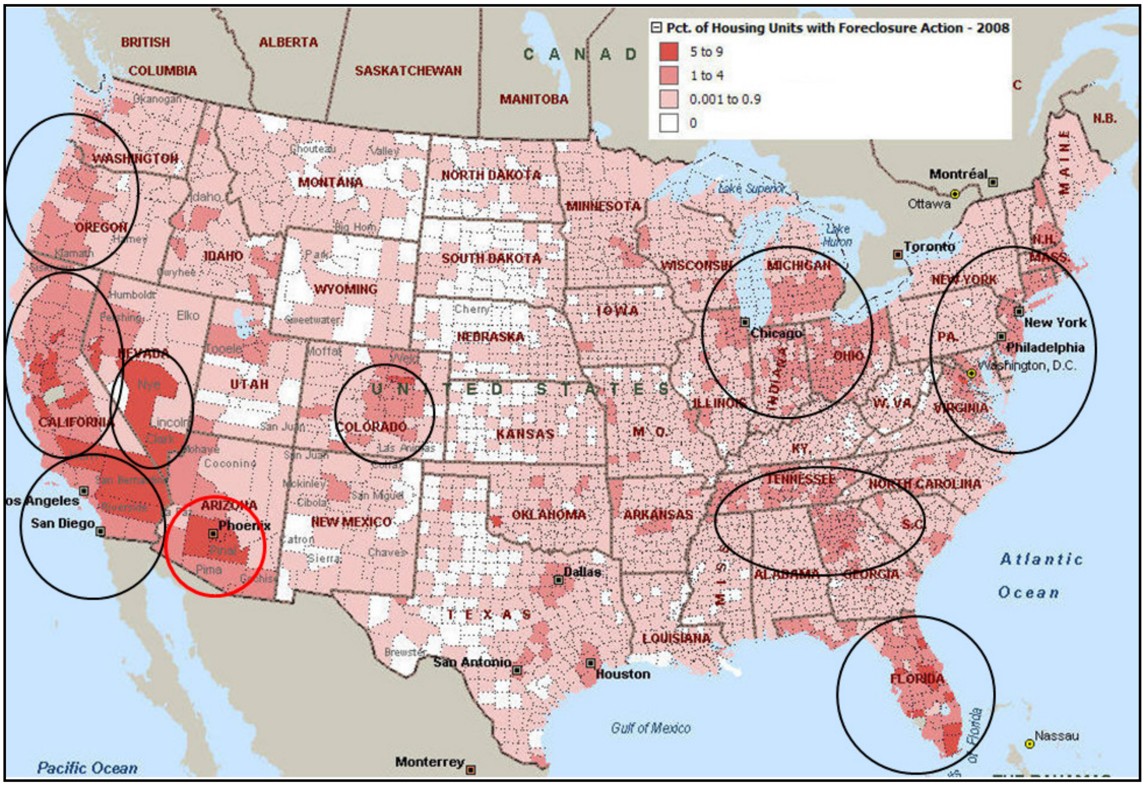

Figure 4.2. 2008 Foreclosure Hot Spots.
Source: RealtyTrac, 2009.

The 2009 Metropolitan Foreclosure Market Report released by RealtyTrac.com illustrated that cities in four Sun Belt states accounted for all of the top 20 foreclosure rates in 2009 among metro areas with a population of 200,000 or more (RealtyTrac, 2010). The Phoenix-Mesa-Scottsdale metro area in Arizona documented the nation’s eighth highest metro foreclosure rate in 2009, with more than 8 percent of its housing units receiving a foreclosure notice during the year (see Figure 4.2).

Since Phoenix’s residential home values have appreciated at a faster rate than comparable markets, resulting in more of a spike than a gradual increase and decrease, Phoenix might be a drastic example of the residential housing market. Moreover, given that Phoenix is one of the worst areas for foreclosures; the results of this study area may not be generalized to all metropolitan areas in the U.S. However, it provides useful lessons for areas with similar housing problems in Sun Belt states, such as Las Vegas, Los Angeles, Miami, San Diego, San Francisco, and many other metropolitan areas in California. Thus, this study will quantify the upper bounds of the effects of foreclosures on home prices for the U.S. housing market.

The Phoenix area was selected for this research because it was a representative sample among the top cities affected during the recent foreclosure and housing price wave. This study will estimate the effects of foreclosures on property values in terms of different scenarios. In the best scenario, neighboring foreclosed properties have fewer impacts on existing property values in a good market condition, but in the worst scenario, they seriously affect nearby property values in a bad market condition. Thus, the case study of Phoenix will show evidence of how housing policies and private practices for housing have shaped uneven residential development.

To test the importance of housing cycles and justify 2005 as a boom year and 2008 as a bust year, Figure 4.3 shows the housing cycles in Phoenix from 2003 to 2008, using year over year median home price growth for single family properties. It clearly illustrated that Phoenix began to go into a housing slump at the beginning of 2007 while 2005 was in the middle of housing booms.

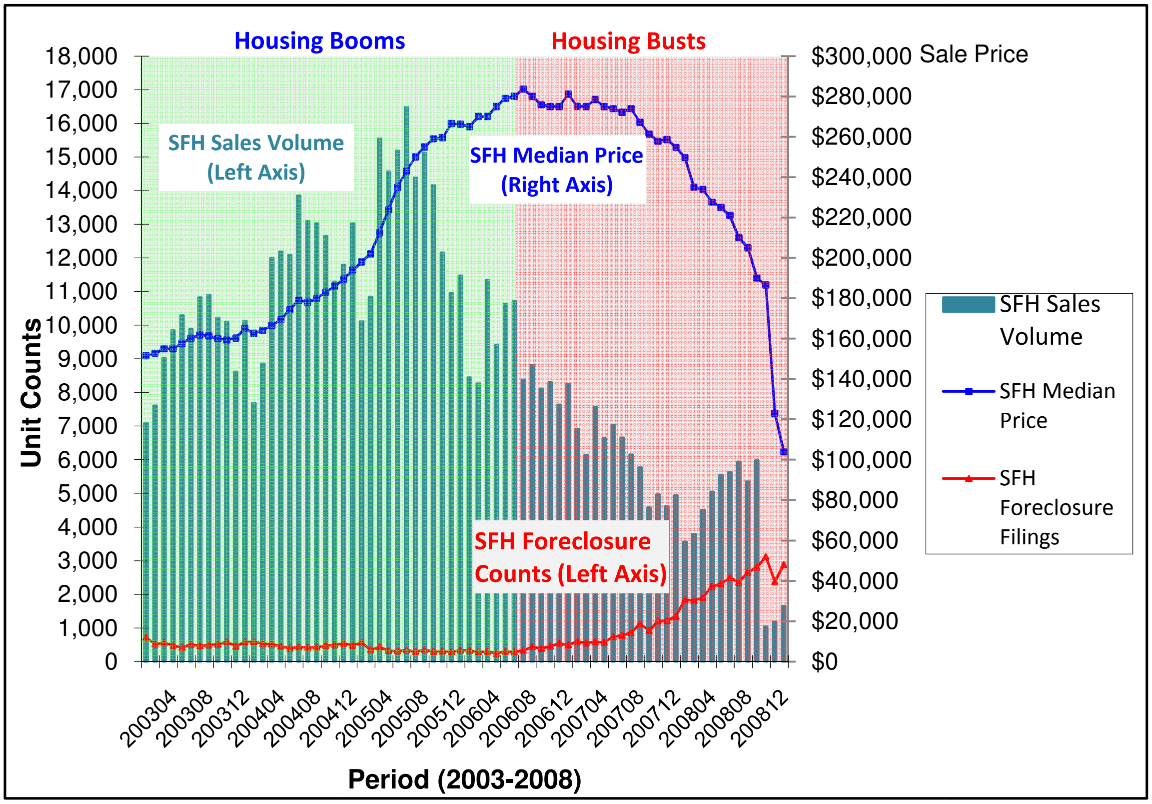

Figure 4.3. Single Family Housing Median Price for Phoenix: 2003-2008.
Source: Information Market, 2009.

4.2.2 Data Sets

4.2.2.1 Property Sales Data

The data sets, which were purchased from the Maricopa County Assessor Office, contain sale prices, property characteristics, and location information for single family homes and condos/townhomes that sold during 2005 and 2008 in Phoenix, Maricopa County, Arizona.[8] This study utilizes data in different years to capture how the effects of

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[8] Condo housing type includes some townhome types in the property information of Maricopa County Assessor. Thus, the term “condo” in this study includes some townhome types.

foreclosures on nearby property values may vary over the housing cycles. To test for differences in differing housing market cycles, it separately examines the foreclosure effects on sales that took place during 2005 as a housing boom year and on sales that took place during 2008 as a housing bust year. Thus, this study created four sample data sets of existing home sales: two consist of single family homes and condos sold in 2005, representing an upward market scenario; the other two contain single family homes and condos sold in 2008, representing a recent downside market scenario in the Phoenix housing market.

Matching sales and property information data to the corresponding geographic file is a key to this study since spatial variables are generated with GIS. After GIS procedures, the sales and foreclosure filings are placed in real space and sorted by using MS Access software.

For the study sample, this study uses only sale samples of existing housing units rather than newly built housing units and residential zoning with similar housing density and property types within the study area. These single family home sales and condo sales would be representative housing property sales in neighborhoods and be used as comparable benchmarks for residential valuation.

For typical home sales, this study is limited to typical home sales by arm's length transactions, which have never been under foreclosure in the two years prior to the transaction. However, for distressed sales associated with previous foreclosures, this study is limited to home sales that had at least one foreclosure filing in the two years prior to the 2005 housing sale samples and the 2008 housing sale samples in the Phoenix area. Distressed sales related to the foreclosure process not only include non-typical transactions such as short sales, foreclosure sales, bank owned sales, but also include properties canceled in the foreclosure process and sold later as urgent sales. All sales and foreclosure data originate from deeds, not mortgage information; thus, distressed sales associated with foreclosure are at the point that new owners already have taken over ownership of the property.

The procedures of cleaning data (removing inconsistent and incomplete observations such as missing structural characteristics, transfers, grants, quick claims, etc.) and eliminating outliers (consisting of those in the top and bottom 2% of sale prices) are to avoid erroneously recorded or atypical transactions from the sample data.[9]

Full housing samples in this study consist of all single family homes and condos which faced a foreclosure in the two years prior to the transaction and single family homes and condos that were sold by arm's length transactions in Phoenix, Arizona during 2005 and 2008.

Figure 4.4 illustrates that the 2005 single family home sample consists of 2,214 distressed sales and 28,601 typical sales. The 2008 single family home sample consists of 6,730 distressed sales and 6,155 typical sales. The 2005 condo sample consists of 256 distressed sales and 5,949 typical sales. The 2008 condo sample consists of 538

[9] If the condo transactions on the ground level and on upper level with different ownership (multi-floor semi-detached homes) occur in the same year, this study just includes an average price for them since GIS recognizes the location of property based on X-Y coordinate and codes one time for the same location. Duplicated condo transactions on the same property with multiple stories cause trouble in constructing a spatial weight matrix. See the detailed technological issues of spatial weight matrices in section 5.2.3.2. In addition, if there are repeated transactions on a single family home or condo during sample period, only the last transactions in the year are included in the sample data set and then coded in GIS.

distressed sales and 1,465 typical sales.

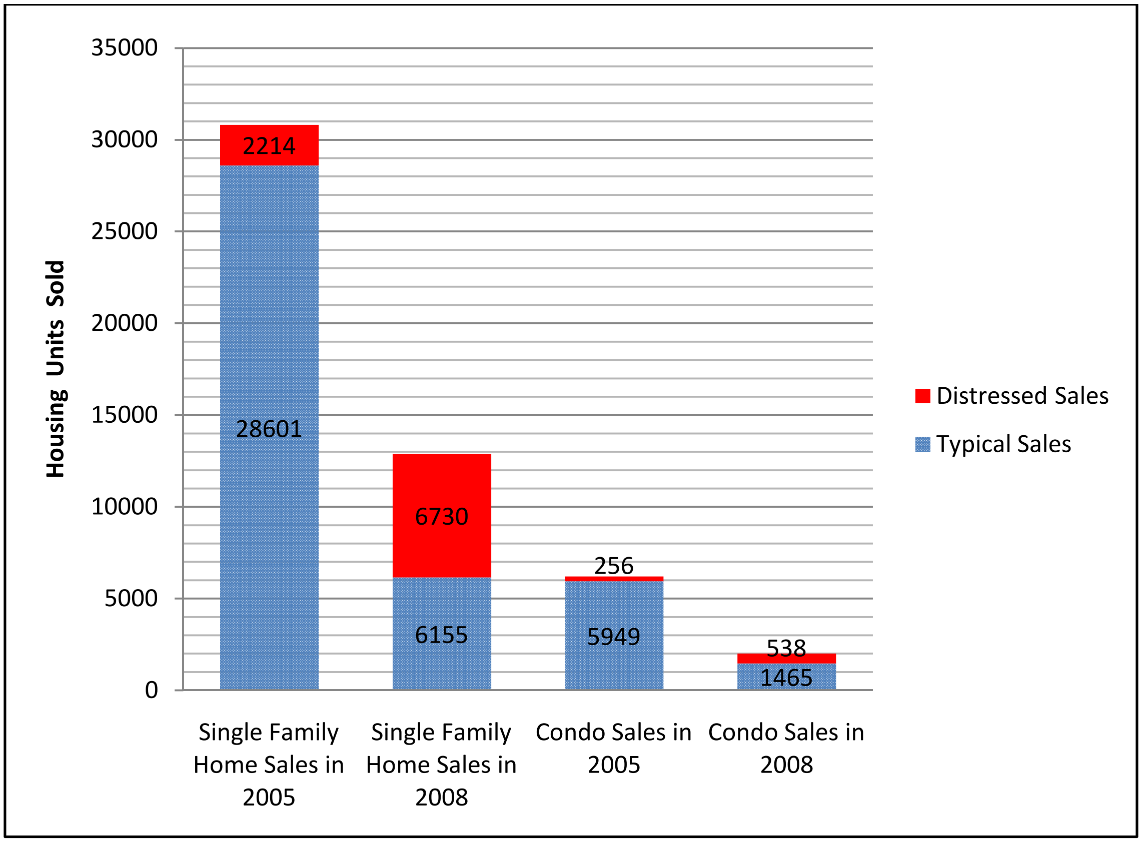

Figure 4.4. Home Sales Samples in 2005 and 2008.

4.2.2.2 Foreclosure Data

For foreclosure data, this study focuses on the beginning stage of the foreclosure process. Thus, the filing of the foreclosure notices, the term "Foreclosure Start" (the pre-foreclosure stage at 90 days late in mortgage payments) or simply "Foreclosure" is used in this study. The information on foreclosure filings are obtained from the public records of the Maricopa County Recorder's Office. However, the format of the database cannot be easily transformed for academic analysis. Even if the databases include detailed addresses or parcel ID numbers, many of those datasets only have legal descriptions of the properties, which are very difficult to code into geographic information or merge with other datasets. Thus, foreclosure data was purchased in an excel format from the private database vendor “Foreclosure Radar.”[10]

Figure 4.5 presents the comparison of foreclosure data during different housing cycles. Foreclosure filings increased tremendously in 2007-2008 (housing busts), compared to 2004-2005 (housing booms). The foreclosure filings for single family homes increased from 7,424 in 2004-2005 to 31,778 in 2007-2008, which is about a 428% increase. The foreclosure filings of condos increased from 803 in 2004-2005 to 2,992 in 2007-2008, which is about a 372% increase.

Figure on page 91 (Figure 4.6) shows the density of foreclosure filings for single family homes during 2004-05 (left, red dots) and 2007-08 (right, red dots) and home sale transactions during 2005 (left, green dots) and 2008 (right, green dots). Figure on page 92 (Figure 4.7) shows the number of foreclosure filings for condos during 2004-05 (left, purple dots) and 2007-08 (right, purple dots) and condo sale transactions during 2005 (left, blue dots) and 2008 (right, blue dots) in the Phoenix area.

[10] ForeclosureRadar.com, based in California, provides reliable information on properties in every phase of the foreclosure process by membership. The information covers foreclosures in California, Arizona, Nevada, Oregon, and Washington. The original data comes from the county assessor or records office.

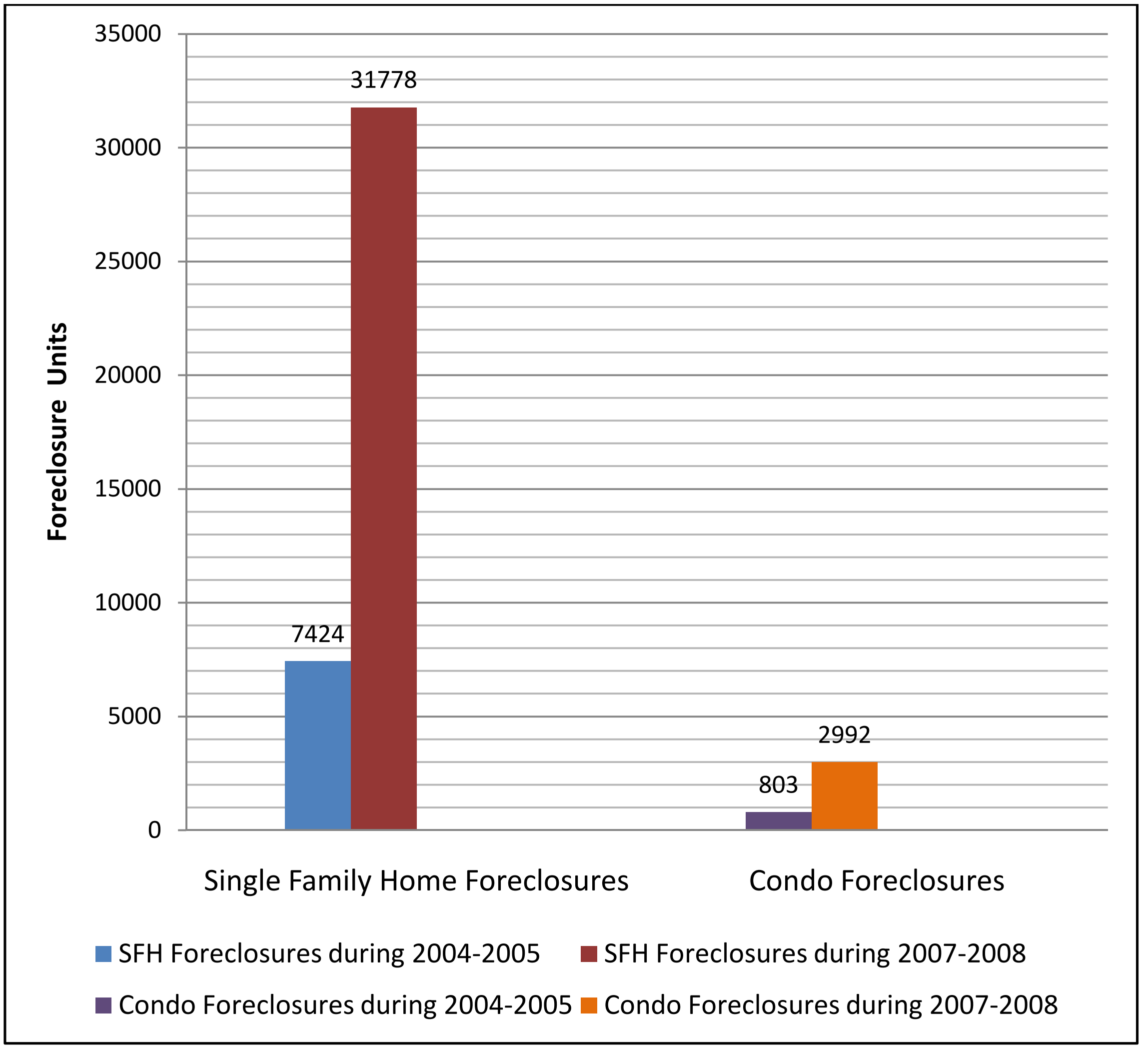

Figure 4.5. Units of Foreclosure Starts in Phoenix during 2004 - 2005 and 2007 - 2008.

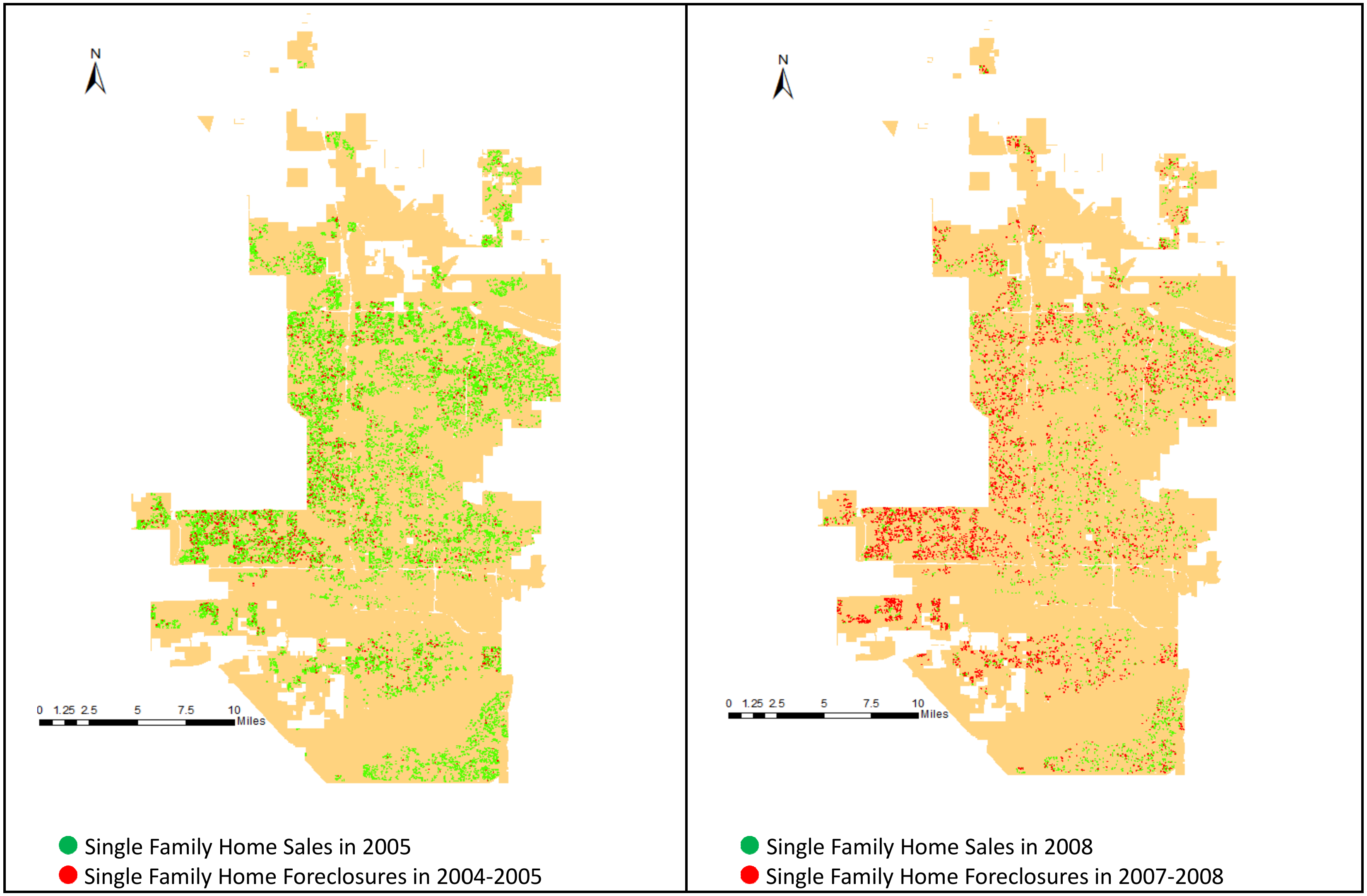

Figure 4.6. Single Family Home Sales in 2005 and 2008 and Single Family Home Foreclosures in 2004-2005 and 2007-2008.

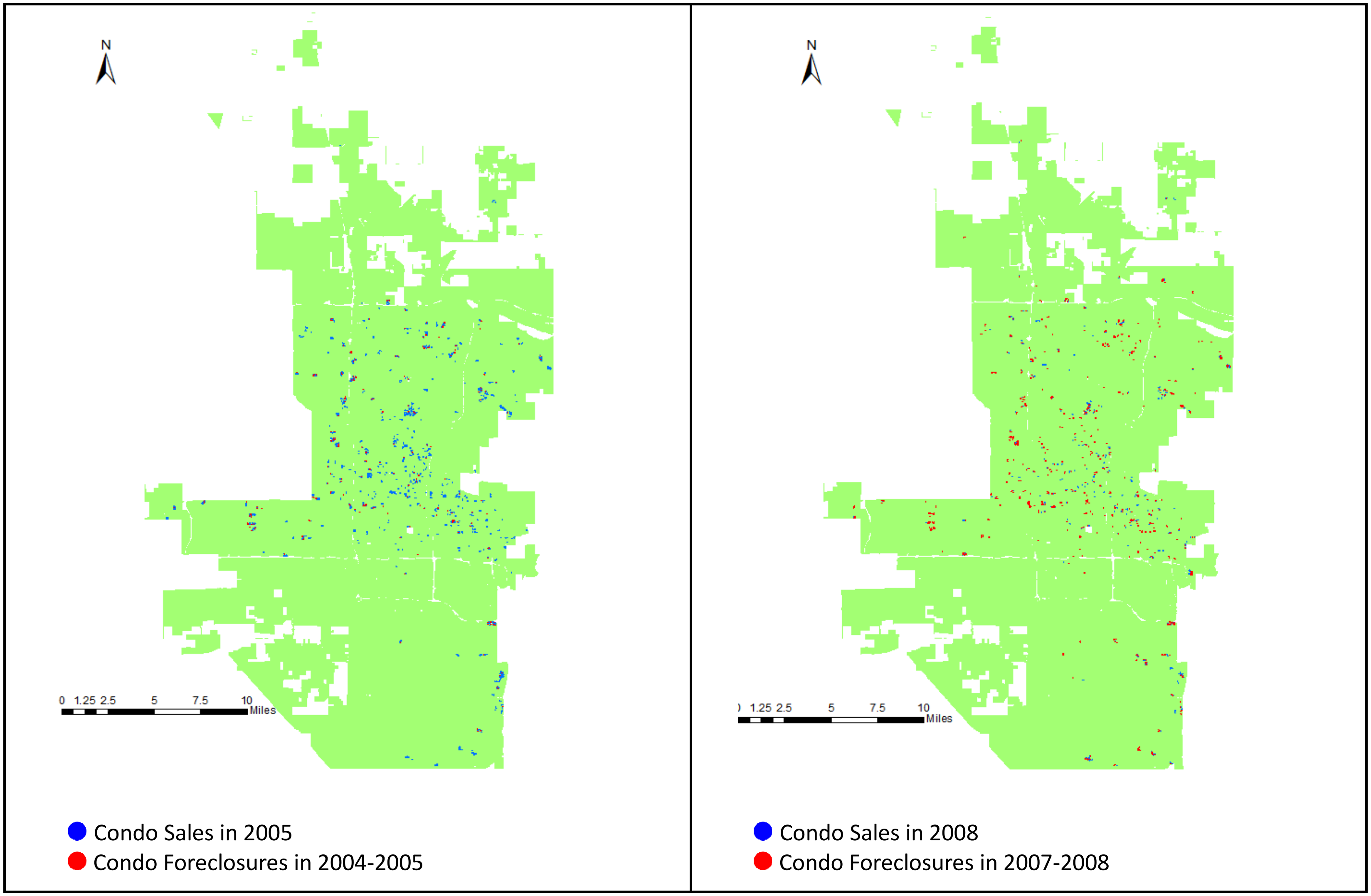

Figure 4.7. Condo Sales in 2005 and 2008 and Condo Foreclosures during 2004-2005 and 2007-2008.

One of the key points of this study is how to measure the foreclosure impact on nearby home prices. Recently, Lin, Rosenblatt, and Yao (2009) found that the spillover effects of foreclosures were significant within 0.6 miles and 5 years of foreclosure. The price-depressing spillover effect was the most severe (-8.7%) on adjacent properties within 2 years of foreclosure, and it diminished to as low as -1.7% at a distance of about 0.6 miles (0.9km). Schuetz, Been, and Ellen (2008) presented a study of residential (single and multi-family) property sales and foreclosure notices in New York City between 2000 and 2005. The authors identified properties with foreclosure notices and nearby non-distressed sales in both physical space (within 250 feet; 250-500 feet; 500-1000 feet) and time (less than 18 months and greater than 18 months).

Their findings suggest the importance of preventing early foreclosures since foreclosures tend to have bigger price-depressing effects on nearby properties. Based on previous research, this study constructed foreclosure data sets for two prior years before the home sales transactions to address an appropriate timeline for foreclosure impact. In doing so, this study assumes that the number of foreclosures within a specific distance have effects on nearby sale prices in two prior years.[11] Thus, the foreclosure filing as the first stage of the foreclosure process is used here as a proxy for proceeding to actual foreclosure sales and REOs (real estate owned properties by lenders).

However, the difficulty in accessing accurate, comprehensive, and timely data on all foreclosed properties, REOs (real estate owned properties by lenders), and vacant

[11] If there are repeated foreclosures in the same locations around a single family home sale or condo sale in two prior years before the transaction date, GIS software counts only one foreclosure event in the same year, avoiding duplicated counts of foreclosure. The measured foreclosure is the first foreclosure event among duplicated ones in foreclosure time lines.

properties still remains in this study. These troubled properties with different time lines may cause issues of spatial dependency and omitted variables. Furthermore, property condition in these data sets was left out due to data limitation, even though it is an important determinant of property value measurement. Thus, the success of future research would be highly dependent on the quality of the local data, and would possibly introduce further timing issues. Given the appropriate data, it could provide interesting insights into the typical sequencing of foreclosure problems.

4.3 Research Methodologies

4.3.1 Traditional Hedonic Model

4.3.1.1 Basic Theory and Functional Form

This hedonic price function is a typical econometric regression model. The traditional hedonic price models are generally estimated by ordinary least squares (OLS), which is the standard technique, used to estimate unknown coefficients. Rosen (1974) defines hedonic prices as the prices of attributes so the hedonic prices can be found from both the market prices of products and the number of characteristics contained in the products. Regression analysis has two strengths: first, it can be used to value a large number of properties and/or factors. Second, it can be used to explain value as well as estimate it. The ability of regression analysis to explain price means that it can be used to estimate the value of individual characteristics and their marginal contribution to the value of the property (Sirmans, Macpherson, and Zietz, 2009).

Each independent variable will have its own slope coefficient which will indicate the relationship of the particular predictor with the dependent variable, controlling for all other independent variables in the regression. A crucial implication is that results are more accurate if one can control for as many attributes as possible in the multiple regression. The traditional hedonic house price model is specified as:

$$\textit{Housing Price} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \quad + \beta_n X_n \quad + \varepsilon, \qquad [4.1]$$

$\beta_0 = \textit{Y Intercept}$

$\beta_{0\ldots\ldots}\beta_n = \textit{Coefficient of Variables } 1\ldots\ldots n$

$\varepsilon = \textit{Residuals}$

Where, the coefficient β of each predictor may be interpreted as the amount by which the dependent variable changes as the independent variable increases by one unit (holding all other variables constant). This equation indicates that the price of the house is a function of its physical characteristics (square footage, rooms, building age, etc.) and other factors such as school quality and external factors. The regression estimates give the implicit price of each variable or characteristic.

There is no strong theoretical basis for choosing the correct hedonic functional form. Previous findings (see Halverson and Pollakowski, 1980; Malpezzi, 2002; Malpezzi, Ozanne, and Thibodeau, 1980) suggest that the semi-log functional form helps alleviate heteroskedasticity, which was the problem of changing variances in the error term. The resulting coefficient can be interpreted as approximately the percentage of change in the value given as a unit of change in the independent variable.

4.3.1.2 Model Construction for this Research

Linear effects test for nearby foreclosures

The hedonic price model was chosen to estimate the effect of foreclosures on existing housing prices. A semi-logarithmic model may help reduce the problems of heteroskedasticity (Halverson and Pollakowski, 1980; Malpezzi, 2002; Malpezzi, Ozanne, and Thibodeau, 1980). Thus, the equation is estimated with the selling price as the dependent variable in semi-log form followed by five vectors for this research:

$$lnP = \beta_0 + \Sigma\beta_1 H + \Sigma\beta_2 M + \Sigma\beta_3 S + \Sigma\beta_4 SF + \Sigma\beta_5 CF + \varepsilon \quad [4.2]$$

Where the term *H* denotes housing physical characteristics, *M* indicates quarter dummies controlling for market price trends, *S* stands for selling characteristics associated with foreclosure status on the property, *SF* denotes neighboring foreclosure filings for single family homes, and *CF* is neighboring foreclosure filings for condos, respectively.

Extensive previous research regarding housing values indicates a positive relationship typically exists between property characteristics and the dependent variables. Housing physical variables include total acreage of lot size (LOT_SIZE), square footage of the living area (LIVING_AREA), building age (AGE), garage (GARAGE), swimming pool (POOL), and stories (STORY) of each home type.

The building age (AGE) variable represents a slightly more complex situation. Typically, the age of housing stock is viewed as an indication of deterioration or obsolescence thereby resulting in lower property values. However, there are older homes in some neighborhoods whose values have remained competitive with newer homes. Furthermore, Goodman and Thibodaeu (1995) found that there was actually a curvilinear pattern between age and housing valuation, meaning that not controlling for the nonlinear effects of age causes heteroskedasticity in the model's residuals. Thus, a quadratic form was allowed to control curvilinear pattern.

Quarter dummy variables are included to account for whether the property was sold in the second, third, or fourth quarter, with the first quarter being the omitted dummy variable. There are no sign expectations in any of the time-related variables because both supply and demand for housing will change during each period.

A vector for selling characteristics of properties, which is related to foreclosure status, measures the marginal impact of renter occupancy status and cash transaction on selling prices. These two variables, depending on foreclosure status, tend to be associated with the price discount in the transaction event.

The final two terms related to foreclosure variables will account for the potential marginal impact of neighboring foreclosures by counting foreclosures within specific distances.

Nonlinear effects test for nearby foreclosures

The previous studies for foreclosure effects were mainly based on a linear model of the relationship between foreclosure growth and housing price change. One possible concern is that the impact of foreclosures on prices may reflect nonlinear effects as discussed in the section of hypotheses and conceptual models (that is, a rise in foreclosures at a specific distance has a diminishing negative effect on nearby home prices as the rise in foreclosures increases) Thus, equation [4.3] was extended to allow for nonlinear effects in quadratic form:

$$lnP = \beta_0 + \Sigma\beta_1 H + \Sigma\beta_2 Q + \Sigma\beta_3 S + \Sigma\beta_4 SF + \Sigma\beta_5 SF^2 + \Sigma\beta_6 CF + \Sigma\beta_7 CF^2 + \varepsilon, \quad [4.3]$$

This specification also allows the marginal price impact to vary with the frequency of existing foreclosures in an area. It is expected that few foreclosures will have a small price-depressing impact in the neighborhoods. But, as foreclosures begin to accumulate during housing bust cycles, the cumulative price-depressing impact will be larger in areas with a high density of foreclosures.

Concept measurement of neighboring foreclosures

One of significant challenges in this study is how to isolate and measure the impact of neighboring foreclosures on home sale prices. Essentially, this study defines "nearby" or "neighboring" in three alternative ways (three rings) in order to measure fixed effects for these micro-neighborhood level or smaller scales. In the presentation of the models, these are referred to as Ring 1 (0 to 500 feet), Ring 2 (501 to 1000 feet), and Ring 3 (1001 to 1500 feet).

In this fashion, the impact can be estimated over different spatial scales since the effect can vary with distance. Thus, this approach would allow for the notion of distance decay of the impact, where the effect of the externality decreases as distance increases. This approach avoids having to choose an arbitrary distance within which the externality (foreclosure) is hypothesized to have an impact, and beyond which there is no impact expected. This procedure also provides a better way to capture the impact of spatial heterogeneity on house prices. Note that the measured effects of the three concentric rings (maximum distance = 1500 feet) chosen are assumed to impact all properties equally within each concentric circle (see Figure 4.8).

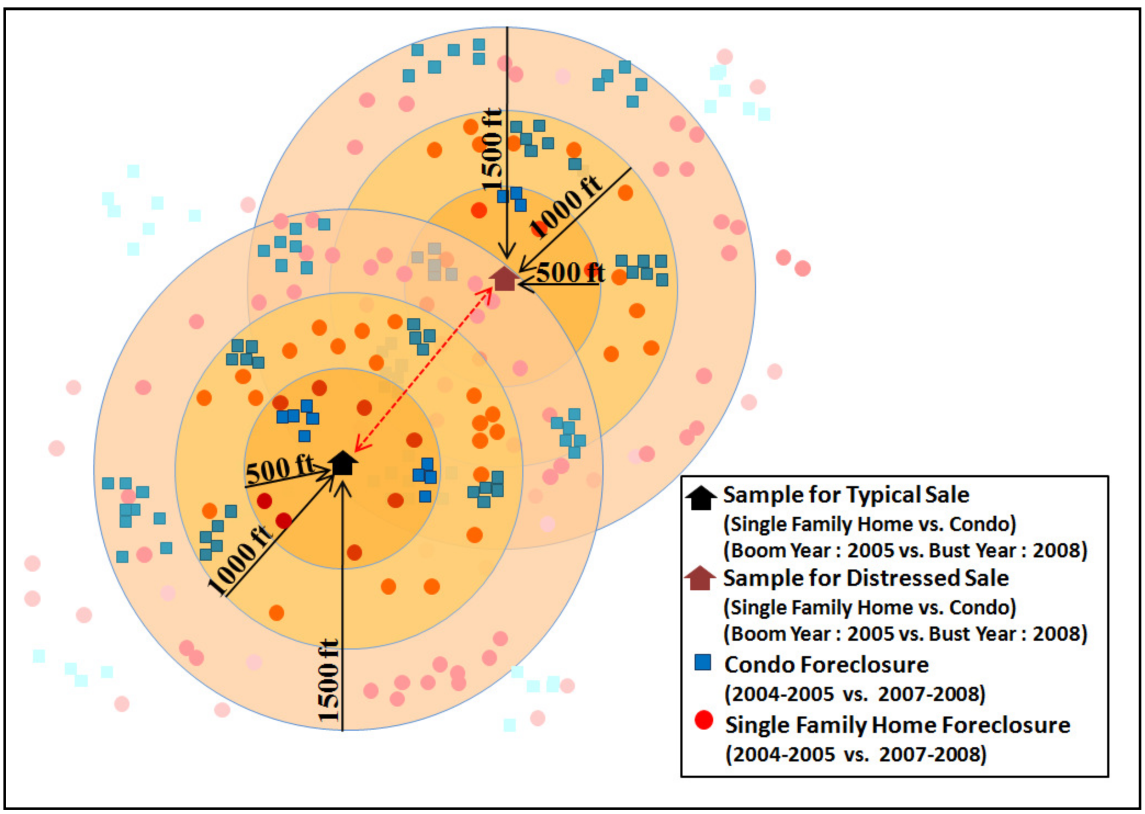

Figure 4.8. Concept Measurements of Neighboring Foreclosure Effects on Existing Home Sale Prices.

This study applies to the model of spatial fixed effects. A review of the literature (see tables on pages 46-47 [Table 2.2]) does suggest different size rings be included in hedonic regressions as seen in Figure 4.8. This measurement was designed in anticipation that there would be observable patterns of change in property values with closer proximity to foreclosures. Improvements in the field of Geographic Information Systems (GIS) support efficient and accurate measurement.

In order to minimize the problem of reverse causation, the spatial structure of the model put in sample sale as the central focus of surrounding foreclosures using the rings and measuring the price impact of foreclosures.

However, reverse-causality bias (or endogeneity) could be a problem if a drop in housing prices in one community is particularly large when compared to another community. This drop could lead to more foreclosures in the given community. If an estimator that does not control for endogeneity of nearby home prices and spatial dependence in this case, the results might overstate or understate the effect of foreclosures on given home prices. The next section will discuss the special methodologies for controlling for endogeneity and spatial dependence.

4.3.1.3 Model Validation

The ordinary least squares (OLS) estimation is referred to as a best linear unbiased estimator (BLUE) since OLS estimates coefficients by minimizing the sum of the squared prediction errors. Thus, several assumptions about the structure of the population data are required in order to apply ordinary least squares (OLS) analysis and should be checked to assure that the conclusions are true for a population (Ott and Longnecker, 2001; Field, 2005). In order to obtain the best linear unbiased estimator (BLUE) and make statistical inferences about the population regression and its inferential tests in a strict sense, first, there is no perfect multicollinearity. That is, there should be no perfect linear relationship among independent variables. Second, the random error terms have a constant variance (are homoskedastic). Third, the random errors in the model are normally distributed with a mean of 0. Finally, the random error terms are uncorrelated (independent). When these four assumptions are satisfied, an OLS estimator is said to be the best linear unbiased estimator (BLUE) in that it is linear, unbiased, and has minimum variance in the class of all linear unbiased estimators.

First, multicollinearity refers to the existence of general interrelationship correlation among independent variables in a regression model. It often occurs in cross-section data when two or more variables track each other closely. Consequently, the estimates will have very large estimated variances, resulting in non-significant coefficients for the estimates. If any correlated pairs have a value above 0.80, it indicates multicollinearity (Cohen, West, and Aiken, 2003).

There are two commonly used collinearity diagnostics: the variance inflation factor (VIF) and the tolerance. The VIF shows whether or not an independent variable has a strong linear relationship with other independent variable(s). In general, using a VIF of 10 is problematic; multicollinearity can also be detected by variance inflation factors. A tolerance statistic is the VIF's reciprocal (tolerance = 1 / VIF). A tolerance value below .1 designates a potential problem (Fox, 1991).

Second, heteroskedasticity occurs when residuals are not constant between observations. Heteroskedasticity occurs more frequently in cross-section studies when there is a wide range of explanatory variables which have diverse information sources. A log transformation is one way in which heteroskedasticity can be removed because this transformation reduces the variation in the variables. However, taking the logs may not prevent the problem. Thus, the Breusch-Pagan test, developed by Breusch and Pagan, is conducted for heteroskedasticity in the error distribution, conditional on a set of variables which are presumed to influence the error variance (Anselin, 2005). The test statistic, a Lagrange multiplier measure, has a chi-squared distribution under the null hypothesis of homoskedasticity.

Third, error, represented by residuals, should be normally distributed for each set of values of the independents. The central limit theorem assumes that when error is not normally distributed, when the sample size is large, the sample distribution of the coefficients will still be normal. Therefore, violations of this assumption usually have little impact on substantive conclusions for large samples (Cohen, West, and Aiken, 2003). The Jarque-Bera test in GeoDa software is often used to examine the normality of the distribution of the errors (Anselin, 2005).

A final assumption is that the residual terms should be uncorrelated for any two observations. The Durbin-Watson test can be used to test for any severe correlations among errors. As a rule of thumb, values greater than 3 or less than 1 can be problematic (Field, 2005).

These four assumptions have been challenged by many empirical studies which deal with spatial data like cross-sectional housing price data.

4.3.2 Spatial Hedonic Model

4.3.2.1 Spatial Autocorrelation and Model Specification Test

Spatial autocorrelation, or spatial dependence, is the situation where the dependent variable or error term at each location is correlated with observations of the dependent variable or values for the error term at other locations. Biased estimates of standard errors, inaccurate predicted values, and inefficient least squares estimates may result from disregarding the presence of spatial dependence (Anselin, 1988; Kelejian and Prucha, 1998). Thus, when one runs hedonic housing price models with cross-sectional data, it is necessary to test for spatial autocorrelation because of the given the nature of the data in which observations cluster together in space.

Spatial autocorrelation is usually calculated using spatial statistics software.[12] The best-known and most widely used test statistic for spatial correlation is Moran’s I, which was generalized to regression residuals by Cliff and Ord (1972). In the hedonic price model context, this statistic checks for similarities among housing prices and attribute data in relation to the spatial relationships in the spatial weight matrix.

Moran's I coefficient is used to carry inferential hypothesis tests about the existence of significant autocorrelation among values at neighboring points. Thus, pairs of neighboring samples are formed, each pair being weighted by the inverse of the

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[12] Geoda, developed by Luc Anselin, is a free Windows program for the construction of spatial weights matrices and estimations of the cross-sectional SAR and SEM models. Moran’s I test is one of the computation functions in GeoDa. It is available at http://geodacenter.asu.edu/

squared distance between the two samples. The index is a measure of the overall spatial relationship across geographical units and is defined as:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \quad \frac{\sum_i \sum_j w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2} \qquad [4.4]$$

Where, n is the sample size, y_i is the sale price of a house i with sample mean $\bar{y}$, and w_{ij} is the distance-based weight which is the inverse distance between houses i and j. Like a correlation coefficient, a positive Moran's value stands for a positive spatial autocorrelation (for instance, similar, or clustered observations, zero for a random pattern) and a negative value for negative spatial autocorrelation (for instance, a dissimilar, contrasting pattern) (Goodchild, 1986). If Moran's I coefficient is statistically significant, which indicates the existence of significant autocorrelation among values at neighboring points, the next challenge is to characterize the spatial pattern in the residuals and incorporate that characterization into the regression model itself.

The second test is a Lagrange Multiplier (LM) test that Anselin and Hudak (1992) propose based on the Lagrange Multiplier principle. It is based on the least-squares residuals and calculations involving the spatial weight matrix and is defined as:

$$LM = \left(\frac{1}{T}\right) * \left[\frac{e'We}{\sigma^2}\right]^2 \sim x^2 \qquad [4.5]$$

The null hypothesis for the LM test states that the classical regression specification is the correct specification, implying that spatial autocorrelation is not present. LM tests also indicate which spatial regression model (spatial lag or error) is the correct model. Five Lagrange Multiplier test statistics are reported in the diagnostic output in following Figure 4.9 (Anselin, 2005). The LM-Lag and Robust LM-Lag pertain to the spatial lag model as the alternative. The next LM-Error and Robust LM-Error refer to the spatial error model as the alternative.

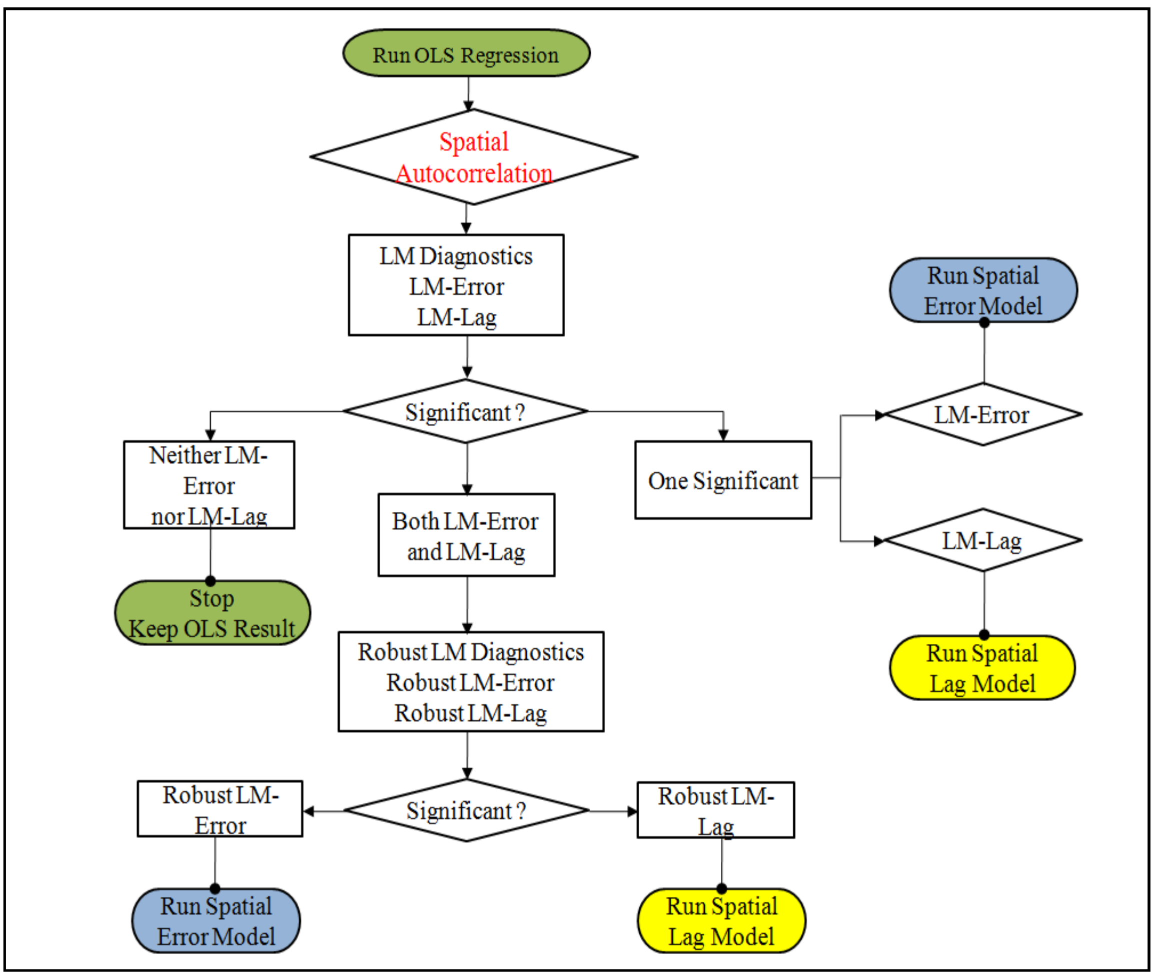

Figure 4.9. Spatial Regression Decision Process.
Source: Anselin, 2005; 199.

If LM-Error rejects the null, but LM-Lag does not, estimate a spatial error model, and vice versa. When both LM test statistics reject the null hypothesis, proceed to the bottom part of the graph and consider the robust forms of the test statistics. Typically, only one of them will be significant, or one will be orders of magnitude more significant than the other. In that case, the decision is simple: estimate the spatial regression model matching the (most) significant statistic. If both LM-Lag and LM-Error are significant, the robust tests help us understand what type of spatial dependence may be at work. The comparison between the two LM diagnostics can also be used as a guide to choose the better alternative model. In essence, the larger the significant LM statistic is the better the alternative (Anselin and Rey, 1991).

4.3.2.2 Spatial Weight Matrix

According to Anselin and Hudak (1992), a unique characteristic of spatial econometrics is that the spatial arrangement of the observations is made explicit by using a spatial weight matrix. The spatial weight matrix is generally used in econometric analyses in two ways. The first use is for the computation of various standardization coefficients used in tests for spatial autocorrelation such as the Moran's I and the Lagrange Multiplier (LM) tests as previously discussed. The second use of the spatial weight matrix is to estimate the spatial autoregressive parameter with the vector of dependent variables, the matrix of explanatory variables, or the vector of residuals in the spatial autoregressive processes.

Several types of spatial structure can be used: contiguity, nearest neighbors, or distance-based functions (Dubin, 2009). But two basic types of spatial weight matrices are common. The first type establishes a relationship based upon shared borders or vertices of lattice or irregular polygon data, often called contiguity-based spatial weight matrices. The second type establishes a relationship based upon the distance between observations, often called distance-based spatial weight matrices. The spatial weight matrix embodies the form of the underlying relationship between observations and/or their associated error terms.

The most frequently used spatial weight matrix in the literature is the first-order contiguity matrix (row-standardized so that each row's elements sum to one). That is, regions will be considered to be related if their boundaries share common points. There are three types of contiguity that are commonly considered: rook contiguity, bishop contiguity, and queen contiguity. The availability of polygon (or lattice) data permits the construction of contiguity-based spatial weight matrices. Rook contiguity exists when two polygons share a common border. Bishop contiguity exists when two polygons share a common vertex (more often referred to in GIS as a node). In addition, queen contiguity is combination of rook and bishop contiguity (Dubin, 2009).

Another class of spatial weight matrices is distance-based. These types of spatial weight matrices are based upon the distance between observations. Distance-based spatial weight matrices are widely used in applications where the polygon data does not exist or is not appropriate. Examples include locations of airports, parks, businesses, house sales transactions, etc. When distance variables are included as explanatory variables in the model, using a distance-based weight matrix (such as an inverse distance weight matrix) could produce a kind of multicollinearity between the spatial structure and the explanatory variables that makes interpretation and inference problematic (Wilhelmsson, 2002). Hence, researchers prefer to produce spatial structure by a *k*-nearest neighbors' weight matrix. The general form of a *k*-nearest neighbors' weight matrix $W(k)$ is defined as follows:

$$W_{ij}(k) = 0 \text{ if } i = j, \forall k$$

$$W_{ij}(k) = 1 \text{ if } d_{ij} \leq d_i(k) \text{ and } W_{ij} = W_{ij}(k) / \textstyle\sum_j W_{ij}(k)$$

$$W_{ij}(k) = 0 \text{ if } d_{ij} > d_i(k) \qquad [4.6]$$

In W, the elements W_{ij} indicate the way unit i is spatially connected to unit j where the elements W_{ij} on the diagonal are set to zero. These elements are non-stochastic, non-negative, and finite. In order to normalize the outside influence upon each unit, the weight matrix is standardized so that the elements of a row sum up to one.[13]

Emerging advance technology in the fields of spatial econometrics and statistics as well as geographical information systems (GIS) has exploited the spatial nature of housing data. Spatial regression deals with the specification and estimation as well as diagnostic checking of regression models that incorporate spatial effects (Anselin, 2006).

[13] For a more extensive discussion, see Anselin (2002, pp. 256-260) and Anselin (2006, pp. 909-910).

4.3.2.3 Theory of the Spatial Hedonic Model

To ensure that ordinary least squares (OLS) is the best linear unbiased estimator and predictor, there is a set of ideal conditions that must be satisfied: the OLS must be independent of the errors and the errors themselves must be independent, homoskedastic, and normally distributed. However, when dealing with cross sectional data on geographic units, existence of spatial autocorrelation or dependence (either in the dependent variable or the error term) violates the basic assumptions for the OLS estimator. Hence, employing an OLS estimator in the analysis might lead to misleading model interpretations when there is significant spatial autocorrelation (Anselin, 1988).[14] A typical example in housing market research is housing prices. The housing prices in a neighborhood will affect or be affected by the housing prices in adjacent neighborhoods.

There are two types of alternatives that incorporate spatial dependence in the model explicitly (see Anselin, 1988; Anselin and Hudak, 1992; Smirnov and Anselin, 2001 for detailed discussions). They represent two closely related but different spatial effects. Figure 4.10 illustrates the concept of maximum likelihood (ML) Spatial Lag and Error models.

[14] Anselin (2006) and Anselin and Lozano-Gracia (2008a) provide a recent comprehensive review of this field. The explicit consideration of spatial effects through the application of spatial econometrics has become more commonplace in empirical studies of housing and real estate markets after some pioneer work by Dubin (1988) and Can (1990, 1992), among others. Reviews of the basic specifications and estimation methods applied to these spatial hedonic models are provided in Anselin (1988); Basu and Thibodeau (1998); Can and Megboluge (1997); Pace, Barry, and Sirmans (1998); Dubin, Pace, and Thibodeau (1999); Gillen, Thibodeau, and Wachter (2001); Kelejian and Prucha (1998); and Pace and LeSage (2004); among others.

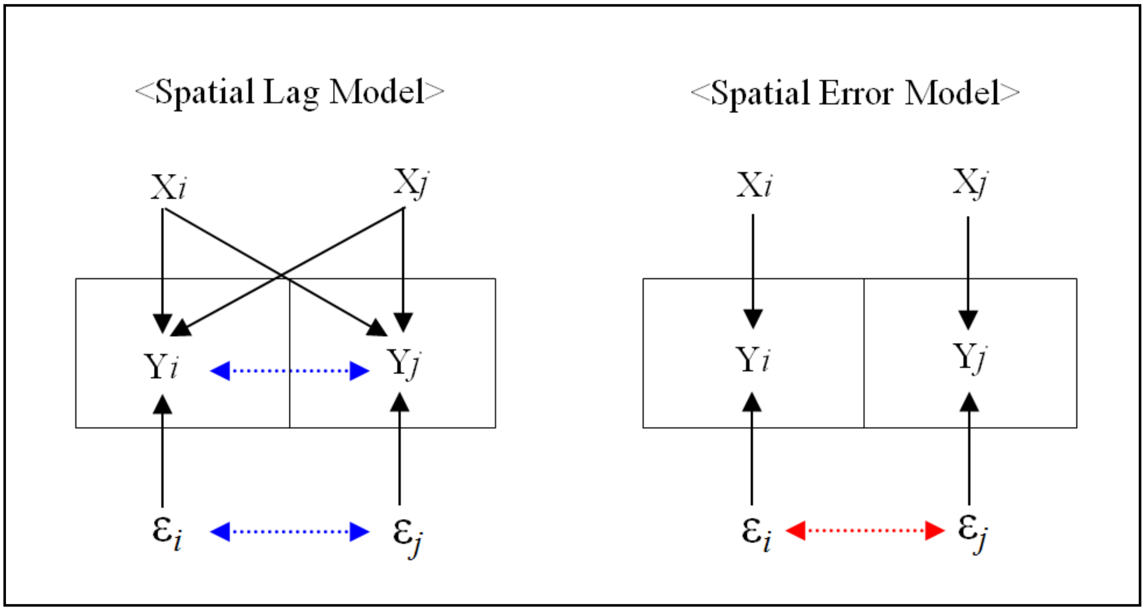

Figure 4.10. ML Spatial Lag and Error Models.
Source: Baller et al., 2001.

The first is the dependence in the spatially lagged dependent variable (similar to the time series autocorrelation), which is referred to by Anselin and Ray (1991) as "substantive dependence" in that the model form is intended to capture either interaction effects, market heterogeneity, or both. This type of dependence suggests that spatial spillover is dominant in the development. The substantive dependence model can be expressed as:

$$y = \rho Wy + \beta X + \varepsilon \quad [4.7]$$

Where, W is a spatial weight matrix describing the spatial linkage among spatial units; Wy is a so-called spatially lagged dependent variable; ρ is the spatial coefficient of the spatially lagged dependent variable; X is the n × k matrix of unit characteristics with the associated k × 1 coefficient vector β; and ε is the error term. The result of ignoring this form of spatial autocorrelation is similar to the consequences of omitting a significant explanatory variable in the right hand side of the OLS regression model.

The spatial lag model is an appropriate tool when capturing neighborhood price spillover effects. That is, this model assumes that the spatially weighted sum of neighborhood housing prices (the spatial lag) enters as an explanatory variable in the specification of housing price formation. This spillover effect only occurs among neighborhoods in close proximity. This specification, therefore, is in accord with the standard real-estate appraisal process of using comparable sales prices.

The second is the dependence in the regression's error term, or the "nuisance" dependence, which is referred by Anselin and Ray (1991) as spatial autocorrelation in omitted variables, or unobserved externalities and heterogeneities relegated to the error term. It is more likely a result from the mismatch between the boundaries of the spatial process and data collection units. The nuisance dependence model usually takes a spatially autoregressive error in the following form:

$$y = \beta X + \varepsilon$$

$$\varepsilon = \lambda W\mu + \mu \qquad [4.8]$$

Where λ is the spatial autoregressive coefficient of the error; W is the spatial weighting matrix; ε is the spatial error term; and μ is another error term. The spatial multiplier now pertains to the unobserved variables (the errors μ) but not to the explanatory variables of the model (X). In other words, the price at any location is a function of the local characteristics and also of the omitted variables at neighboring locations. The residuals, μ, are assumed to be uncorrelated with each other; the dependence is accounted for in the spatial weight matrix. The spatial dependence in the error term μ is an independent and identically distributed (i.i.d.) error term.

The error term in a statistical model is an unobservable random variable representing the effects of all those unexplained factors that cause property to differ from the population mean. The error term accounts for omitted variables, an incorrect functional form, and an inadequate sampling. The consequences of ignoring spatial error dependence are the same as the result of ignoring heteroskedasticity. OLS estimates of the spatial error model are unbiased but are inefficient since the correlation between error terms is ignored. As a result, inference based on t and F statistics will be misleading and indications of fit based on R^2 will be incorrect (Anselin, 1988).

In house pricing models, the error term also accounts for a transaction error that represents the difference between transaction prices and the expected market price relative to other houses in the market (Can and Megbolugbe, 1997). The spatial error model uses the correlated errors on nearby properties to improve the overall prediction.

4.3.3 Alternatives of ML Spatial Hedonic Models

4.3.3.1 General Method of Moments (GMM)

Although the estimations of a parametric spatial error model are most commonly based on the maximum likelihood principle, a large sample size, like housing sale data, causes significant estimation problems in the maximum likelihood (ML) approach (Anselin, 1988; Dubin, 1988). Techniques have been developed to overcome these estimation problems. One of the most promising of these models to overcome large spatial problems is the generalized moments (GM) estimation technique developed by Kelejian and Prucha (1998). To date, the general method of moments (GMM) provides the researcher with a flexible form for estimation and hypotheses on large data sets in a broad range of topics. The general method of moments (GMM or GM),[15] as the name suggests, can be thought of as a generalization of the classic method of moments. The key to GMM estimation is the population moment conditions that are derived from the assumptions of the economic model.

In general terms, GM requires weaker assumptions than the ML application, which is potentially limited to large datasets. Kelejian and Prucha (1998, 1999) initially treated the spatial autoregressive coefficient in the spatial autoregressive (SAR) error process as a nuisance parameter and the basic results were obtained. The GMM approach allows for the estimation of the spatially autoregressive parameter without computing the Jacobian of the covariance matrix, which is the determinant in the likelihood function

[15] One can think of any distribution of data (e.g., mean, skew, and variance) as a moment in a descriptive statistic. In classic statistic models, a researcher needs to construct a moment that has any data series centered on zero by shifting, detrending, etc.

and related to the computation obstacle for large datasets such as counties and housing data (Kelejian and Prucha, 1998, 1999).

In a standard SAR model, for the most conventional estimation method of the maximum likelihood (ML) error terms are assumed to follow a normal distribution. However, the GMM estimator is consistent irrespective of errors' normality required in maximum likelihood (Kelejian and Prucha, 1998, 1999). While the GM method requires some multiplication and the calculation of the trace of a weight matrix, it involves neither the calculation of the determinant nor the eigenvalues of a weight matrix (Bell, 2000).[16]

4.3.3.2 General Spatial Two-Stage Least-Squares (GS2SLS) with Instruments

The spatial patterns are richer than those implied by either the spatial error or the spatial lag model (Kelejian and Prucha, 1998). Unfortunately, endogeneity (reverse causation) is generally a common problem in the real world. For instance, foreclosures lead to a decline in neighborhood property values. The reverse causation or endogeneity may also be true: falling property values may lead to an increase in foreclosures because if house prices drop dramatically, the borrower may owe more than the house is worth, which may cause more borrowers to default on their mortgages. If both of these inferences are true, this would cause an undesirable feedback loop (reverse causation) between property values and foreclosures. Such correlation (reverse causation or

[16] The computation of eigenvalues becomes impractical and computationally unstable for medium and large-sized data sets ($n > 1000$) (Anselin, 2006).

endogeneity) may occur when there are relevant explanatory variables which are omitted from the model, or when the covariates are subject to measurement error. In this situation, ordinary linear regression generally produces biased and inconsistent estimates (Anselin, 2006).

When endogeneity violate assumptions of ordinary least squares (OLS) regression, two-stage least-squares regression (2SLS), using instrumental variables, is the most common suggested alternative (Anselin, 1988; Kelejian and Prucha, 1998, 1999, 2004; Lee, 2003, 2006). New endogenous variables replace the problematic causal variables in 2SLS. The purpose of the first stage is to create new variables which do not violate OLS regression's non-recursive assumption. At the second stage, the regression is simply computed in an ordinary least squares (OLS) form, but using the newly created variables. At this point, problematic causal variables are replaced by new created variables, called instrumental variables. Statistically, an instrument is a variable that does not itself belong in the explanatory equation but should meet two requirements. They should be not correlated with the disturbance term in the underlying regression model and are correlated with the endogenous explanatory variable.

The GMM method and the classic 2SLS method are considered for the estimation of mixed spatial autoregressive models. These methods have a computational advantage over the maximum likelihood method as discussed in the previous section. The GMM estimators improve upon the classic two-stage least-squares (2SLS) estimators, introducing additional moment functions in the GMM framework (Lee, 2002).

The spatial lag model can be formulated as a linear model that contains an endogenous variable (Wy) and exogenous variables (X). As reduced form:

$$y = Z\gamma + \varepsilon \qquad [4.9]$$

Where, Z = [Wy, X], resulting in the spatial two-stage least-squares estimator (S2SLS), and $\gamma = [\rho, \beta]$. The presence of the spatially lagged dependent variable Wy introduces a form of endogeneity. Under typical specifications, Wy will be correlated with the disturbances ε, which motivates an instrumental variable approach, a classic solution to the endogeneity problem. The spatial two-stage least-squares estimator is an extension of the standard two-stage least-squares estimator that includes specific instruments for the spatially lagged dependent variable (for more extensive discussion, see Anselin, 1988; Kelejian and Prucha, 1998, 1999, 2004; Lee, 2003, 2006). Instrumental variables least squares regression provides a way to obtain consistent parameter estimates. Specifically, the matrix of instruments can be defined in the following way:

$$H = [X, WX, W^2X] \qquad [4.10]$$

H includes (1) all exogenous explanatory variables in the equation, (2) their spatially weighted values (lagged explanatory variables) and (3) the square of the spatially weighted values. The generalized method of moments can be used and the resulting instrument in the following way:

$$\gamma_{S2SLS} = [\hat{Z}^T\hat{Z}]^{-1}\hat{Z}^T y \qquad [4.11]$$

A valid instrumental variable must be correlated with the independent variable but not with the error term in the underlying regression model. Inference on the γ_{S2SLS} is based on the asymptotic variance matrix as follows:

$$AsyVar[\gamma_{S2SLS}] = \sigma^2[Z^TZ]^{-1} \qquad [4.12]$$

with $\sigma^2 = e^Te/n$ and $e = y - Z\gamma_{S2SLS}$.

The estimated residuals and a generalized method of moments can be used in the second step to consistently estimate the autoregressive parameter and the variance of the independent and identically distributed (i.i.d.) error term, ρ and σ^2 (Kelejian and Prucha, 1999).

Recently, Kelejian and Prucha (2010) provide results concerning the joint asymptotic distribution of instrument and GMM estimators in the regression model. Their results involve testing the joint hypothesis of no spatial spillovers originated from the endogenous variables or from the disturbances.

In the context of spatial hedonic models for foreclosure impacts on housing prices, this endogeneity has received little attention in the literature although strong negative effects between foreclosure and price change might be expected.

4.3.3.3 Heteroskedasticity and Autocorrelation Consistent (HAC) Estimator

This final part deals with the possible presence of unknown heteroskedasticity in the disturbance. When the researchers attempt to model macro-scale patterns in property values and heterogeneous housing units as parcels, hedonic models are plagued by heteroskedasticity since spatial housing units may differ in important characteristics (e.g., size of living area). Thus, homoskedasticity is a strong assumption that may not hold in the real world and causes spatial problems. If variances of the disturbances or structure of heteroskedasticity are known, one may remove the heteroskedasticity by some appropriate transformations in conventional ML or GMM techniques. But one may not have accurate information about the nature of the heteroskedasticity in a model.

The ML approach for the Spatial Lag or Error model by treating the independent and identically distributed (i.i.d.) disturbances does not taking into account the presence of unknown heteroskedastic disturbances (Kelejian and Prucha, 2007). In contrast, the GMM obtained from carefully designed moment conditions can be robust against an unknown heteroskedasticity form. Recently unknown heteroskedasticity was elaborated upon in a Kelejian and Prucha (2007)'s proposal. The basic idea is to avoid specifying a particular spatial process or spatial weights matrix and to extract the spatial covariance terms from weighted averages of cross-products of residuals, using a kernel function (Anselin, 2006). This yields a so-called heteroskedastic and spatial autocorrelation consistent (HAC) estimator, which is proposed by Kelejian and Prucha (2007). The distinctive methodological aspect of this approach allows for the remaining spatial error autocorrelation of an unknown heteroskedastic form. Thus, the spatial HAC estimator is robust against possible misspecification of the disturbances and allows for (unknown) forms of heteroskedasticity and correlation across spatial units. The disturbance vector is assumed to be generated by the following general process:

$$\varepsilon = R\xi \quad [4.13]$$

Where, ξ is a vector of disturbances and R is an n x n spatial matrix whose elements are unknown (for technical details see Lee, 2002, 2003, 2004; Kelejian and Prucha, 1998, 1999, 2004, 2007, 2010). The asymptotic distribution of corresponding instrument variable (IV) estimators involves the variance covariance matrix as follows:

$$\Psi = n^{-1} H^{T} \sum H \quad [4.14]$$

Where, $\Sigma = RR^{T}$ denotes the variance covariance matrix of ξ.

Kelejian and Prucha (2007) propose to estimate the r, s, elements of Ψ by:

$$\hat{\Psi}_{rs} = n^{-1} \sum_{i=1}^{n} \sum_{i=1}^{n} h_{ir} h_{js} \hat{\varepsilon}_i \hat{\varepsilon}_j K(d^{*}_{ij} / d) \quad [4.15]$$

Where, the subscripts refer to the elements of the matrix of instruments H and the vector of estimated residuals ε. Kelejian and Prucha (2007) also contains a generalization of several distance measures. As Anselin and Lozano-Gracia (2008a) point out, the core of the HAC technique is a non-parametric estimator for the spatial covariance, using weighted averages of cross-products of residuals. The range is determined by a kernel function. The kernel function determines which pairs *i, j* are included in the cross products in equation [4.15]. Based on the spatial HAC estimator of *W* given in equation [4.15], the asymptotic variance covariance matrix of the S2SLS estimator of the parameters vector is given by:

$$\widehat{\Phi} = n^2(\hat{Z}^T\hat{Z})^{-1} Z^T H(H^T H)^{-1}\widehat{\Psi}(H^T H)^{-1} H^T Z(\hat{Z}^T\hat{Z})^{-1} \quad [4.16]$$

To sum up, Kelejian and Prucha (2007) proposed an estimation theory to allow for heteroskedasticity, and corresponding joint hypothesis tests for the presence of spatial dependencies in the endogenous variables, exogenous variables, and/or disturbances. Anselin and Lozano-Gracia (2008b) provided a typical example of empirical applications that required the use of spatial heteroskedasticity and autocorrelation consistent (HAC) estimators.

5. DATA ANALYSIS AND RESULTS

5.1 Descriptive Statistics

5.1.1 Characteristics of the Continuous Variables

Descriptive analyses for all variables were conducted to examine the data characteristics and distribution. Table on page 123 (Table 5.0) presents the descriptions of all variables for this study.

To compare typical sale prices to distressed sale prices, this study defines home sales as follows: for typical home sales, this study limits to typical home sales by arm's length transactions, which have never been under foreclosure in the two years prior to sale; and distressed sales related to the foreclosure. This study limits distressed sales to home sales that had at least one foreclosure filing in two years prior to sale transaction for the 2005 housing samples and the 2008 housing samples in the Phoenix area. Full housing samples in this study consist of both distressed single family home sales which previously faced foreclosure in the two years prior to the sale transactions and typical single family homes that were sold by arm's length transactions in Phoenix, Arizona, in 2005 and 2008.

The full single family home sample consists of 28,601 typical sales and 2,214 distressed sales in 2005 and 6,155 typical sales and 6,730 distressed sales in 2008. The full condo sample consists of 5,949 typical sales and 256 distressed sales in 2005 and 1,465 typical sales and 538 distressed sales in 2008. The mean sale price of single family homes was \$256,024 for 2005 full samples and \$198,429 for 2008 full samples. The mean sale price of condos was \$153,409 for 2005 full samples and \$164,296 for 2008 full samples.

The characteristics of the continuous variables of single family homes are summarized in table on page 124 (Table 5.1) and table on page 124 (Table 5.2).

Table on page 124 (Table 5.1) indicated that the average single family homes sold in 2005 had 8,050 square feet of lot size, 1,638 square feet of living area, 6 rooms, and was about 27 years old. Table on page 124 (Table 5.2) indicated that the average single family homes sold in 2008 had 7,963 square feet of lot size, 1,709 square feet of living area, 6 rooms, and was about 28 years old. Thus, both single family home samples for 2005 and 2008 had very similar housing characteristics.

The characteristics of the continuous variables of condos are summarized in table on page 125 (Table 5.3) and table on page 125 (Table 5.4).

Table on page 125 (Table 5.3) indicated that the average condo sold in 2005 had 1,444 square feet, 1,119 square feet of living area, has 4.5 rooms, and was about 58 years old. Table on page 125 (Table 5.4) indicated that the average condo sold in 2008 had 1,395 square feet, 1,122 square feet of living area, 4.4 rooms, and was about 78 years old. Thus, the main difference between 2005 and 2008 is building age. It seems to suggest that the transactions mainly occurred in older condo properties.

Tables on pages 126-127 (Tables 5.5 through 5.8) indicated that the mean sale price of typical single family homes was $250,560 for the 2005 samples and $252,424 for the 2008 samples. On the other hand, the mean sale price for distressed single family homes was $197,417 for the 2005 samples and $149,056 for the 2008 samples.

Table 5.0. Description of Variables.

LN_2005 (2008) SALE PRICE	Log (Sale Prices of Existing Single Family Homes in 2005 (2008) vs. Log (Sale Prices of Existing Condos in 2005 (2008))
LN_LOT SIZE	Log (Lot size in square feet)
AGE	The age of the house at the time it is sold
AGE_2	The square of building age
LN_LIVING AREA	Log (Square feet of interior space)
STORY (dummy)	(Dummy variable) 1= the single family home has 2 or more stories / (1= Condo complex consists of multi-floor semi-detached homes)
GARAGE (dummy)	(Dummy variable) 1= the home has a garage or carport
POOL (dummy)	(Dummy variable) 1= the home has a swimming pool
2nd_ QUARTER (dummy)	(Dummy variable) 1= Sold in 2nd quarter
3rd_ QUARTER (dummy)	(Dummy variable) 1= Sold in 3rd quarter
4th_ QUARTER (dummy)	(Dummy variable) 1= Sold in 4th quarter
DISTRESSED SALE (dummy)	(Dummy variable) 1= Distressed sale: property sale that had a foreclosure filing in two years prior to the sale transaction
RENTER (dummy)	(Dummy variable) 1= Renter occupied home
INT_D-S AND RENTER	(Dummy variable): Interaction of distressed sale and renter occupied home
CASH SALE (dummy)	(Dummy variable) 1= Cash sale
INT_D-S AND CASH SALE	(Dummy variable): Interaction of distressed sale and cash sale transaction
SFH_FC_1R_C	# of neighboring single family home foreclosures in two years prior to the sale transaction date within 500 feet
SFH_FC_1R_C^2	# of the square of neighboring single family home foreclosures in two years prior to the sale transaction date within 500 feet
SFH_FC_2R_C	# of neighboring single family home foreclosures in two years prior to the sale transaction date within 501 to 1000 feet
SFH_FC_2R_C^2	# of the square of neighboring single family home foreclosures in two years prior to the sale transaction date within 501 to 1000 feet
SFH_FC_3R_C	# of neighboring single family home foreclosures in two years prior to the sale transaction date within 1001 to 1500 feet
SFH_FC_3R_C^2	# of the square of neighboring single family home foreclosures in two years prior to the sale transaction date within 1001 to 1500 feet
CON_FC_1R_C	# of neighboring condo or townhome foreclosures in two years prior to the sale transaction date within 500 feet
CON_FC_1R_C^2	# of the square of neighboring condo or townhome foreclosures in two years prior to the sale transaction date within 500 feet
CON_FC_2R_C	# of neighboring condo or townhome foreclosures in two years prior to the sale transaction date within 501 to 1000 feet
CON_FC_2R_C^2	# of the square of neighboring condo or townhome foreclosures in two years prior to the sale transaction date within 501 to 1000 feet
CON_FC_3R_C	# of neighboring condo or townhome foreclosures in two years prior to the sale transaction date within 1001 to 1500 feet
CON_FC_3R_C^2	# of the square of neighboring condo or townhome foreclosures in two years prior to the sale transaction date within 1001 to 1500 feet

Table 5.1. Descriptive Statistics of Contiguous Variables for Full Single Family Home Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2005 PRICE		80000	795000	256023.72	129175.296	1.535	.014	2.285	.028
LOT_SIZE		836	217859	8050.04	5044.847	**10.243**	.014	**217.964**	.028
AGE		1	105	27.05	18.686	.434	.014	-.565	.028
LIVING_AREA		384	8408	1638.19	557.200	1.351	.014	**3.470**	.028
ROOMS		2	15	6.14	1.350	.755	.014	.735	.028
Valid N (listwise)	30815								

Table 5.2. Descriptive Statistics of Contiguous Variables for Full Single Family Home Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2008 PRICE		31500	762500	198428.91	126796.272	1.400	.022	2.370	.043
LOT_SIZE		1754	137712	7963.33	4105.711	**7.649**	.022	**135.180**	.043
AGE		2	108	28.21	19.302	.463	.022	-.623	.043
LIVING_AREA		480	5189	1709.93	604.785	1.284	.022	2.283	.043
ROOMS		2	13	6.31	1.439	.786	.022	.706	.043
Valid N (listwise)	12885								

Table 5.3. Descriptive Statistics of Contiguous Variables for Full Condo Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2005 PRICE		45000	435000	153409.54	77629.357	1.084	.031	.960	.062
LOT_SIZE		101	9800	1433.57	1071.975	2.208	.031	**5.939**	.062
AGE		2	58	23.69	10.291	-.054	.031	-.235	.062
LIVING_AREA		372	3178	1119.32	321.247	1.041	.031	1.492	.062
ROOMS		2	8	4.47	.934	.570	.031	.738	.062
Valid N (listwise)	6205								

Table 5.4. Descriptive Statistics of Contiguous Variables for Full Condo Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2008 PRICE		28000	425000	164295.50	79888.800	.816	.055	.396	.109
LOT_SIZE		272	9935	1394.78	1099.381	2.900	.055	**11.382**	.109
AGE		2	78	21.49	12.189	.281	.055	-.255	.109
LIVING_AREA		369	2712	1122.19	351.707	.925	.055	.798	.109
ROOMS		2	9	4.38	1.047	.359	.055	.397	.109
Valid N (listwise)	2003								

Table 5.5. Descriptive Statistics of Contiguous Variables for Typical Single Family Home Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2005 PRICE		80000	795000	260560.45	130664.705	1.486	.014	2.096	.029
LOT_SIZE		836	217859	8054.83	5104.559	**10.273**	.014	**220.105**	.029
AGE		1	105	26.58	18.785	.489	.014	-.510	.029
LIVING_AREA		384	8408	1649.85	562.947	1.336	.014	**3.406**	.029
ROOMS		2	15	6.17	1.358	.742	.014	.710	.029
Valid N (listwise)	28601								

Table 5.6. Descriptive Statistics of Contiguous Variables for Distressed Single Family Home Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2005 PRICE		95000	775000	197417.10	89386.551	2.579	.052	**8.639**	.104
LOT_SIZE		2115	79324	7988.09	4198.292	**8.835**	.052	**110.322**	.104
AGE		1	89	33.11	16.192	-.239	.052	-.613	.104
LIVING_AREA		529	4434	1487.61	450.513	1.395	.052	**3.581**	.104
ROOMS		3	11	5.84	1.199	.869	.052	1.008	.104
Valid N (listwise)	2214								

Table 5.7. Descriptive Statistics of Contiguous Variables for Typical Single Family Home Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2008 PRICE		32000	762500	252413.94	133413.294	1.193	.031	1.529	.062
LOT_SIZE		1754	137712	8135.21	4655.904	**7.944**	.031	**146.109**	.062
AGE		2	108	28.17	19.584	.733	.031	-.194	.062
LIVING_AREA		480	4806	1753.64	609.012	1.102	.031	1.734	.062
ROOMS		2	13	6.37	1.432	.632	.031	.485	.062
Valid N (listwise)	6155								

Table 5.8. Descriptive Statistics of Contiguous Variables for Distressed Single Family Home Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2008 PRICE		31500	730000	149056.28	96959.802	1.761	.030	**4.555**	.060
LOT_SIZE		1890	70735	7806.12	3521.217	**6.324**	.030	**67.249**	.060
AGE		2	108	28.25	19.041	.194	.030	-1.062	.060
LIVING_AREA		619	5189	1669.96	598.148	1.471	.030	2.946	.060
ROOMS		2	13	6.26	1.442	.928	.030	.953	.060
Valid N (listwise)	6730								

Tables 5.9 through 5.12 indicated that the mean sale price of a typical condo was $154,820 for the 2005 samples and $178,356 for the 2008 samples. On the other hand, mean sale price for distressed condos was $120,624 for the 2005 samples and $126,006 for the 2008 samples.

Table 5.9. Descriptive Statistics of Contiguous Variables for Typical Condo Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2005 PRICE		45000	435000	154820.38	78054.336	1.057	.032	.890	.063
LOT_SIZE		101	9800	1437.59	1078.640	2.209	.032	**5.923**	.063
AGE		2	55	23.60	10.347	-.050	.032	-.261	.063
LIVING_AREA		372	3178	1118.61	321.860	1.051	.032	1.527	.063
ROOMS		2	8	4.47	.933	.573	.032	.780	.063
Valid N (listwise)	5949								

Table 5.10. Descriptive Statistics of Contiguous Variables for Distressed Condo Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2005 PRICE		45600	397900	120624.14	58147.637	1.940	.152	**5.033**	.303
LOT_SIZE		261	5528	1340.11	900.091	1.974	.152	**4.597**	.303
AGE		2	58	25.74	8.668	.101	.152	.455	.303
LIVING_AREA		544	2400	1135.87	306.784	.809	.152	.580	.303
ROOMS		2	7	4.60	.941	.513	.152	-.147	.303
Valid N (listwise)	256								

Table 5.11. Descriptive Statistics of Contiguous Variables for Typical Condo Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2008 PRICE		28875	425000	178356.58	79522.991	.770	.064	.186	.128
LOT_SIZE		340	9706	1426.71	1141.672	2.643	.064	**8.896**	.128
AGE		2	78	21.89	11.992	.338	.064	.002	.128
LIVING_AREA		369	2712	1104.30	355.754	1.026	.064	1.083	.128
ROOMS		2	9	4.33	1.051	.461	.064	.539	.128
Valid N (listwise)	1465								

Table 5.12. Descriptive Statistics of Contiguous Variables for Distressed Condo Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
2008 PRICE		28000	400000	126006.50	67416.021	1.111	.105	1.785	.210
LOT_SIZE		272	9935	1307.84	970.644	**3.893**	.105	**23.208**	.210
AGE		2	58	20.41	12.657	.177	.105	-.883	.210
LIVING_AREA		442	2400	1170.91	335.963	.690	.105	.161	.210
ROOMS		2	8	4.51	1.025	.090	.105	.217	.210
Valid N (listwise)	538								

To examine the data's normality, the skewness and kurtosis for each variable were computed. In general, skewness represents how much data distribution was skewed, and kurtosis shows how peaked or flat the graph of the data distribution is. A zero value of both the skewness and kurtosis indicate that the distribution is perfectly normal. If the value for skewness or kurtosis of a variable is greater than +2 or less than -2, the variable is not normally distributed (Cohen, West, and Aiken, 2003). In this study, the results of skewness and kurtosis indicated that, among the continuous variables of single family home and condo samples, lot size and/or total main living area were not normally distributed. It is necessary that they be transformed to fit a normal distribution.

5.1.2 Correlation Test

A bivariate correlation examines the correlations between two variables without considering other variables; whereas, a partial correlation considers the relationships between two variables while controlling the effects of additional variables. Hence, the bivariate correlation did not show the same relationship in the hedonic price model. However, examining correlations among variables was useful in identifying multicollinearity, which normally represents higher than 0.9 of the correlation value between two independent variables (Field, 2005). The main living area and rooms were very highly correlated in the sample data sets. Hence, the room variable among the housing physical characteristics was excluded in the final models.[17] The variance inflation factor (VIF) or the tolerance value of the variables was carefully checked to verify the problem exactly in the OLS hedonic price models and spatial hedonic models.

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[17] The property information data sets obtained from Maricopa County Assessor Office provides total number of rooms combining beds, baths, living rooms, etc. There is also missing information for the number of room. Thus, this study includes main living area variables and excludes room variables, which was were very highly correlated with main living area variables.

5.1.3 Log Transformation

There are several ways of data transformation such as log, square root, or reciprocal transformation. In general, a number of studies in regard to analyzing property values most commonly used a log transformation when data were not normally distributed (Halvorsen and Palmquist, 1980; Song and Knaap, 2003). The log transformation was performed by taking the logarithm of the dependent variable or the logarithm of both independent and dependent variables.

Tables 5.13 through 16 present the changed values of skewness and kurtosis of the dependent variable and fourteen independent variables after applying the log to the variables. Two variables (lot size and living area) representing high kurtosis or skewness values were log-transformed to fit into normal distribution to be easily interpreted. Also, dependent variables (sale price) were log-transformed. The semi-log functional form helps alleviate heteroskedasticity or the problem of changing variances in the error term (Halverson and Pollakowski, 1980; Malpezzi, 2002; Malpezzi, Ozanne, and Thibodeau, 1980).

Table 5.13. Descriptive Statistics of Log Transformed Contiguous Variables for Full Single Family Home Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LN_2005 SALE PRICES		4.9031	5.9004	5.362657	.1925074	.523	.014	-.303	.028
LN_LOT SIZE		2.9222	5.3382	3.869066	.1605295	1.171	.014	**6.000**	.028
AGE		1	105	27.05	18.686	.434	.014	-.565	.028
LN_LIVING AREA		2.5843	3.9247	3.191763	.1383981	.223	.014	.173	.028
Valid N (listwise)	30815	30815							

Table 5.14. Descriptive Statistics of Log Transformed Contiguous Variables for Full Single Family Home Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LN_2008 SALE PRICES		4.4983	5.8822	5.211372	.2830285	-.278	.022	-.245	.043
LN_LOT SIZE		3.2440	5.1390	3.869575	.1534450	.899	.022	**4.241**	.043
AGE		2	108	28.21	19.302	.463	.022	-.623	.043
LN_LIVING AREA		2.6812	3.7151	3.208590	.1436028	.248	.022	.064	.043
Valid N (listwise)	12885								

Table 5.15. Descriptive Statistics of Log Transformed Contiguous Variables for Full Condo Samples in 2005.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LN_2005 SALE PRICES		10.7100	12.9800	11.819014	.4968285	-.009	.031	-.583	.062
LN_LOT SIZE		4.6150	9.1900	7.066547	.6035818	.559	.031	.076	.062
AGE		2	58	23.69	10.291	-.054	.031	-.235	.062
LN_LIVING AREA		5.9190	8.0640	6.982152	.2747970	.157	.031	.296	.062
Valid N (listwise)	6205								

Table 5.16. Descriptive Statistics of Log Transformed Contiguous Variables for Full Condo Samples in 2008.

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
		Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LN_2008 SALE PRICES		10.2400	12.9600	11.882886	.5280513	-.578	.055	.401	.109
LN_LOT SIZE		5.6060	9.2040	7.050273	.5637092	.992	.055	.821	.109
AGE		2	78	21.49	12.189	.281	.055	-.255	.109
LN_LIVING AREA		5.9110	7.9050	6.976777	.3026573	.123	.055	-.141	.109
Valid N (listwise)	2003								

Compared to the skewness and kurtosis of the original data, the log-transformed variables showed much lower values of skewness and kurtosis. All variables fell into the value between -2 and +2 for skewness and kurtosis. However, the lot variable still indicated slightly higher kurtosis than +2 for the 2005 and 2008 single family home samples. Since the OLS hedonic price models and the spatial hedonic models assume the normal distribution of the data, the transformation of the data will reduce the impact of outliers, and convert non-normal distribution of data to normally distributed data.

5.1.4 Characteristics of the Dummy Variables

Eleven dummy variables are summarized in Table 5.17 for the single family home sample and Table 5.18 for condos. Dummy variables were encoded either "0" or "1" in the dataset; that is, if a value of "0" was given, it meant a certain feature is not included in the house.

The dummies of story, garage, and swimming pool are categorized into housing physical characteristics. The dummies of 2nd quarter, 3rd quarter, and 4th quarter represent housing market price trends. There are three dummies for property that previously faced a foreclosure in two years prior to sale and sold later (distressed sale), a renter occupied home, and cash transactions. These dummies are associated with the selling characteristics of properties. There are two interaction terms for a distressed sale and a renter occupied home; and a distressed sale and a cash transaction. The interaction term is to control for distressed home sales. Figures on pages 136-137 (Figure 5.1 and 5.2) indicated these selling characteristics associated with foreclosure for full samples.

Table 5.17. Descriptive Statistics of Dummy Variables for Full Single Family Home Samples in 2005 and 2008.

Variables	**Dummy Variables for Single Family Home Samples in 2005**					**Dummy Variables for Single Family Home Samples in 2008**				
	N	Minimum	Maximum	Mean	Std. Deviation	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
STORY (dummy)		0	1	.14	.346		0	1	.17	.38
GARAGE(dummy)		0	1	.91	.291		0	1	.92	.272
POOL(dummy)		0	1	.30	.459		0	1	.30	.457
2nd_ QUARTER (dummy)		0	1	.28	.448		0	1	.26	.437
3rd_ QUARTER (dummy)		0	1	.28	.447		0	1	.30	.459
4th_ QUARTER (dummy)		0	1	.22	.411		0	1	.28	.448
DISTRESSED SALE (dummy)		0	1	.07	.258		0	1	.52	.500
RENTER (dummy)		0	1	.15	.358		0	1	.14	.351
INT_D-S AND RENTER		0	1	.02	.127		0	1	.10	.298
CASH SALE (dummy)		0	1	.07	.251		0	1	.21	.409
INT_D-S AND CASH SALE		0	1	.01	.078		0	1	.15	.356
Valid N (listwise)	30815					12885				

Table 5.18. Descriptive Statistics of Dummy Variables for Condo Samples in 2005 and 2008.

Variables	Dummy Variables Condo Samples in 2005					Dummy Variables for Condo Samples in 2008				
	N	Minimum	Maximum	Mean	Std. Deviation	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
STORY (dummy)		0	1	.36	.481		0	1	.28	.450
GARAGE(dummy)		0	1	.89	.317		0	1	.84	.363
POOL(dummy)		0	1	.00	.069		0	1	.01	.086
2nd_ QUARTER (dummy)		0	1	.30	.457		0	1	.30	.457
3rd_ QUARTER (dummy)		0	1	.26	.437		0	1	.23	.423
4th_ QUARTER (dummy)		0	1	.22	.418		0	1	.20	.399
DISTRESSED SALE (dummy)		0	1	.04	.199		0	1	.27	.443
RENTER (dummy)		0	1	.25	.435		0	1	.25	.234
INT_D-S AND RENTER		0	1	.01	.101		0	1	.06	.404
CASH SALE (dummy)		0	1	.15	.355		0	1	.25	.436
INT_D-S AND CASH SALE		0	1	.01	.078		0	1	.09	.292
Valid N (listwise)	6205					2003				

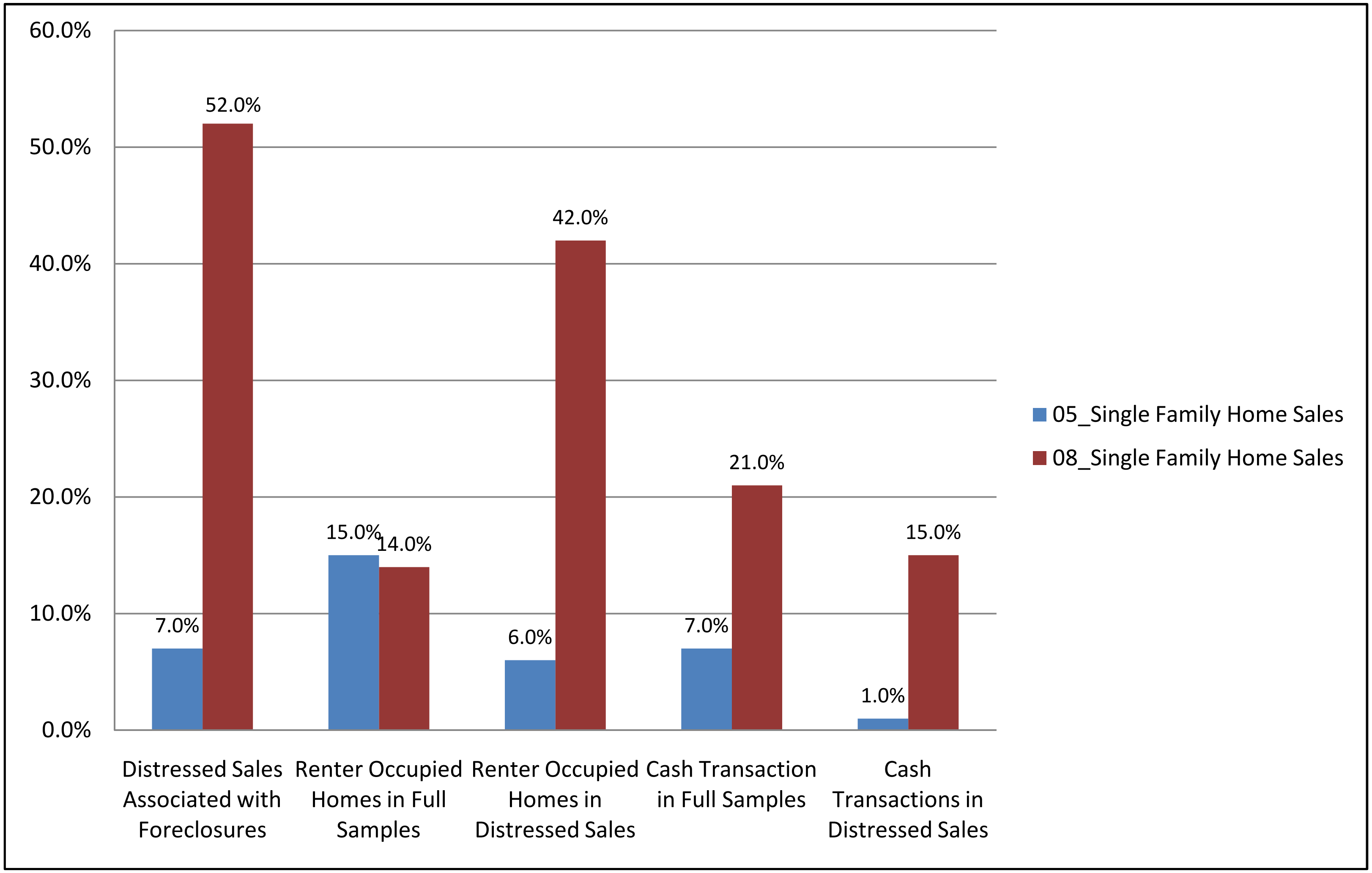

Figure 5.1. Descriptive Statistics of Selling Characteristics for Single Family Home Samples.

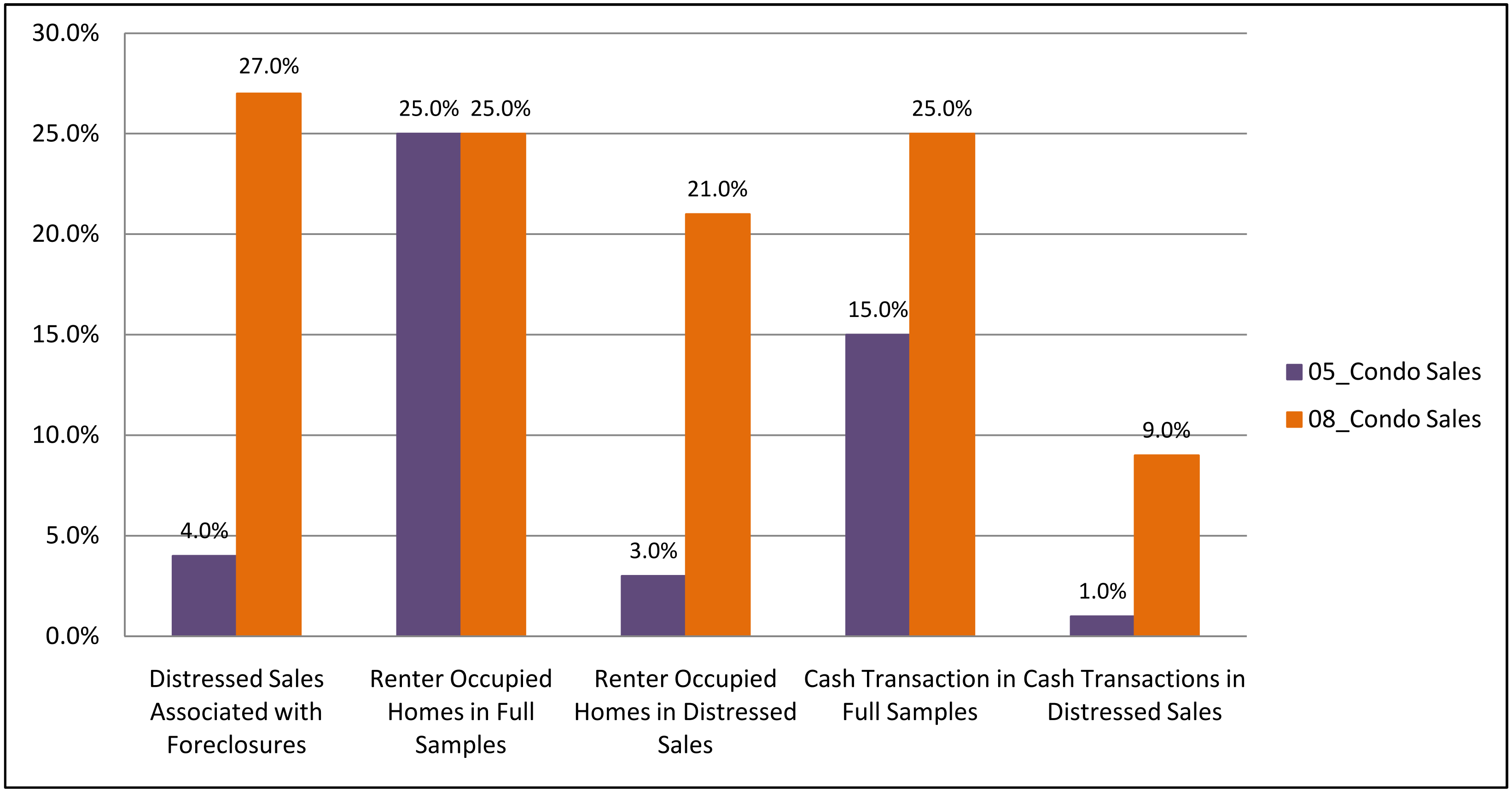

Figure 5.2. Descriptive Statistics of Selling Characteristics for Condo Samples.

5.1.5 Neighboring Foreclosure Variables

Essentially, this study defines "nearby or neighboring" in three alternative ways (three buffers) in order to measure fixed effects for these micro-neighborhood spaces or smaller scales. In the presentation of the models, these are referred to as ring 1 (0 to 500 feet), ring 2 (501 to 1000 feet), and ring 3 (1001 to 1500 feet). In this fashion, the impact can be estimated over different spatial scales, since the effect can vary with distance. Thus, this approach would allow a distance-decay to the impact, where the effect of the externality decreases as distance increases. The counts of neighboring foreclosures greatly increased in a housing bust year (2008) compared to a boom year (2005) in both types of housing.

For 2005 single family home sale samples, the average counts of neighboring single family home foreclosures were 1.18 units in the 500 foot ring (R1), 2.13 units in the 501-1000 foot ring (R2), and 2.90 units in the 1001-1500 foot ring (R3), respectively.

For 2005 single family home sale samples, the average counts of neighboring condo foreclosures were 0.05 units in the 500 foot ring (R1), 0.18 units in the 501-1000 foot ring (R2), and 0.31 units in the 1001-1500 foot ring (R3), respectively.

For 2008 single family home sale samples, the average counts of neighboring single family home foreclosures were 6.22 units in 500 foot ring (R1), 10.54 units in 501-1000 foot ring (R2), and 14.31 units in 1001-1500 foot ring (R3), respectively.

For 2008 single family home sale samples, the average counts of neighboring condo foreclosures were 0.10 units in the 500 foot ring (R1), 0.41 units in the 501-1000 foot ring (R2), and 0.77 units in the 1001-1500 foot ring (R3), respectively.

For 2005 condo sale samples, the average counts of neighboring single family home foreclosures were 0.43 units in the 500 foot ring (R1), 1.67 units in the 501-1000 foot ring (R2), and 3.02 units in the 1001-1500 foot ring (R3), respectively.

For 2005 condo sale samples, the average counts of neighboring condo foreclosures were 1.93 units in the 500 foot ring (R1), 1.60 units in the 501-1000 foot ring (R2), and 1.11 units in the 1001-1500 foot ring (R3), respectively.

For 2008 condo sale samples, the average counts of neighboring single family home foreclosures were 0.72 units in the 500 foot ring (R1), 2.96 units in the 501-1000 foot ring (R2), and 5.51 units in the 1001-1500 foot ring (R3), respectively.

For 2008 condo sale samples, the average counts of neighboring condo foreclosures were 4.56 units in the 500 foot ring (R1), 2.67 units in the 501-1000 foot ring (R2), and 2.09 units in the 1001-1500 foot ring (R3), respectively.

Simple statistics for both Single Family Home and Condo Samples in 2005 (see Tables 5.19-5.20 and figures on pages 141-142 [Figures 5.3-5.4]) illustrated low density (frequency) of foreclosures in the nearby neighborhoods in a housing boom year. However, Simple statistics for both Single Family Home and Condo Samples in 2008 (see Tables 5.19-5.20 and figures on pages 141-142 [Figures 5.3-5.4]) illustrated high density (frequency) of foreclosures, which could create serious impacts on neighborhood housing markets during a housing bust year.

Table 5.19. Descriptive Statistics of Neighboring Foreclosure Variables for Single Family Home Samples in 2005 and 2008.

Foreclosure Variables	**Neighboring Foreclosure Variables for Single Family Home Samples in 2005**					**Neighboring Foreclosure Variables for Single Family Home Samples in 2008**				
	N	Minimum	Maximum	Mean	Std. Deviation	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
SFH_FC_1R_C		0	10	1.18	1.353		0	43	6.22	5.978
SFH_FC_2R_C		0	16	2.13	2.166		0	64	10.54	10.733
SFH_FC_3R_C		0	20	2.90	2.761		0	95	14.31	14.754
CON_FC_1R_C		0	10	.05	.348		0	20	.10	.703
CON_FC_2R_C		0	17	.18	.757		0	42	.41	1.756
CON_FC_3R_C		0	18	.31	1.029		0	44	.77	2.466
Valid N (listwise)	30815					12885				

Table 5.20. Descriptive Statistics of Neighboring Foreclosure Variables for Condo Samples in 2005 and 2008.

Foreclosure Variables	**Neighboring Foreclosure Variables for Condo Samples in 2005**					**Neighboring Foreclosure Variables for Condo Samples in 2008**				
	N	Minimum	Maximum	Mean	Std. Deviation	N	Minimum	Maximum	Mean	Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
SFH_FC_1R_C		0	10	1.18	1.353		0	43	6.22	5.978
SFH_FC_2R_C		0	16	2.13	2.166		0	64	10.54	10.733
SFH_FC_3R_C		0	20	2.90	2.761		0	95	14.31	14.754
CON_FC_1R_C		0	10	.05	.348		0	20	.10	.703
CON_FC_2R_C		0	17	.18	.757		0	42	.41	1.756
CON_FC_3R_C		0	18	.31	1.029		0	44	.77	2.466
Valid N (listwise)	30815					12885				

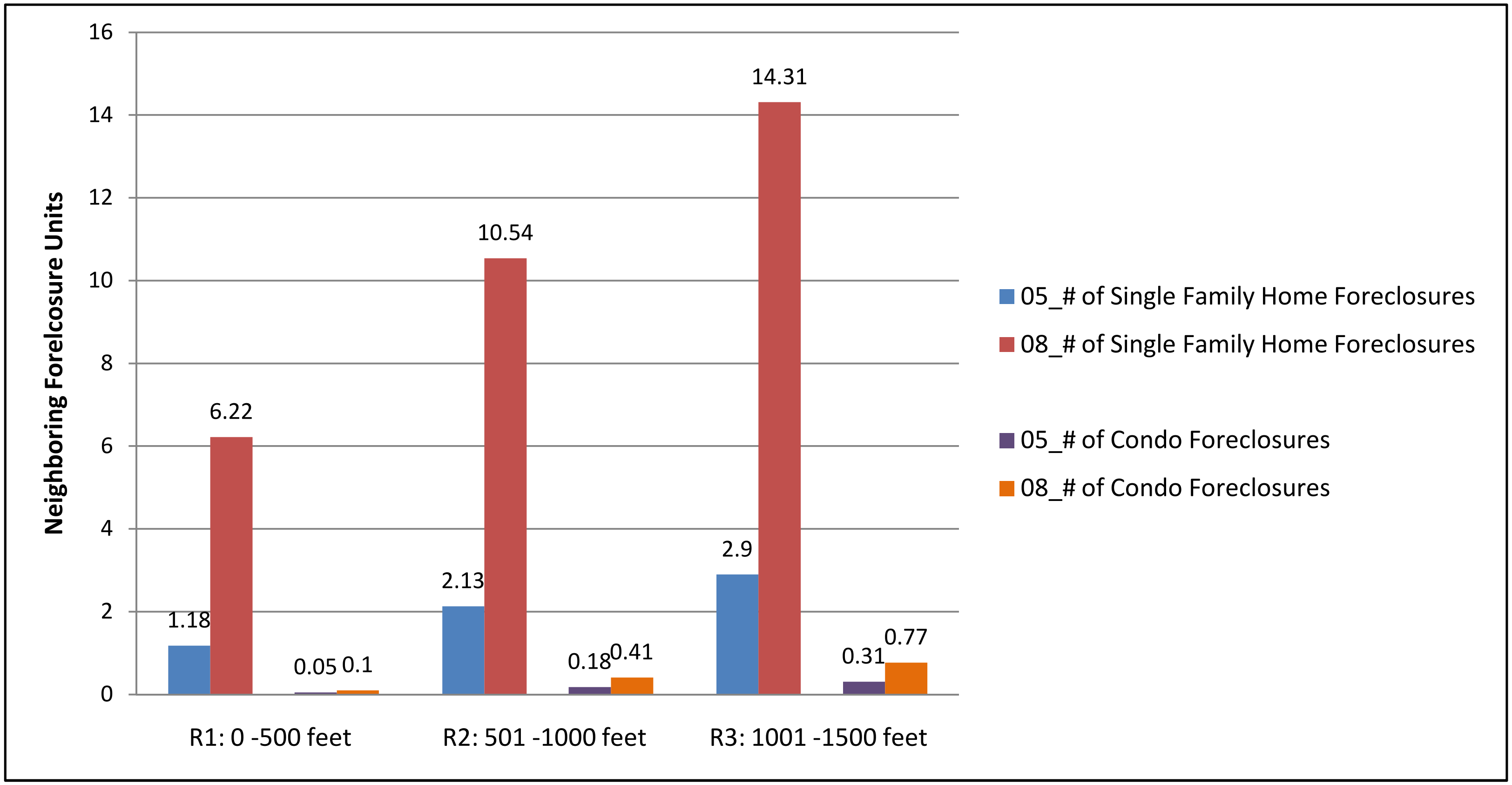

Figure 5.3. Descriptive Statistics of Neighboring Foreclosures for Single Family Home Samples.

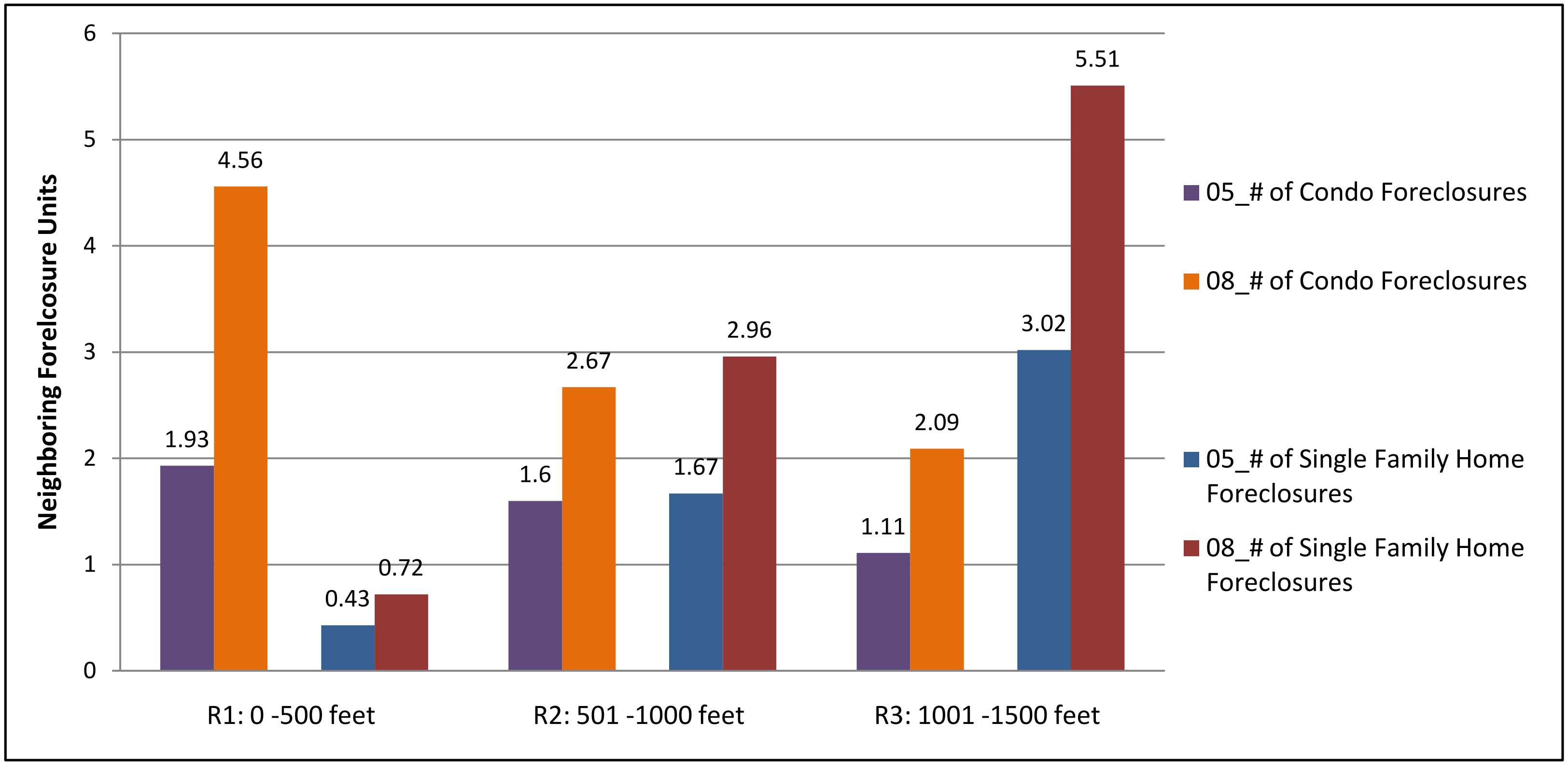

Figure 5.4. Descriptive Statistics of Neighboring Foreclosures for Condo Samples.

5.2 Results of Analysis

5.2.1 Introduction of Modeling Procedures

The modeling process undertaken in this study is broken down into eight stages. First, the OLS1_Prev_Direct model (Model 1) represents the simple study model for direct foreclosure effects as suggested in previous studies (see table on page 36 [Table 2.1]). The OLS1_Prev_Direct model explains the variation in sale price as a function both of the measures of the housing structural characteristics and of market characteristics, including foreclosure status prior to the sale transaction date. This model is used to measure simple direct foreclosure effects on the property itself due to foreclosure status.

Second, the OLS2 _Prev_Spillover model (Model 2) represents a simple previous study model to measure indirect (spillover) foreclosure effects as suggested in previous studies (see tables on pages 46-47 [Table 2.2]). The OLS2 _Prev_Spillover model focuses on the spillover effects that neighboring foreclosures might have on nearby home prices. The OLS2 model estimates only single type of indirect foreclosure effects, which neighboring single family home foreclosures or condo foreclosures are assumed to have negative effects on the same types of home prices.

Third, OLS3_Prev_Both_Effects model (Model 3) combines all variables for both direct and spillover (indirect) effects on existing housing prices. Unlike the OLS2_Prev_Spillover model (Model 2), the OLS3_Prev_Both_Effects model is used to measure separate foreclosure spillovers whether neighboring single family home foreclosures might have negative effects on condo prices or neighboring condo foreclosures might have negative effects on single family home prices. The OLS3_Prev_Both_Effects model estimates the impact of different types of foreclosure externalities on existing home prices in the single model as well as measuring the direct foreclosure effects on the property itself.

As the fourth stage, ML_Spatial_Error model (Model 4) stands for maximum likelihood spatial error model. As the fifth stage, ML_Spatial_Lag model (Model 5) stands for maximum likelihood spatial lag model. The GMM_SAR_Error model (Model 6), for the sixth stage, stands for GMM (generalized method of moments) spatial autoregressive error model. The GMM_2SLS_HAC model (Model 7) stands for the seventh stage stands for GMM (generalized method of moments) spatial two-stage least-squares model with spatial heteroskedasticity and autocorrelation consistent (HAC) estimators. Note that ML_Spatial_Error model (Model 4), ML_Spatial_Lag model (Model 5), GMM_SAR_Error model (Model 6), and GMM_2SLS_HAC_Linear model (Model 7) have the same set of explanatory variables with OLS3_Prev_Both_Effects model (Model 3) except for spatial parameters to measure both the direct and the spillover effects of neighboring foreclosures on existing housing prices. Finally, GMM_2SLS_HAC_Quadratic model (Model 8), for the eighth stage, has additional quadratic terms to measure the nonlinear effects of foreclosures. These models will be discussed and compared regarding their model performance and measurement accuracy in the following section 6.1.

This part reviews the overall empirical results, partly comparing the coefficients obtained using the eight estimation methods under consideration: Three OLSs (ordinary least squares), ML (maximum likelihood) Spatial_Lag and Error models, GMM_SAR_Error (spatial autoregressive error model via generalized method of moments) model, and two GMM_2SLS_HAC (spatial two stage least squares via generalized method of moments with a spatially lagged dependent variable and HAC standard errors) models (Model 7 and 8). Each analytical model includes four estimations: (1) for single family home samples in 2005; (2) for single family home samples in 2008; (3) for condo samples in 2005; (4) for condo samples in 2008.

Three OLS previous study models (OLS1_Prev_Direct, OLS2_Prev_Spillover, and OLS3_Prev_Both Effects) provide benchmarks for the remaining models in this study. OLS1_Prev_Direct model starts with significant variables from OLS previous study models, which are related to value models, and then add interesting variables related to foreclosure status. OLS2_Prev_Spillover model starts with significant variables from OLS previous study models, which are related to value models, and then add interesting variables for neighboring foreclosures. OLS3_Prev_Both Effects model adds interaction terms between distressed sales associated with foreclosure and renter occupancy; and between distressed sales associated with foreclosure and cash transactions to OLS2_Prev_Spillover model.

For each model specification in each data set, ordinary least squares (OLS) estimates are first obtained and then assessed for the presence of spatial autocorrelation using the Lagrange Multiplier (LM) test statistics for error and lag dependence as well as their robust forms (Anselin, 2005; Anselin, Bera, Florax, and Yoon, 1996). If the results consistently show strong evidence of positive residual spatial autocorrelation and both

LM-Lag and LM-Error are significant, the robust tests help us understand what type of spatial dependence with the spatial lag or (and) error alternative by the maximum likelihood method may be at work (Anselin and Rey, 1991).

As an advanced alternative for the spatial lag or error model, this study applies the generalized moments (GM) estimator of Kelejian and Prucha (1999), which does not require an assumption of Gaussian error terms. This study uses a robust estimation technique in the form of instrumental variables (IV) estimation, using a two-stage least-squares method (Anselin, 1988; Kelejian and Robinson, 1993; Kelejian and Prucha, 1998) as well as applying the generalized moments (GM) estimator of Kelejian and Prucha (1999). In addition, to account for the considerable remaining heteroskedasticity, this study implements a heteroskedastically robust form of spatial two-stage least-squares (2SLS), which is a special case of the recently suggested HAC estimator by Kelejian and Prucha (2007).[18]

Last, the GMM_2SLS_HAC Quadratic model (Model 8) includes the quadratic terms of neighboring foreclosures variable to measure the nonlinear effects of neighboring foreclosures like the quadratic age variable to account for the vintage effect for building age. Table 5.21 presents the analytical modeling procedures and Figure 5.5 illustrates the detailed procedures of model specification.

[18] The robust estimation methods are implemented through "Spdep" and "Sphet" packages which are programmed as custom functions in R statistical software. "Spdep" is one of several packages that deal with spatial dependence (Bivand, 2006; Bivand and Portnov, 2004). "Spdep" includes functions for creating and manipulating spatial objects (i.e., creating spatial weights matrices). "Sphet" is a package for estimating and testing a variety of spatial models with heteroskedastic innovations (Piras, 2010). The estimation procedures are based on generalized moments (GM). The results obtained with the spatial HAC estimator implemented in "Sphet" leads to more conservative coefficients than those of the heteroskedasticity correction in the "Spdep" package.

Table 5.21. Analytical Modeling Procedures.

Analytical Models (Dependent Variables: LN_SFH Price in 2005/LN_SFH Prices in 2008/LN_Condo Prices in 2005/LN_Condo Prices in 2008)									
Vectors	**Independent Variables and Definition**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
		OLS1 _Prev _Direct	**OLS2__Prev _Spillover**	**OLS3_Prev _Both Effects**	**ML_Spatial _Error**	**ML_Spatial _Lag**	**GMM_ SAR_Error**	**GMM_2SLS _HAC**	**GMM_2SLS _HAC_Quad**
Spatial Dependence	Spatial Parameter Rho_ Lag	-	-	-	-	O	-	O	O
	Spatial Parameter Lambda_ Error	-	-	-	O	-	O	-	-
Housing Physical Characteristics	Lot Size	O	O	O	O	O	O	O	O
	Age								
	The Square of Age								
	Living Area								
	(Dummy) 2 Stories or More								
	(Dummy) Garage								
	(Dummy) Pool								
Market Characteristics (Sale Trends)	(Dummy) Sold in 2nd Quarter	O	O	O	O	O	O	O	O
	(Dummy) Sold in 3rd Quarter								
	(Dummy) Sold in 4th Quarter								
Selling Factors Associated with Foreclosure Status on the Property	(Dummy) Distressed Sale: property sale that previously faced or is facing a foreclosure	O	-	O	O	O	O	O	O
	(Dummy) Renter Occupied Home	O							
	(Dummy) Interaction of Distressed Sale & Renter Occupied Home	-							
	(Dummy) Cash sale	O							
	(Dummy) Interaction of Distressed Sale & Cash Sale	-							
Neighboring Foreclosures (Linear Test)	Numbers of Neighboring Single Family Home Foreclosures in 3 rings	-	O	O	O	O	O	O	O
	Numbers of Neighboring Condo Foreclosures in 3 rings	-	O	O	O	O	O	O	O
Quadratic Foreclosures (Nonlinear Test)	The Square of Neighboring Foreclosure Numbers in Each of 3 rings	-	-	-	-	-	-	-	O

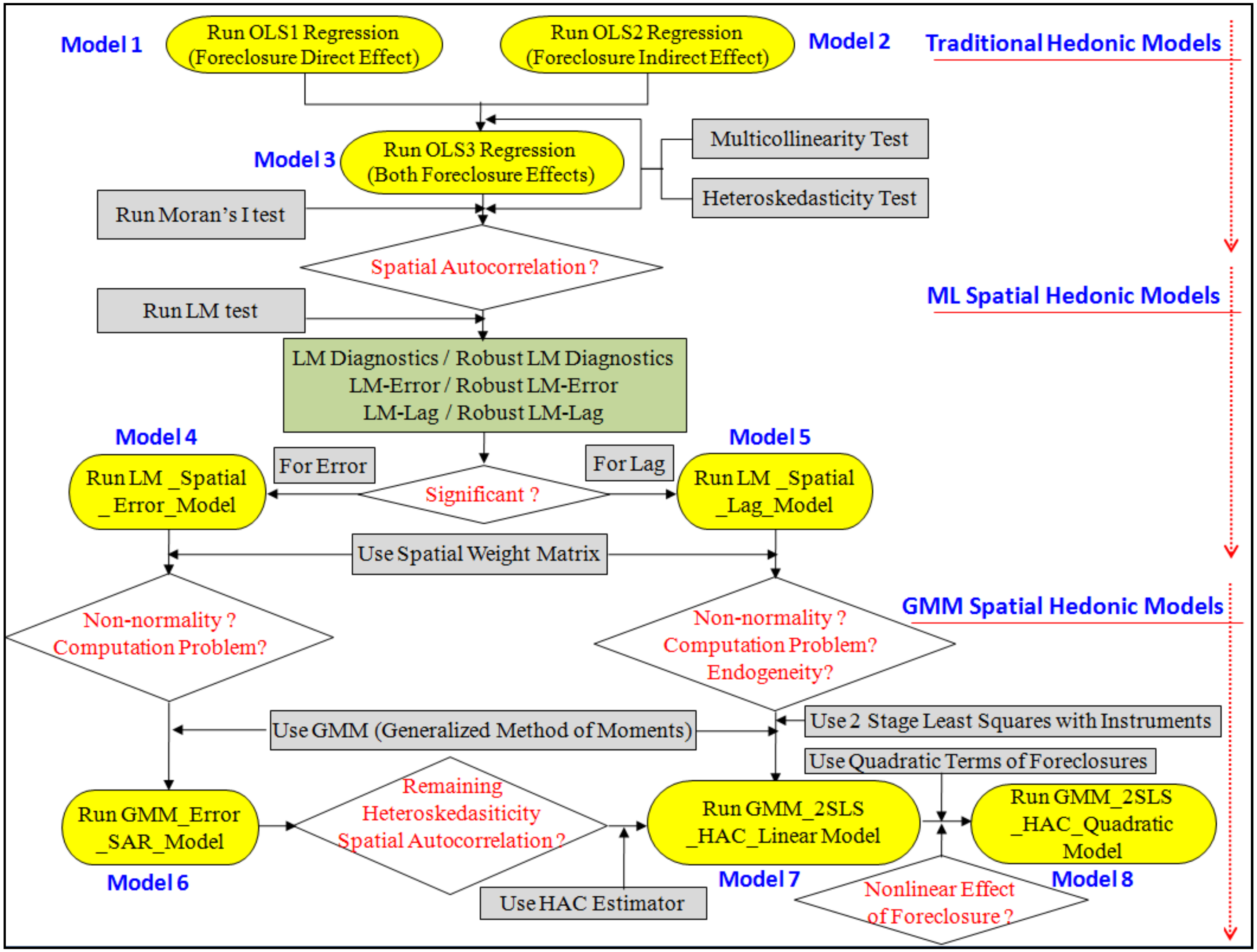

Figure 5.5. Procedure of Model Specification.

5.2.2 Estimation Results of OLS Models with Diagnostics

5.2.2.1 Estimation Results

In this part, most of the discussion on estimation results mainly focuses on the OLS3_Prev_Both_Effects model (Model 3) with full variables rather than the OLS1_Pre_Direct model (Model 1) and the OLS2_Pre_Spillover model (Model 2). The remaining results will only be discussed if there is a necessary comparison.

Regression results of the OLS3_Prev_Both_Effects model (Model 3) are shown in tables on pages 151-152 (Table 5.22 and Table 5.23) for 2005 and 2008 single family homes and tables on pages 153-154 (Table 5.24 and Table 5.25) for condo prices. Among twenty-one independent variables which were normally distributed, most independent variables were statistically significant at a 0.05 or better level of confidence for 2005 and 2008 single family homes and condos in the OLS3_Prev_Both_Effects model.

For the OLS results of single family home samples in 2005, the coefficients of physical characteristics had their expected sign and were, in general, statistically significant as is consistent with earlier findings in the literature. Housing prices increased as both lot size and living area increased. Dummy variables for a swimming pool and garage were also significant. Houses with a garage and swimming pool had a higher value. The strongest predictor of sale price is the square footage, or living area of the home. Sale prices also increased with respect to lot size except for condo samples in 2008. The only exception was story dummy, which was not found to be significant for single family home sample in 2005. For the other samples, the dummy variable for two story (or more) properties was negative, which was an interesting finding that goes counter to theoretical expectations. This interesting finding seems to suggest that buyers for single family homes preferred to one story rather than two or more stories in 2008. In the case of condo sample, the price of multi-floor semi-detached condo type was lower than that of non-multi-floor semi-detached condo type in 2005 and 2008.

As the literature suggests (see among others, Lin, Rosenblatt, and Yao, 2009; Rogers and Winter, 2009; Schuetz, Been, and Ellen, 2008), there appears to be a nonlinear relationship between age and price: prices are higher for more recently built houses but prices decreases as building age increase with nonlinearity. This is a vintage effect of age on prices that is reflected in the positive sign of the quadratic term (Anselin and Lozano-Gracia, 2008b).

As expected, estimations associated with foreclosure status were statistically significant for negative neighborhood impacts of neighboring foreclosures on home sale prices. Model fit was good overall, with an adjusted R^2 of 0.723 in the OLS3_Prev_Both Effects model (Model 3) for single family home samples in 2005. However, the Lagrangian Multiplier diagnostics for the OLS residuals indicated evidence of both error and lag spatial autocorrelation and the robust test indicated both error and lag model processes. Detailed discussion for all variables in the other samples will be included in the 5.2.7 estimation of results of vectors.

Table 5.22. Diagnostics of Muticollinearity for 2005 Single Family Home Samples: OLS3_Prev_Both Effects Model.

Independent Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	**2.530**	.020		128.731	.000		
LN_LOT SIZE	**.181**	.005	.151	39.991	.000	.621	1.611
AGE	**-.004**	.000	-.418	-39.035	.000	.077	12.936
AGE_2	**4.501E-5**	.000	.287	28.127	.000	.085	11.743
LN_LIVING AREA	**.674**	.006	.484	113.690	.000	.487	2.052
STORY (dummy)	**.004**	.002	.007	1.918	.055	.711	1.407
GARAGE (dummy)	**.052**	.002	.078	24.165	.000	.840	1.191
POOL (dummy)	**.047**	.001	.111	33.543	.000	.805	1.242
2nd_ QUARTER (dummy)	**.053**	.002	.123	32.744	.000	.630	1.586
3rd_ QUARTER (dummy)	**.090**	.002	.210	55.980	.000	.629	1.589
4th_ QUARTER (dummy)	**.110**	.002	.235	64.019	.000	.654	1.528
DISTRESSED SALE (dummy)	**-.018**	.003	-.025	-7.111	.000	.731	1.369
RENTER (dummy)	**-.024**	.002	-.044	-13.726	.000	.868	1.153
INT_D-S AND RENTER	**-.012**	.006	-.008	-2.068	.039	.643	1.555
CASH SALE (dummy)	**-.011**	.002	-.014	-4.443	.000	.883	1.132
INT_D-S AND CASH SALE	-.005	.008	-.002	-.551	.582	.762	1.313
SFH_FC_1R_C	**-.012**	.000	-.086	-25.214	.000	.760	1.316
SFH_FC_2R_C	**-.010**	.000	-.117	-31.714	.000	.655	1.526
SFH_FC_3R_C	**-.011**	.000	-.156	-42.826	.000	.668	1.498
CON_FC_1R_C	**-.003**	.002	-.006	-1.779	.075	.868	1.152
CON_FC_2R_C	**-.003**	.001	-.014	-4.022	.000	.763	1.310
CON_FC_3R_C	**-.004**	.001	-.024	-7.263	.000	.841	1.189

Dependent Variable: LN_Single Family Home Sale Prices in 2005
R^2= .728, Adjusted R^2 = .727, Durbin-Watson = 1.141

Table 5.23. Diagnostics of Muticollinearity for 2008 Single Family Home Samples: OLS3_Prev_Both Effects Model.

Independent Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	**2.291**	.040		56.944	.000		
LN_LOT SIZE	**.193**	.010	.104	19.623	.000	.586	1.707
AGE	**-.004**	.000	-.306	-19.958	.000	.071	14.147
AGE_2	**4.174E-5**	.000	.195	13.583	.000	.080	12.451
LN_LIVING AREA	**.749**	.012	.380	60.939	.000	.427	2.342
STORY (dummy)	**-.022**	.004	-.030	-5.853	.000	.631	1.585
GARAGE (dummy)	**.076**	.005	.073	16.414	.000	.845	1.184
POOL (dummy)	**.039**	.003	.062	13.659	.000	.797	1.254
2nd_ QUARTER (dummy)	-.006	.004	-.009	-1.559	.119	.517	1.935
3rd_ QUARTER (dummy)	**-.036**	.004	-.059	-9.841	.000	.465	2.148
4th_ QUARTER (dummy)	**-.073**	.004	-.115	-18.101	.000	.410	2.438
DISTRESSED SALE (dummy)	**-.095**	.003	-.168	-33.034	.000	.640	1.563
RENTER (dummy)	**-.068**	.006	-.084	-11.312	.000	.302	3.316
INT_D-S AND RENTER	**.020**	.007	.021	2.751	.006	.273	3.658
CASH SALE (dummy)	**-.075**	.005	-.108	-14.381	.000	.294	3.397
INT_D-S AND CASH SALE	**-.051**	.006	-.065	-7.923	.000	.249	4.009
SFH_FC_1R_C	**-.008**	.000	-.160	-21.095	.000	.288	3.472
SFH_FC_2R_C	**-.003**	.000	-.110	-11.741	.000	.191	5.243
SFH_FC_3R_C	**-.002**	.000	-.126	-14.688	.000	.227	4.401
CON_FC_1R_C	-.002	.002	-.005	-1.130	.259	.835	1.197
CON_FC_2R_C	**-.002**	.001	-.014	-2.790	.005	.677	1.477
CON_FC_3R_C	.000	.001	-.003	-.663	.508	.770	1.299

Dependent Variable: LN_Single Family Home Sale Prices in 2008
R^2= .728, Adjusted R^2 = .727, Durbin-Watson = .958

Table 5.24. Diagnostics of Muticollinearity for 2005 Condo Samples: OLS3_Prev_Both Effects Model.

Independent Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	**5.542**	.111		49.843	.000		
LN_LOT SIZE	**.031**	.008	.038	3.770	.000	.519	1.927
AGE	**-.020**	.001	-.422	-14.985	.000	.065	15.380
AGE_2	**.000**	.000	.124	4.503	.000	.068	14.743
LN_LIVING AREA	**.938**	.020	.519	47.375	.000	.429	2.330
STORY (dummy)	**-.132**	.010	-.128	-13.873	.000	.608	1.646
GARAGE (dummy)	-.007	.013	-.005	-.580	.562	.767	1.305
POOL (dummy)	**.249**	.052	.035	4.784	.000	.973	1.028
2nd_ QUARTER (dummy)	**.132**	.010	.121	13.114	.000	.603	1.659
3rd_ QUARTER (dummy)	**.251**	.011	.221	23.916	.000	.604	1.657
4th_ QUARTER (dummy)	**.362**	.011	.304	33.208	.000	.615	1.626
DISTRESSED SALE (dummy)	**-.049**	.022	-.020	-2.262	.024	.691	1.447
RENTER (dummy)	**-.049**	.009	-.043	-5.520	.000	.838	1.194
INT_D-S AND RENTER	-.020	.043	-.004	-.456	.648	.662	1.511
CASH SALE (dummy)	**-.035**	.011	-.025	-3.367	.001	.913	1.096
INT_D-S AND CASH SALE	-.062	.053	-.010	-1.181	.238	.751	1.332
SFH_FC_1R_C	.000	.004	-.002	-.204	.839	.795	1.258
SFH_FC_2R_C	**-.018**	.002	-.084	-8.483	.000	.526	1.901
SFH_FC_3R_C	**-.023**	.001	-.160	-16.041	.000	.515	1.942
CON_FC_1R_C	**-.029**	.002	-.142	-15.376	.000	.604	1.657
CON_FC_2R_C	**-.012**	.002	-.063	-6.209	.000	.494	2.024
CON_FC_3R_C	**-.027**	.002	-.120	-13.776	.000	.684	1.463

Dependent Variable: LN_Condo Sale Prices in 2005
R^2= .682, Adjusted R^2 = .680, Durbin-Watson = 1.297

Table 5.25. Diagnostics of Muticollinearity for 2008 Condo Samples: OLS3_Prev_Both Effects Model.

Independent Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	**6.092**	.195		31.228	.000		
LN_LOT SIZE	-.023	.018	-.024	-1.244	.214	.458	2.183
AGE	**-.021**	.002	-.479	-10.915	.000	.090	<u>11.092</u>
AGE_2	**.000**	.000	.181	4.201	.000	.094	<u>10.659</u>
LN_LIVING AREA	**.942**	.037	.540	25.212	.000	.379	2.636
STORY (dummy)	**-.221**	.020	-.188	-11.280	.000	.624	1.604
GARAGE (dummy)	**.106**	.021	.073	5.001	.000	.811	1.233
POOL (dummy)	**.279**	.083	.046	3.362	.001	.947	1.056
2nd_ QUARTER (dummy)	-.004	.019	-.003	-.209	.834	.663	1.509
3rd_ QUARTER (dummy)	-.026	.021	-.020	-1.207	.227	.604	1.655
4th_ QUARTER (dummy)	-.038	.024	-.029	-1.571	.116	.509	1.964
DISTRESSED SALE (dummy)	**-.227**	.021	-.190	-10.654	.000	.545	1.836
RENTER (dummy)	.013	.020	.011	.663	.507	.664	1.507
INT_D-S AND RENTER	**-.108**	.039	-.050	-2.777	.006	.540	1.853
CASH SALE (dummy)	**-.062**	.020	-.051	-3.094	.002	.629	1.590
INT_D-S AND CASH SALE	**-.175**	.037	-.097	-4.769	.000	.423	2.361
SFH_FC_1R_C	**-.013**	.006	-.034	-2.006	.045	.619	1.616
SFH_FC_2R_C	**-.007**	.003	-.047	-2.112	.035	.351	2.851
SFH_FC_3R_C	**-.015**	.002	-.181	-8.713	.000	.403	2.481
CON_FC_1R_C	**-.012**	.002	-.126	-7.574	.000	.628	1.592
CON_FC_2R_C	-.003	.002	-.024	-1.574	.116	.733	1.365
CON_FC_3R_C	**-.008**	.002	-.052	-3.468	.001	.775	1.290

Dependent Variable: LN_Condo Sale Prices in 2008
R^2= .655, Adjusted R^2 = .652, Durbin-Watson = 1.392

5.2.2.2 Diagnostics

Data for this study consists of four cross-sectional independent observations. Given the nature of the data, it is necessary to test for four traditional assumptions: multicollinearity (highly correlated independent variables), heteroskedasticity (non-constant variance), serial autocorrelation (observations auto correlated together in time), and normality of the errors. Biased estimates of standard errors, inaccurate predicted values and inefficient least squares estimates may result from disregarding the presence of any of these problems. To test these assumptions of the model, ordinary least squares statistical procedures were conducted using both GeoDa and SPSS software.

Multicollinearity is the inter correlation between the explanatory variables included in the regression model. It was tested using SPSS statistic software. As a rule of thumb, variance inflation factor (VIF) values which are larger than 10 and tolerance statistics which are less than .1 are considered to be problematic (Fox, 1991). Therefore, all independent variables except age and square of age do not seem to be engaged in any significant multicollinearity problem in all these models. Interaction terms may not be a problem for multicollinearity unless the colinearity is so high that it disrupts the computer algorithm designed to isolate the relevant standard errors (Jaccard and Turrisi, 2003).

Diagnostics for heteroskedasticity is for the test of the variance of the error term as BLUE (Best Linear Unbiased Estimator). Heteroskedasticity was tested using the Lagrange Multiplier (LM) test developed by Breusch and Pagan (Breusch-Pagan test) and the Koenker-Bassett test for heteroskedasticity was supplemented through GeoDa software (Anselin, 2005). Heteroskedasticity is the situation where the random regression error does not have a constant variance over all observations The Breusch-Pagan test and Koenker-Bassett test assume homoskedastic errors. Results from them rejected the null hypothesis of homoskedastic disturbance terms in spatial cross-sectional data for each sample (see the Breusch-Pagan test and Koenker-Bassett test rows in Tables 5.26 through 5.29). The characteristics of the spatial pattern in the data and the cross-sectional data set imply that the assumptions of homoskedastic and uncorrelated error terms may not be realistic. However, this is not necessarily a surprise because the error variance could well be affected by the spatial dependence in the data.

The Jarque-Bera test is used to examine the normality of the distribution of the errors. The low probability of the test score indicates non-normal distribution of the error terms. Results from the Jarque-Bera test for the OLS3_Prev_Both Effects model (Model 3) indicated that the null hypothesis of homoskedastic disturbance terms (normality of the residuals) is statistically rejected. However, it is not a big problem due to the large data sets.

Serial autocorrelation was tested using the Durbin-Watson test using SPSS statistic software. Results from the test indicated that serial autocorrelation was not a problem in the data for all data sets (see the bottom notes in tables on pages 151-154 [Tables 5. 22 through 5.25]). As a rule of thumb, the value which is close to 2 indicates no serial autocorrelation (Norušis, 2005). This OLS3_Prev_Both Effects model (Model 3) is not considered to be problematic for serial autocorrelation.

Table 5.26. OLS Regression Diagnostics for 2005 Single Family Home Samples.

Regression Diagnostics (OLS_Models)		OLS1_Prev _Direct	OLS2_Prev _Spillover	OLS3_Prev _Both_Effects
Test on Normality of Errors				
	Jarque-Bera Test	468.3***	874.8***	880.6***
Diagnostics for Heteroskedasticity				
	Breusch-Pagan Test	2791.8***	2590.5***	2821.5***
	Koenker-Bassett Test	2225.7***	1833.7***	1995.5***

Notes. N = 30,815. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.
OLS is Ordinary Least Squares.
Prev_Direct denotes simple previous study model for direct foreclosure effects on existing home prices.
Prev_Spillover denotes simple previous study model for indirect foreclosure effects on existing home prices.
Prev_Both_Effects denotes the model for both direct and indirect foreclosure effects on existing home prices.

Table 5.27. OLS Regression Diagnostics for 2008 Single Family Home Samples.

Regression Diagnostics (OLS_Models)		OLS1_Prev _Direct	OLS2_Prev _Spillover	OLS3_Prev _Both_Effects
Test on Normality of Errors				
	Jarque-Bera Test	693.8***	1399.4***	2919.2***
Diagnostics for Heteroskedasticity				
	Breusch-Pagan Test	1396.6***	1920.7***	2391.6***
	Koenker-Bassett Test	890.6***	1096.6***	1114.3***

Notes. N = 12,885. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.
OLS is Ordinary Least Squares.
Prev_Direct denotes simple previous study model for direct foreclosure effects on existing home prices.
Prev_Spillover denotes simple previous study model for indirect foreclosure effects on existing home prices.
Prev_Both_Effects denotes the model for both direct and indirect foreclosure effects on existing home prices.

Table 5.28. OLS Regression Diagnostics for 2005 Condo Samples.

Regression Diagnostics (OLS_Models)		**OLS1_Prev _Direct**	**OLS2_Prev _Spillover**	**OLS3_Prev _Both_Effects**
Test on Normality of Errors				
	Jarque-Bera Test	489.5***	766.4***	1149.6***
Diagnostics for Heteroskedasticity				
	Breusch-Pagan Test	656.6***	580.5***	863.2***
	Koenker-Bassett Test	411.4***	314.9***	428.1***

Notes. N = 6,205. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1.
OLS is Ordinary Least Squares.
Prev_Direct denotes simple previous study model for direct foreclosure effects on existing home prices.
Prev_Spillover denotes simple previous study model for indirect foreclosure effects on existing home prices.
Prev_Both_Effects denotes the model for both direct and indirect foreclosure effect on existing home prices.

Table 5.29. OLS Regression Diagnostics for 2008 Condo Samples.

Regression Diagnostics (OLS_Models)		**OLS1_Prev _Direct**	**OLS2_Prev _Spillover**	**OLS3_Prev _Both_Effects**
Test on Normality of Errors				
	Jarque-Bera Test	98.6***	91.2***	80.5***
Diagnostics for Heteroskedasticity				
	Breusch-Pagan Test	239.0***	160.6***	257.3***
	Koenker-Bassett Test	166.4***	115.5***	180.3***

Notes. N = 2,003. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1.
OLS is Ordinary Least Squares.
Prev_Direct denotes simple previous study model for direct foreclosure effects on existing home prices.
Prev_Spillover denotes simple previous study model for indirect foreclosure effects on existing home prices.
Prev_Both_Effects denotes the model for both direct and indirect foreclosure effect on existing home prices.

5.2.3 Tests for Spatial Dependence and Constructing a Spatial Weight Matrix

5.2.3.1 Tests for Spatial Dependence

Spatial autocorrelation, or spatial dependence, is the situation where the dependent variable or error term at each location is correlated with observations of the dependent variable or values for the error term at other locations. Due to the given characteristic of cross sectional housing data, spatial autocorrelation must be tested.

The use of a spatial matrix is for the computation of various standardization coefficients used in tests for spatial autocorrelation, such as the Moran's I and the Lagrange multiplier (LM) tests. The best-known and most widely used test statistic for spatial correlation is Moran’s I. In the hedonic price model, this statistic checks for similarities among housing prices and the spatial relationships of data in the spatial weight matrix. Spatial autocorrelation is calculated using spatial statistics software R or GeoDa for this study.

Hypothesis tests for the existence of significant autocorrelation among values at neighboring points was carried out through Moran's I. Based on Moran's I test, results presented in Table 5.30 and Table 5.31 indicated that the value was estimated by 0.157 for 2005 single family home data, 0.099 for 2008 single family home data, 0.299 for 2005 condo data, and 0.054 for 2008 condo data respectively. They were highly significant at a 0.001 level of confidence.

Spatial autocorrelation was also tested using the Lagrange Multiplier (LM) test. The Lagrange Multiplier (LM) test is based on the least-squares residuals and calculations involving the spatial weight matrix (Anselin, 1988). The presence of autocorrelation is tested with the Lagrange Multiplier (LM) test. The null hypothesis is the absence of spatial dependence. If none of the tests are significant, then one can choose the OLS model. The resulting LM statistic for OLS3_Prev_Both_Effects model (Model 3) had strong evidence of very significant positive residual spatial autocorrelation supported by both LM-Error and LM-Lag test statistics (see Table 5.30 and Table 5.31). The LM test was also used for selection of the type of spatial model that best fits the data through robust form (see figure on page 105 [Figure 4.9] for the selection process). In empirical practice, the need for such a specification follows from the result of model diagnostics (Anselin, 2006). The results shown in Table 5.30 and Table 5.31 indicated that LM-Error, LM-Lag, and both robust forms were significant at a 0.1 or better level of confidence.

Table 5.30. Diagnostics of Spatial Dependence for Single Family Home Samples.

	Contiguity-Based Spatial Weight (Test: Rook-Based Contiguity)		**Distance-Based Spatial Weight** (Test: k =10-Nearest Neighbors)	
Diagnostics	**Housing Boom _2005**	**Housing Bust _2008**	**Housing Boom _2005**	**Housing Bust _2008**
Moran's *I*	0.157***	0.0988***	0.149***	0.0943***
LM_Lag[1]	3210.1***	977.7***	4279.7***	1258.9***
R_LM_lag[2]	1336.2***	617.4***	1660.2***	723.49***
LM_Error[3]	2218.7***	366.3***	3859.90***	641.07***
R_LM_Error[4]	344.8***	6.00***	1240.75***	105.63***

Notes. Moran's *I* is the Moran's test adapted to OLS residuals (Cliff and Ord 1981). 1. LM_Lag is the Lagrange Multiplier test for spatially lagged endogenous variables and 2. R_LM_Lag is its robust version. 3. LM_Error is the Lagrange Multiplier test for residual spatial autocorrelation and 4. R_ LM_Error is its robust version (Anselin, 2005). Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

Table 5.31. Diagnostics of Spatial Dependence for Condo Samples.

	Contiguity-Based Spatial Weights (Test: Rook-Based Contiguity)		Distance-Based Spatial Weight (Test: k =10-Nearest Neighbors)	
Diagnostics	**Housing Boom _2005**	**Housing Bust _2008**	**Housing Boom _2005**	**Housing Bust _2008**
Moran's *I*	0.299***	0.054***	0.292***	0.377***
LM_Lag[1]	917.5***	18.04***	1149.8***	20.85***
R_LM_lag[2]	51.80***	4.02*	44.78***	6.89**
LM_Error[3]	1605.4***	16.77***	3188.7***	17.07***
R_LM_Error[4]	739.6***	2.75·	2083.7***	3.10·

Notes. Moran's *I* is the Moran's test adapted to OLS residuals (Cliff and Ord 1981). 1. LM_Lag is the Lagrange Multiplier test for spatially lagged endogenous variables and 2. R_LM_Lag is its robust version. 3. LM_Error is the Lagrange Multiplier test for residual spatial autocorrelation and 4. R_ LM_Error is its robust version (Anselin, 2005). Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

5.2.3.2 Constructing a Spatial Weight Matrix

Another use of spatial weight matrix is for computation of spatial parameters coefficients such as rho (ρ) and lambda (λ). Several types of spatial structures may be used to find the best fit for the spatial data characteristics: contiguity through a common boundary, nearest neighbors, and distance-based functions. In practice, most empirical works use the standard spatial lag and spatial error specifications with spatial weights derived from contiguity or nearest neighbor criteria (Anselin and Lozano-Gracia, 2008b). However, there is little formal guidance in the choice of the correct spatial weights (Anselin and Le Gallo, 2006).

In this study, two common spatial matrices are considered. First, a simple contiguity (common boundaries) weights matrix is used between the locations of sales transactions by using Thiessen polygons to define neighboring sales; the space is partitioned into polygons to specify neighbors. This effectively turns the spatial representation of the sample from points into polygons (Anselin and Le Gallo, 2006). The neighboring observations are then used to construct a spatial weight matrix. In this study, the contiguity matrix for each data set contained an average of 6 neighbors for each location as the criterion to define neighbors.

As another matrix for this study, the *k*-nearest neighbor matrix is supplemented based on a nearest neighbor relationship among the locations as another popular criterion to define neighbors. When the transactions distribution is spatially diversified with large sets of transactions, *k*-nearest neighbors' matrices are constructed to capture the same number of nearest neighbors' impacts on the given observation. It is parallel to the idea that most real estate specialists or home buyers choose a certain number of nearby properties as comparables. In the recent empirical section,[19] the *k*-nearest neighbor matrix uses 8 to 10 nearest neighbors. This study used 10-nearest neighbors' matrices for the GMM models as suggested by previous studies (Kelejian and Prucha, 1998, 1999).

[19] The robust estimation methods are implemented through the "Spdep" and "Sphet" packages, which are programmed as custom functions in R statistical software.

5.2.4 Estimation Results of ML Spatial Lag and Error Models with Diagnostics

5.2.4.1 Estimation Results

The hedonic models were estimated using ordinary least squares (OLS) regression procedures. Next, statistical tests were conducted to verify that model assumptions held using results from the OLS regression. Hedonic models are also estimated using maximum likelihood (ML) spatial estimation procedures as an alternative since OLS estimation is either biased or inefficient (Anselin, 1988). Measurements of fit were estimated for the ML spatial lag and error model and compared to those of the OLS models. The estimates of the Spatial Lag and Error hedonic model by maximum likelihood were given in the columns ML Spatial Lag and Error model in tables on pages 173-180 (Tables 5.32 through 5.34). Most coefficients were strongly significant, including a significant positive coefficient for spatial lags or errors.

Comparing the traditional hedonic price function of the OLS models, the ML spatial hedonic models (Spatial Lag and Error models) used the same set of explanatory variables. The improvement of the ML spatial lag and error model can be attributed to the use of a spatial parameter that is ignored by the traditional OLS models. Most coefficients, except for a few variables in the ML Spatial Lag and Error model, were significant with the expected signs similar to the OLS results. The ML Spatial Lag and Error model, as indicated by the spatial diagnostics, included a term to account for the spatial parameter, lambda (λ) for the ML Spatial Error model and rho (ρ) for the ML Spatial Lag model (Model 5). These variables were statistically significant, which were expected.

One of our primary interests is to obtain unbiased estimates of the effects of foreclosures on existing housing prices. As discussed earlier, omission of spatial dependence, whether lagged dependences or error terms, from the price equation might result in a biased or overstated negative foreclosure effect. Comparing model OLS1_Direct_Effects model (Model 1) with ML_Spatial_Error model (Model 4), direct foreclosure effect (price discount) was reduced from -14.96% for 2008 single family home samples in the OLS1_Prev_Direct (Model 1) to about -8.91% for 2008 single family home samples in the ML_Spatial_Error model (Model 4) (see the rows of DISTRESSED SALE in table on page 175 [Table 5.33]).

The estimates of the ML Spatial Lag model (Model 5) also indicated that the misspecified models based on OLS would overestimate the size of discounts associated with foreclosure when spatial dependence was not controlled for. The rows of DISTRESSED SALE in table on page 175 (Table 5.33) indicated that controlling for spatial lag autocorrelation reduced the direct foreclosure effects (for instance, -5.23% discount for 2008 single family home samples) in the ML Spatial Lag model (Model 5), compared to the results (for instance, -9.08% discount for 2008 single family home samples) of OLS3_Prev_Both_Effect models (Model 3). These results implied that estimates of foreclosure discount reported by previous OLS studies were higher than the foreclosure discount measured by the ML Spatial Error model (Model 4) or the Lag model (Model 5). One can attribute the overestimated difference to the spatial effect of housing prices in spatial hedonic models.

5.2.4.2 Diagnostics

Based on Moran's I test and the LM specification test, both the ML Spatial Lag and Error model were tested.

Tables on pages 173-180 (Tables 5.32 through 5.34) indicated that the spatial parameter lambda (λ) coefficients in the ML Spatial Error model were estimated by 0.3872 for 2005 single family home samples, 0.2616 for 2008 single family home samples, 0.5359 for 2005 condo samples, and 0.1449 for 2008 condo samples, respectively.

Tables on pages 173-180 (Tables 5.32 through 5.34) indicated that the spatial parameter rho (ρ) coefficients in the ML Spatial Lag model (Model 5) were estimated by 0.2511 for 2005 single family home samples, 0.2190 for 2008 single family home samples, 0.3157 for 2005 condo samples, and 0.0990 for 2008 condo samples, respectively. They were highly significant at a 0.001 level of confidence. This indicated that home sale prices had a stronger spatial dependence during a housing boom year (2005) than in a housing bust year (2008) since sale transactions actively occurred in a strong housing market and a housing boom year (2005).

As a result, the OLS's goodness-of-fit, R^2, which is based on the decomposition of the total sum of squares, is no longer applicable. Likelihood function based goodness-of-fit statistics, mainly log-likelihood and Akaike Information Criterion (AIC), are used to measure the spatial model's goodness-of-fit (Anselin, 2005). Moreover, these statistics are directly comparable to their OLS estimator. The model with the highest LIK or lowest AIC is considered the better model (Anselin, 2005).

When the values of the ML Spatial Error model were compared to those for the OLS3_Prev_Both_Effects model (Model 3) for the 2005 single family home prices in table on page 173 (Table 5.32), it indicated an increase in the log-likelihood from 27080.2 (for the OLS3_Prev_Both_Effects model) to 28086.2 (for the ML Spatial Error model). Compensating for the improved fit for the added variable (the the spatial lambda coefficient), the AIC (from -54116.4 to -56124.0) decreased relative to that of OLS3_Prev_Both_Effects model (Model 3), suggesting an improvement of fit for the spatial error specification.

When the values of the ML Spatial Lag model (Model 5) were compared to those for OLS3_Prev_Both_Effects model (Model 3) for the 2005 single family home price in table on page 173 (Table 5.32), it indicated an increase in the log-likelihood from 27080.2 (for the OLS3_Prev_Both_Effects model) to 28451.3 (for the ML Spatial Lag model). Compensating for the improved fit for the added variable (the spatial rho coefficient), the AIC (from -54116.4 to -56855.0) decreased relative to that of OLS3_Prev_Both_Effects model (Model 3), suggesting an improvement of fit for the spatial lag specification. Therefore, the overall performance of the ML Spatial Error model (Model 4) or lag model (Model 5) was determined by the AIC, which gives some insight into the improvement of the model specification. It concludes that controlling spatial autocorrelation improves the model performance.

The question is which of the two models is better? It is not so clear theoretically but the model with the highest log likelihood or lowest AIC is considered the better model (Anselin, 1992). In this case, the spatial error model has greater log likelihood or the lower AIC values than the spatial lag model.

5.2.5 Estimation Results of GMM_SAR_Error Models

The GMM_SAR model is a spatially autoregressive error model estimated via the generalized method of moments (GMM). While the maximum likelihood (ML) model is the best available estimator within the classical statistics approach, this dependence on the probability distribution can become a weakness for two main reasons: computational infeasibility for large data set and restrictions on the normal distribution of the data (Bell, 2000).

Using an actual micro-level housing data set for this study, the maximum likelihood estimator was not computationally feasible in this case involving large-sized samples.[20] On the other hand, the GM approach allowed for introducing more flexibility into the structure of the spatial weight matrix quite easily. In this study, the generalized moments (GM) estimator developed by Kelejian and Prucha (1998, 1999) is presented, which is computationally simple irrespective of the sample size. The maximum-likelihood estimations with the generalized-moments (GM) estimations are also compared.

However, the value of the lambda (λ) of the GMM_ SAR_Error model is little different with the value of the lambda (λ) of the ML spatial error model estimate since different weight matrices for the two models are used as mentioned previously. Note that

[20] With the 10-nearest neighbors' matrices for the ML Spatial Lag and Error Model, this case fails to obtain the estimation for 2005 single family home samples due to computation problems. So, ML Spatial hedonic models are based on contiguity based matrices (rook based contiguity).

the ML Spatial Error model only contains results for contiguity based spatial weights since computation for this model is only available on contiguity spatial weights (rook-based contiguity) in R or GeoDa software. All three GMM models are given in 10-nearest neighbors' weights based on previous studies.[21]

The estimates of the spatial error model by maximum likelihood (ML) and the generalized method of moments (GMM) are comparable. It appears that the spatial econometric estimates confirm the effects of the significant explanatory variables and that a significant positive spatial autocorrelation of the errors is found. For example, the lambda (λ) from the ML Spatial Error model (Model 4) for single family home samples in 2005 was 0.3872; from GMM_SAR_Error model (Model 6) was 0.4411 (see the rows of Spatial Parameter_ Lambda in table on page 173 [Table 5.32]).

The spatial autocorrelation parameter lambda (λ) was positive in both the ML Spatial Error model and GMM_SAR_Error model (Model 6). However, since the lambda (λ) of GMM estimation does not depend on the assumption of normally distributed error terms, it is not possible to conduct a t-test of the significance of this coefficient. Thus, it includes "(non-parametric)" in place of the t-statistics for lambda (λ) in tables on pages 173-180 (Tables 5.32 through 5.35, see the rows of Spatial Parameter_ Lambda for the GMM_SAR_Error model [Model 6]). However, note that it relies on the results of the specification tests for evidence of the presence of spatial autocorrelation through an LM test like the ML Spatial Error model (Model 4).

The GMM_SAR_Error model (Model 6) which was carried out for the spatial

[21] See the previous studies of Kelejian and Prucha (1998, 1999) for the detailed discussion.

error model estimation had the expected sign and the significance of the estimated parameters did not change much compared to the results of the ML Spatial Error model (Model 4). Values and inferences of the GMM_SAR_Error model estimation were close to those of the ML error model estimation with the error correction (see tables on pages 173-180 [Tables 5.32 through 5.35]).

When maximum likelihood (ML) approach was used as the estimation method, a useful alternative measure was the value of the maximized log-likelihood. It can possibly be adjusted for the number of parameters in the model in an Akaike Information Criterion (AIC) or other information criterion. However, there is no corresponding measure for the models estimated by GMM. Thus, the rows of diagnostics for GMM models have blanks in tables on pages 173-180 (Tables 5.32 through 5.35).

5.2.6 Estimation Results of GMM_2SLS_HAC Models

In all models, strong evidence of spatial autocorrelation was found and all OLS models tested were significant for heteroskedasticity using a Breusch-Pagan test and Koenker-Bassett test. However, one form of dependence arises when the selling price of a house is affected by selling prices of neighboring units. The source of potential bias is the endogenous spatially lagged price variable which accounts for spatial dependence. That is, if error terms associated with houses i and j are correlated, the price of house i, which is the lagged explanatory variable for the price of house j, will be correlated with the error term in the price of the house i equation. Thus, the estimated coefficient of the lagged price variable will be biased. When endogeneity violates assumptions of ordinary least squares (OLS) regression, two-stage least-squares (2SLS) regression using instrumental variables is the most common suggested alternative (Anselin, 1988; Kelejian and Prucha, 1998, 1999, 2004; Lee, 2003, 2006). New endogenous variables in 2SLS replace the problematic causal variables. In this research, the endogeneity of the spatially lagged dependent variable (weighted neighborhood prices) is accounted for by using instruments of the spatially lagged exogenous variables (weighted neighborhood housing characteristics) for the two-stage least-squares (2SLS) regression.[22]

In order to account for the remaining spatial error autocorrelation and heteroskedasticity, the most appropriate specification is using a Heteroskedasticity and Spatial Autocorrelation Consistent (HAC) estimator of the standard errors. In practice, classical standard errors seriously underestimate the imprecision of the estimates in the presence of remaining spatial correlation and spatial heterogeneity (Anselin and Lozano-Gracia, 2008b). Therefore, the results of the GMM_2SLS_HAC models assess the effect of addressing endogeneity and spatial dependence in combination.

Last, this study suggests an estimation procedure for cross-sectional spatial models that contain a spatially lagged dependent variable and control for a spatially autocorrelated error terms. This study gives empirical results for a large micro-level sample with modest assumptions regarding the distribution of the disturbances through general method of moments (GMM).

[22] As an additional instrument to address the endogenous foreclosure variable, ideally, such appropriate instruments should be correlated with influences of foreclosures but that should be uncorrelated with house prices. But I was not able to find such an instrument without detailed household information or loan information data.

The estimates of the OLS models and ML Spatial Error (Model 4) or Lag model (Model 5) assume normality. But the GMM_2SLS (the spatial two-stage least-squares estimate via GMM), based on the use of the spatially lagged explanatory variables as instruments, were robust to non-normality and consistent, but not necessarily efficient (Lee, 2003). In the results of tables on pages 173-180 (Tables 5.32 through 5.35, see the row of Spatial Parameter_ Lambda for GMM_SAR_Error model [Model 6] and Rho for GMM_2SLS_HAC models [Models 7 and 8]), the GMM_SAR_Error model indicated a strong positive and significant spatial autoregressive coefficient of disturbance terms, suggesting significant spatial autocorrelation of error terms. On the other hand, the GMM_2SLS_HAC models indicated a positive and significant spatial autoregressive coefficient of lagged terms, suggesting a spatial similarity in given individual housing prices and neighboring home selling prices. To illustrate, the estimation rho (ρ) was positive and significant, with a coefficient of 0.27, indicating that a 1% increase in the weighted neighboring single family home selling price led to a rise in the sale price of given single family housing sample by 0.27% in 2005 (see table on page 173 [Table 5.32], the rows of Spatial Parameter_ Rho for GMM_2SLS_HAC_Quadratic model [Model 8]).

The results of the generalized moments of spatial model estimation are presented in the column labeled "GMM"s of tables on pages 173-180 (Tables 5.32 through 5.35). For most variables, the parameter estimates and statistical significance were little different between the GMM_SAR_Error estimates (Model 6) and GMM_2SLS_HAC estimates (Models 7 and 8). In terms of study significance, the main changes were obtained for the coefficient (DISTRESSED SALE) of direct foreclosure effect and indirect foreclosure effect (SFH_FC_R_C or CON_FC_R_C), which became slightly smaller in magnitude and slightly less significant at a 0.05 or better level of confidence for the two GMM_2SLS_HAC models. More importantly, the magnitude of the coefficient of the direct foreclosure effect for the GMM_2SLS_HAC was much smaller at a significance of a 5% or better level of confidence because the GMM 2SLS_HAC_Quadratic model was able to account for some missing variables via instruments (the characteristics of neighboring housing units). It dropped to as much as half of what it was for the OLS models for single family home samples in 2008. To illustrate, the OLS3_Prev_Both_Effects model (Model 3) implied a -8.91% discount (see the row of DISTRESSED SALE in table on page 175 [Table 5.33]). When correcting endogeneity and spatial autocorrelation, the foreclosure discount was about -3.42% in the GMM_2SLS_HAC_Quadratic model (Model 8).

Moreover, OLS models and ML spatial error or lag models (Models 4 or 5) still suggest a high degree of heteroskedasticity. To take this into account, the GMM_2SLS_HAC_model estimate used a HAC correction estimator. Relative to the OLS estimates, all coefficients associated with foreclosure variables were smaller in absolute values. This suggests that the GMM_2SLS_HAC models (Models 7 and 8), controlling for the presence of three spatial effects (spatial autocorrelation, endogeneity, and spatial heteroskedasticity), would tend to deflate the values of the variables associated with foreclosure compared to OLS estimates that ignore the spatial effects.

Table 5.32. Estimated Marginal Impacts of Foreclosures on Existing Single Family Home Prices in a 2005 Housing Boom Year.

Vector	Independent Variable	The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Price in 2005)							
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
		OLS1 _Prev _Direct	**OLS2_Prev _Spillover**	**OLS3_Prev _Both Effects**	**ML_Spatial _Error**	**ML_Spatial _Lag**	**GMM_ Error _SAR**	**GMM_2SLS _HAC**	**GMM_2SLS _HAC_Quad**
Spatial Weight Matrix (Lag)	W_LN_PRICE_ Spatial Parameter_ Rho for lag	-	-	-	-	2.511E-01*** (57.004)	-	2.87E-01*** (44.9978)	2.73E-01*** (43.8928)
Spatial Weight Matrix (Error)	Spatial Parameter_ Lambda for error	-	-	-	3.872E-01*** (52.093)	-	4.411E-01 (non-parametric)	-	-
Housing Physical Characteristics	LN_LOT SIZE	2.24E-01*** (44.765)	1.82E-01*** (39.785)	1.81E-01*** (39.991)	1.87E-01*** (42.720)	1.81E-01*** (43.158)	1.88E-01*** (43.128)	1.82E-01*** (32.481)	1.74E-01*** (31.664)
	AGE	-6.72E-03*** (-56.846)	-4.45E-03*** (-40.425)	-4.30E-03*** (-39.035)	-4.45E-03*** (-39.185)	-4.48E-03*** (-43.208)	-4.47E-03*** (-39.181)	-4.52E-03*** (-34.774)	-4.27E-03*** (-33.631)
	AGE_2	8.07E-05*** (46.909)	4.63E-05*** (28.840)	4.50E-05*** (28.127)	4.77E-05*** (29.019)	5.23E-05*** (34.626)	4.79E-05*** (29.051)	5.36E-05*** (25.474)	5.04E-05*** (24.475)
	LN_LIVING AREA	7.71E-01*** (118.947)	6.78E-01*** (113.549)	6.74E-01*** (113.690)	6.53E-01*** (113.440)	6.44E-01*** (119.127)	6.52E-01*** (113.700)	6.41E-01*** (94.612)	6.23E-01*** (93.682)
	STORY_dummy	2.22E-03 (1.012)	4.11E-03* (2.077)	3.77E-03• (1.918)	1.69E-03 (0.898)	2.42E-03* (2.211)	1.29E-03 (0.691)	2.16E-03 (1.216)	1.04E-03 (0.591)
	GARAGE_dummy	6.20E-02*** (25.943)	5.31E-02*** (24.538)	5.19E-02*** (24.165)	5.05E-02*** (24.812)	4.94E-02*** (25.127)	5.03E-02*** (24.823)	4.87E-02*** (20.536)	4.82E-02*** (20.730)
	POOL_dummy	5.42E-02*** (34.997)	4.84E-02*** (34.554)	4.67E-02*** (33.543)	4.36E-02*** (33.071)	4.20E-02*** (31.880)	4.29E-02*** (32.613)	4.13E-02*** (29.594)	4.09E-02*** (30.118)
Market Characteristics	2nd QUARTER _dummy	5.20E-02*** (28.987)	5.21E-02*** (32.057)	5.28E-02*** (32.744)	5.26E-02*** (34.658)	5.29E-02*** (34.566)	5.24E-02*** (34.672)	5.27E-02*** (34.241)	5.35E-02*** (35.607)
	3rd QUARTER _dummy	8.66E-02*** (48.099)	8.96E-02*** (55.003)	9.05E-02*** (55.980)	9.21E-02*** (60.439)	9.11E-02*** (59.344)	9.19E-02*** (60.598)	9.11E-02*** (59.888)	9.32E-02*** (62.509)
	4th QUARTER _dummy	1.02E-01*** (53.319)	1.08E-01*** (62.520)	1.10E-01*** (64.019)	1.11E-01*** (68.246)	1.10E-01*** (67.310)	1.10E-01*** (68.320)	1.10E-01*** (67.903)	1.12E-01*** (70.600)
Selling Factors related to Foreclosure Status on the Property	DISTRESSED SALE _dummy	-5.06E-02*** (-20.276)	-	-1.85E-02*** (-7.111)	-1.20E-02 (-0.841)	3.55E-05 (NA)	-2.59E-04 (-0.098)	-2.42E-03 (-0.955)	-2.19E-03 (-0.897)
	RENTER _dummy	-2.27E-02*** (-12.477)	-	-2.36E-02*** (-13.726)	-2.20E-02*** (-13.612)	-2.19E-02*** (-13.514)	-2.21E-02*** (-13.707)	-2.21E-02*** (-13.416)	-2.14E-02*** (-13.220)
	INT_D-S AND RENTER	-	-	-1.16E-02* (-2.068)	-9.83E-03• (-1.865)	-1.19E-02* (-2.114)	-1.09E-02* (-2.068)	-1.18E-02* (-2.173)	-1.09E-02* (-2.059)
	CASH SALE _dummy	-1.10E-03 (-0.424)	-	-1.08E-02*** (-4.443)	-1.40E-02*** (-6.107)	-1.33E-02*** (-15.011)	-1.42E-02*** (-6.241)	-1.34E-02*** (-4.707)	-1.53E-02*** (-5.528)
	INT_D-S AND CASH SALE	-	-	-4.61E-03 (-0.551)	-5.12E-03 (-0.648)	-5.70E-03 (-0.736)	-4.27E-03 (-0.542)	-4.55E-03 (-0.503)	-2.51E-03 (-0.279)

Table 5.32. Continued.

Vector	Independent Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
		OLS1 _Prev _Direct	OLS2_Prev _Spillover	OLS3_Prev _Both Effects	ML_Spatial _Error	ML_Spatial _Lag	GMM_ Error _SAR	GMM_2SLS _HAC	GMM_2SLS _HAC_Quad
Neighboring SFH Foreclosures within 3 rings	SFH_FC_1R_C	-	-1.32E-02*** (-27.473)	-1.22E-02*** (-25.214)	-1.07E-02*** (-22.957)	-1.00E-02*** (-22.578)	-1.04E-02*** (-22.307)	-9.63E-03*** (-21.853)	-2.12E-02*** (-22.072)
	SFH_FC_1R_C2	-	-	-	-	-	-	-	2.75E-03*** (15.318)
	SFH_FC_2R_C	-	-1.02E-02*** (-31.040)	-1.04E-02*** (-31.714)	-8.84E-03*** (-27.982)	-8.18E-03*** (-26.479)	-8.59E-03*** (-27.322)	-7.91E-03*** (-26.733)	-2.02E-02*** (-29.147)
	SFH_FC_2R_C2	-	-	-	-	-	-	-	1.71E-03*** (22.093)
	SFH_FC_3R_C	-	-1.08E-02*** (-42.112)	-1.09E-02*** (-42.826)	-8.65E-03*** (-34.880)	-8.42E-03*** (-34.894)	-8.32E-03*** (-33.652)	-8.14E-03*** (-33.473)	-1.86E-02*** (-32.683)
	SFH_FC_3R_C2	-	-	-	-	-	-	-	1.11E-03*** (23.167)
Neighboring Condo Foreclosures within 3 rings	CON_FC_1R_C	-	-	-3.14E-03• (-1.779)	-3.33E-03* (-1.967)	-2.13E-03• (-1.722)	-3.20E-03• (-1.899)	-2.28E-03 (-1.378)	-3.07E-03 (-0.918)
	CON_FC_1R_C2	-	-	-	-	-	-	-	2.73E-04 (0.392)
	CON_FC_2R_C	-	-	-3.48E-03*** (-4.022)	-3.71E-03*** (-4.499)	-3.44E-03*** (-4.343)	-3.79E-03*** (-4.613)	-3.31E-03*** (-3.989)	9.63E-05 (0.062)
	CON_FC_2R_C2	-	-	-	-	-	-	-	-5.10E-04* (-2.407)
	CON_FC_3R_C	-	-	-4.41E-03*** (-7.263)	-4.06E-03*** (-6.944)	-3.96E-03*** (-6.936)	-4.12E-03*** (-7.080)	-4.06E-03*** (-7.053)	-1.65E-03 (-1.532)
	CON_FC_3R_C2	-	-	-	-	-	-	-	-3.08E-04* (-2.166)
Adjusted R-squared		0.661	0.723	0.727	-	-	-	-	-
Log likelihood		23740.1	26821.0	27080.2	28086.2	28451.3	-	-	-
AIC (Akaike information criterion)		-47452.1	-53613.9	-54116.4	-56124.0	-56855.0	-	-	-
J-B test on normality of errors		468.3***	874.8***	880.6***	-	-	-	-	-
B-P test for heteroskedasticity		2791.8***	2590.5***	2821.5***	-	-	-	-	-
K-B test for heteroskedasticity		2225.7***	1833.7***	1995.5***	-	-	-	-	-

Notes. **N = 30,815**. *t* values (OLSs and GMM_2SLS_HACs) or *z* values (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous model for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for the spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using the rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and 10-nearest neighbors spatial weights (Kelejian and Prucha 1999). A GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and 10-nearest neighbors spatial weights (Kelejian and Prucha, 2007, 2010).

Table 5.33. Estimated Marginal Impacts of Foreclosures on Existing Single Family Home Prices in a 2008 Housing Bust Year.

Vector	Independent Variable	The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Price in 2008)							
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
		OLS1 _Prev _Direct	OLS2_Prev _Spillover	OLS3_Prev _Both Effects	ML_Spatial _Error	ML_Spatial _Lag	GMM_ Error _SAR	GMM_2SLS _HAC	GMM_2SLS _HAC_Quad
Spatial Weight Matrix (Lag)	W_LN_PRICE_ Spatial Parameter_ Rho for lag	-	-	-	-	2.190E-01*** (31.734)	-	2.64E-01*** (26.894)	1.97E-01*** (20.581)
Spatial Weight Matrix (Error)	Spatial Parameter_ Lambda for error	-	-	-	2.616E-01*** (18.336)	-	3.420E-01 (non-parametric)	-	-
Housing Physical Characteristics	LN_LOT SIZE	2.80E-01*** (24.310)	1.58E-01*** (14.155)	1.93E-01*** (19.623)	1.88E-01*** (19.373)	1.78E-01*** (18.797)	1.84E-01*** (19.060)	1.75E-01*** (15.989)	1.54E-01*** (14.761)
	AGE	-3.73E-03*** (-14.238)	-5.70E-03*** (-22.521)	-4.48E-03*** (-19.958)	-4.42E-03*** (-19.507)	-4.35E-03*** (-20.027)	-4.41E-03*** (-19.424)	-4.33E-03*** (-15.310)	-4.54E-03*** (-16.455)
	AGE_2	4.29E-05*** (11.872)	5.29E-05*** (15.198)	4.17E-05*** (13.583)	4.24E-05*** (13.635)	4.72E-05*** (15.850)	4.32E-05*** (13.839)	4.82E-05*** (11.081)	4.92E-05*** (11.523)
	LN_LIVING AREA	8.84E-01*** (61.532)	7.73E-01*** (55.323)	7.49E-01*** (60.939)	7.33E-01*** (60.474)	7.25E-01*** (60.909)	7.29E-01*** (60.378)	7.22E-01*** (52.050)	6.91E-01*** (51.915)
	STORY_dummy	-3.36E-02*** (-7.402)	-2.05E-02*** (-4.678)	-2.25E-02*** (-5.853)	-2.07E-02*** (-5.497)	-2.23E-02*** (-5.912)	-2.09E-02*** (-5.585)	-2.29E-02*** (-7.089)	-2.00E-02*** (-6.538)
	GARAGE_dummy	8.57E-02*** (15.674)	8.96E-02*** (17.058)	7.57E-02*** (16.414)	7.05E-02*** (15.646)	6.92E-02*** (15.641)	7.06E-02*** (15.762)	6.85E-02*** (11.643)	6.45E-02*** (11.249)
	POOL_dummy	5.65E-02*** (16.936)	4.26E-02*** (13.231)	3.86E-02*** (13.659)	3.60E-02*** (13.054)	3.40E-02*** (12.422)	3.58E-02*** (13.065)	3.32E-02*** (12.538)	2.98E-02*** (11.872)
Market Characteristics	2nd QUARTER _dummy	-2.64E-02*** (-6.089)	-1.60E-02*** (-3.833)	-5.73E-03 (-1.559)	-7.85E-03* (-2.189)	-9.24E-03** (-2.604)	-8.09E-03* (-2.271)	-9.58E-03** (-2.866)	2.27E-03 (0.694)
	3rd QUARTER _dummy	-8.56E-02*** (-19.993)	-5.68E-02*** (-13.656)	-3.63E-02*** (-9.841)	-3.82E-02*** (-10.639)	-4.12E-02*** (-11.575)	-3.83E-02*** (-10.730)	-4.19E-02*** (-12.116)	-2.38E-02*** (-7.016)
	4th QUARTER _dummy	-1.59E-01*** (-35.238)	-1.19E-01*** (-26.613)	-7.27E-02*** (-18.101)	-7.67E-02*** (-19.529)	-8.24E-02*** (-21.283)	-7.74E-02*** (-19.778)	-8.39E-02*** (-20.922)	-7.33E-02*** (-18.921)
Selling Factors related to Foreclosure Status on the Property	DISTRESSED SALE _dummy	-1.62E-01*** (-54.879)	-	-9.53E-02*** (-33.634)	-9.33E-02*** (-27.434)	-5.37E-02*** (-17.485)	-8.99E-02*** (-24.800)	-4.38E-02*** (-13.642)	-3.48E-02*** (-11.187)
	RENTER _dummy	-7.02E-02*** (-16.619)	-	-6.76E-02*** (-11.312)	-6.42E-02*** (-10.989)	-6.39E-02*** (-10.805)	-6.45E-02*** (11.092)	-6.49E-02*** (-7.791)	-5.95E-02*** (-7.320)
	INT_D-S AND RENTER	-	-	2.04E-02** (2.751)	1.57E-02* (2.168)	1.88E-02* (2.541)	1.60E-02* (2.220)	2.02E-02* (2.105)	1.60E-02· (1.727)
	CASH SALE _dummy	-1.25E-01*** (-33.563)	-	-7.48E-02*** (-14.381)	-7.40E-02*** (-14.601)	-7.48E-02*** (-14.841)	-7.28E-02*** (-14.435)	-7.38E-02*** (-9.988)	-7.81E-02*** (-10.909)
	INT_D-S AND CASH SALE	-	-	-5.13E-02*** (-7.923)	-4.97E-02*** (-7.859)	-4.96E-02*** (-7.874)	-5.11E-02*** (-8.132)	-5.07E-02*** (-5.886)	-4.68E-02*** (-5.631)

Table 5.33. Continued.

Vector	Independent Variable	Model 1 OLS1 _Prev _Direct	Model 2 OLS2_Prev _Spillover	Model 3 OLS3_Prev _Both Effects	Model 4 ML_Spatial _Error	Model 5 ML_Spatial _Lag	Model 6 GMM_ Error _SAR	Model 7 GMM_2SLS _HAC	Model 8 GMM_2SLS _HAC_Quad
Neighboring SFH Foreclosures within 3 rings	SFH_FC_1R_C	-	-1.07E-02*** (-26.403)	-7.58E-03*** (-21.095)	-7.06E-03*** (-19.869)	-6.20E-03*** (-17.679)	-6.93E-03*** (-19.611)	-5.96E-03*** (-17.347)	-1.49E-02*** (-20.366)
	SFH_FC_1R_C2	-	-	-	-	-	-	-	3.96E-04*** (15.223)
	SFH_FC_2R_C	-	-3.12E-03*** (-11.138)	-2.89E-03*** (-11.741)	-2.67E-03*** (-11.090)	-2.38E-03*** (-9.933)	-2.63E-03*** (-10.955)	-2.33E-03*** (-9.882)	-7.24E-03*** (-15.187)
	SFH_FC_2R_C2	-	-	-	-	-	-	-	1.20E-04*** (12.272)
	SFH_FC_3R_C	-	-3.05E-03*** (-16.370)	-2.41E-03*** (-14.688)	-2.30E-03*** (-14.205)	-2.07E-03*** (-12.927)	-2.25E-03*** (-13.952)	-1.95E-03*** (-11.576)	-4.49E-03*** (-13.398)
	SFH_FC_3R_C2	-	-	-	-	-	-	-	4.56E-05*** (9.433)
Neighboring Condo Foreclosures within 3 rings	CON_FC_1R_C	-	-	-2.03E-03 (-1.130)	-1.74E-03 (-0.999)	-1.27E-03 (-0.514)	-1.95E-03 (-1.123)	-1.58E-03 (-0.865)	-1.68E-03 (-0.482)
	CON_FC_1R_C2	-	-	-	-	-	-	-	-3.15E-05 (-0.120)
	CON_FC_2R_C	-	-	-2.23E-03** (-2.790)	-2.05E-03** (-2.641)	-2.02E-03** (-2.662)	-1.97E-03* (-2.539)	-1.74E-03• (-1.874)	7.59E-04 (0.576)
	CON_FC_2R_C2	-	-	-	-	-	-	-	-1.47E-04* (-2.460)
	CON_FC_3R_C	-	-	-3.53E-04 (-0.663)	-2.75E-04 (-0.527)	-1.34E-04 (NA)	-3.81E-04 (-0.734)	-6.19E-05 (-0.096)	-3.08E-04 (-0.297)
	CON_FC_3R_C2	-	-	-	-	-	-	-	1.83E-05 (0.343)
Adjusted R-squared		0.699	0.722	0.786	-	-	-	-	-
Log likelihood		5724.2	6236.0	7931.2	8102.8	8363.8	-	-	-
AIC (Akaike information criterion)		-11420.4	-12443.9	-15818.3	-16158.0	-16680.0	-	-	-
J-B test on normality of errors		693.8***	1399.4***	2919.2***	-	-	-	-	-
B-P test for heteroskedasticity		1396.6***	1920.7***	2391.6***	-	-	-	-	-
K-B test for heteroskedasticity		890.6***	1096.6***	1114.3***	-	-	-	-	-

Notes. **N= 12,885**. *t* values (OLSs and GMM_2SLS_HACs) or *z* values (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using a rook contiguity weight. A GMM_SAR_Error (Spatial Simultaneous Autoregressive Error Model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and 10 nearest neighbors spatial weights (Kelejian and Prucha, 1999). A GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and 10 nearest neighbors spatial weights (Kelejian and Prucha, 2007, 2010).

Table 5.34. Estimated Marginal Impacts of Foreclosures on Existing Condo Prices in a 2005 Housing Boom Year.

Vector	Independent Variable	The Results of Analytical Models (Dependent Variable: LN_Condo Sale Price in 2005)							
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
		OLS1 _Prev _Direct	**OLS2_Prev _Spillover**	**OLS3_Prev _Both Effects**	**ML_Spatial _Error**	**ML_Spatial _Lag**	**GMM_ Error _SAR**	**GMM_2SLS _HAC**	**GMM_2SLS _HAC_Quad**
Spatial Weight Matrix (Lag)	W_LN_PRICE_ Spatial Parameter_ Rho for lag	-	-	-	-	3.157E-01*** (29.477)	-	1.57E-01*** (7.451)	1.38E-01*** (6.456)
Spatial Weight Matrix (Error)	Spatial Parameter_ Lambda for error	-	-	-	5.359E-01*** (38.186)	-	6.162E-01 (non-parametric)	-	-
Housing Physical Characteristics	LN_LOT SIZE	-2.22E-02* (-2.434)	1.08E-02 (1.245)	3.09E-02*** (3.770)	5.26E-02*** (6.046)	2.09E-02** (2.669)	5.37E-02*** (6.134)	2.42E-02* (2.529)	3.06E-02** (3.210)
	AGE	-3.39E-02*** (-22.643)	-2.70E-02*** (-18.899)	-2.04E-02*** (-14.985)	-1.82E-02*** (-12.003)	-1.45E-02*** (-15.451)	-1.69E-02*** (-10.997)	-1.72E-02*** (-9.988)	-1.56E-02*** (-8.812)
	AGE_2	3.64E-04*** (12.051)	2.33E-04*** (8.078)	1.23E-04*** (4.503)	8.46E-05** (2.850)	5.72E-05*** (3.291)	6.61E-05* (2.2027)	8.56E-05* (2.364)	5.77E-05 (1.550)
	LN_LIVING AREA	1.10E+00*** (49.790)	1.01E+00*** (48.320)	9.38E-01*** (47.375)	8.99E-01*** (46.509)	8.60E-01*** (48.513)	8.93E-01*** (46.400)	9.01E-01*** (39.288)	8.92E-01*** (38.746)
	STORY_dummy	-2.42E-01*** (-23.814)	-1.45E-01*** (-14.318)	-1.32E-01*** (-13.873)	-1.03E-01*** (-10.999)	-1.10E-01*** (-12.538)	-1.01E-01*** (-10.765)	-1.23E-01*** (-11.096)	-1.16E-01*** (-10.428)
	GARAGE_dummy	8.94E-02*** (6.320)	5.43E-02*** (4.044)	-7.45E-03 (-0.580)	-3.25E-03 (-0.264)	-1.08E-03 (-1.190)	-1.46E-03 (-0.120)	-1.07E-02 (-0.584)	-2.61E-03 (-0.140)
	POOL_dummy	2.89E-01*** (4.885)	2.68E-01*** (4.814)	2.49E-01*** (4.784)	2.13E-01*** (4.676)	2.75E-01*** (5.661)	2.09E-01*** (4.617)	2.65E-01*** (6.674)	2.51E-01*** (6.384)
Market Characteristics	2nd QUARTER _dummy	1.07E-01*** (9.406)	1.20E-01*** (11.141)	1.32E-01*** (13.114)	1.29E-01*** (14.649)	1.21E-01*** (12.909)	1.33E-01*** (15.0789	1.28E-01*** (12.846)	1.29E-01*** (12.972)
	3rd QUARTER _dummy	1.91E-01*** (16.217)	2.12E-01*** (19.084)	2.51E-01*** (23.916)	2.50E-01*** (26.997)	2.37E-01*** (24.223)	2.52E-01*** (27.503)	2.45E-01*** (24.366)	2.48E-01*** (24.789)
	4th QUARTER _dummy	3.02E-01*** (24.644)	3.33E-01*** (28.746)	3.62E-01*** (33.208)	3.55E-01*** (36.438)	3.39E-01*** (33.467)	3.51E-01*** (36.359)	3.51E-01*** (32.221)	3.49E-01*** (32.450)
Selling Factors related to Foreclosure Status on the Property	DISTRESSED SALE _dummy	-1.51E-01*** (-7.368)	-	-4.88E-02* (-2.262)	-1.42E-02 (-0.763)	-3.80E-02· (-1.806)	-2.27E-02 (-1.226)	-4.51E-02* (-2.555)	-3.76E-02* (-2.153)
	RENTER _dummy	-7.08E-02*** (-7.163)	-	-4.95E-02*** (-5.520)	-4.30E-02*** (-5.446)	-4.49E-02*** (-5.343)	-4.42E-02*** (-5.654)	-4.93E-02*** (-5.161)	-5.65E-02*** (-5.938)
	INT_D-S AND RENTER	-	-	-1.98E-02 (-0.456)	-4.14E-02 (-1.091)	-2.01E-02 (-0.429)	-2.91E-02 (-0.780)	-1.76E-02 (-0.474)	-6.60E-03 (-0.178)
	CASH SALE _dummy	-2.50E-02* (-2.140)	-	-3.54E-02*** (-3.367)	-3.91E-02*** (-4.262)	-3.51E-02*** (-3.532)	-3.86E-02*** (-4.235)	-3.51E-02** (-2.946)	-4.14E-02*** (-3.516)
	INT_D-S AND CASH SALE	-	-	-6.23E-02 (-1.181)	-6.46E-02 (-1.420)	-5.96E-02 (-1.126)	-7.11E-02 (-1.573)	-6.74E-02 (-1.412)	-5.23E-02 (-1.103)

Table 5.34. Continued.

Vector	Independent Variable	Model 1 OLS1 _Prev _Direct	Model 2 OLS2_Prev _Spillover	Model 3 OLS3_Prev _Both Effects	Model 4 ML_Spatial _Error	Model 5 ML_Spatial _Lag	Model 6 GMM_ Error _SAR	Model 7 GMM_2SLS _HAC	Model 8 GMM_2SLS _HAC_Quad
Neighboring SFH Foreclosures within 3 rings	SFH_FC_1R_C	-	-	-9.13E-04	4.66E-03	2.32E-03	6.12E-03	2.75E-04	5.96E-03
				(-0.204)	(1.098)	(NA)	(1.451)	(0.055)	(0.573)
	SFH_FC_1R_C2	-	-	-	-	-	-	-	-1.09E-03
									(-0.406)
	SFH_FC_2R_C	-	-	-1.84E-02***	-1.85E-02***	-1.51E-02***	-1.81E-02***	-1.66E-02***	-2.10E-02***
				(-8.483)	(-8.892)	(-7.786)	(-8.844)	(-6.770)	(-4.635)
	SFH_FC_2R_C2	-	-	-	-	-	-	-	6.16E-04
									(1.560)
	SFH_FC_3R_C	-	-	-2.28E-02***	-1.65E-02***	-1.37E-02***	-1.60E-02***	-1.86E-02***	-3.87E-02***
				(-16.041)	(-11.563)	(-10.562)	(-11.250)	(-9.604)	(-10.620)
	SFH_FC_3R_C2	-	-	-	-	-	-	-	1.59E-03***
									(6.347)
Neighboring Condo Foreclosures within 3 rings	CON_FC_1R_C	-	-3.96E-02***	-2.86E-02***	-2.64E-02***	-2.32E-02***	-2.63E-02***	-2.58E-02***	-3.82E-02***
			(-20.604)	(-15.376)	(-14.641)	(-13.283)	(-14.700)	(-11.785)	(-9.777)
	CON_FC_1R_C2	-	-	-	-	-	-	-	1.34E-03***
									(4.025)
	CON_FC_2R_C	-	-4.90E-03*	-1.16E-02***	-1.18E-02***	-8.84E-03***	-1.26E-02***	-1.04E-02***	-1.51E-02***
			(-2.507)	(-6.209)	(-6.531)	(-4.932)	(-7.065)	(-5.143)	(-4.332)
	CON_FC_2R_C2	-	-	-	-	-	-	-	1.27E-04
									(0.545)
	CON_FC_3R_C	-	-2.34E-02***	-2.68E-02***	-2.52E-02***	-2.26E-02***	-2.43E-02***	-2.48E-02***	-2.64E-02***
			(-11.381)	(-13.776)	(-13.866)	(-12.720)	(-13.522)	(-11.531)	(-6.370)
	CON_FC_3R_C2	-	-	-	-	-	-	-	2.68E-04
									(0.855)
Adjusted R-squared		0.588	0.635	0.680	-	-	-	-	-
Log likelihood		-1703.8	-1333.3	-913.1	-349.1	-526.2	-	-	-
AIC (Akaike information criterion)		3435.6	2694.7	1870.3	746.2	1100.5	-	-	-
J-B test on normality of errors		489.5***	766.4***	1149.6***	-	-	-	-	-
B-P test for heteroskedasticity		656.6***	580.5***	863.2***	-	-	-	-	-
K-B test for heteroskedasticity		411.4***	314.9***	428.1***	-	-	-	-	-

Notes. **N= 6,205**. *t* values (OLSs and GMM_2SLS_HACs) or *z* values (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using a rook contiguity weight. GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and 10 nearest neighbors spatial weights (Kelejian and Prucha, 1999). A GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and 10-nearest neighbors spatial weights (Kelejian and Prucha, 2007, 2010).

Table 5.35. Estimated Marginal Impacts of Foreclosures on Existing Condo Prices in a 2008 Housing Bust Year.

Vector	Independent Variable	The Results of Analytical Models (Dependent Variable: LN_Condo Sale Price in 2008)							
		OLS1 _Prev _Direct	**OLS2_Prev _Spillover**	**OLS3_Prev_ Both Effects**	**ML_Spatial _Error**	**ML_Spatial _Lag**	**GMM_ Error _SAR**	**GMM_2SLS _HAC**	**GMM_2SLS _HAC_Quad**
Spatial Weight Matrix (Lag)	W_LN_PRICE_ Spatial Parameter_ Rho for lag	-	-	-	-	9.896E-02*** (4.305)	-	1.84E-01*** (5.279)	1.63E-01*** (4.774)
Spatial Weight Matrix (Error)	Spatial Parameter_ Lambda for error	-	-	-	1.449 E-01*** (4.343)	-	1.929E-01 (non-parametric)	-	-
Housing Physical Characteristics	LN_LOT SIZE	-5.41E-02** (-2.745)	-4.60E-02* (-2.181)	-2.27E-02 (-1.244)	-2.42E-02 (-1.318)	-2.51E-02 (-1.412)	-1.82E-02 (-0.992)	-2.32E-02 (-1.287)	-2.38E-02 (-1.331)
	AGE	-2.17E-02*** (-10.558)	-2.47E-02*** (-11.178)	-2.08E-02*** (-10.915)	-2.08E-02*** (-10.904)	-2.05E-02*** (-10.833)	-2.09E-02*** (-10.964)	-2.02E-02*** (-11.592)	-2.00E-02*** (-11.226)
	AGE_2	1.69E-04*** (4.084)	1.97E-04*** (4.423)	1.60E-04*** (4.201)	1.55E-04*** (4.053)	1.53E-04*** (4.043)	1.55E-04*** (4.071)	1.46E-04*** (4.032)	1.46E-04*** (3.970)
	LN_LIVING AREA	1.02E+00*** (24.921)	9.80E-01*** (22.620)	9.42E-01*** (25.212)	9.43E-01*** (25.256)	9.40E-01*** (25.505)	9.34E-01*** (25.027)	9.33E-01*** (24.925)	9.30E-01*** (25.099)
	STORY_dummy	-2.84E-01*** (-13.531)	-2.93E-01*** (-13.029)	-2.21E-01*** (-11.280)	-2.21E-01*** (-11.248)	-2.21E-01*** (-11.429)	-2.15E-01*** (-10.969)	-2.15E-01*** (-10.837)	-2.06E-01*** (-10.468)
	GARAGE_dummy	1.15E-01*** (4.972)	6.74E-02** (2.749)	1.07E-01*** (5.001)	9.96E-02*** (4.668)	9.61E-02*** (4.533)	9.52E-02*** (4.449)	8.80E-02*** (3.511)	9.57E-02*** (3.757)
	POOL_dummy	3.37E-01*** (3.699)	3.12E-01** (3.220)	2.79E-01*** (3.362)	2.83E-01*** (3.453)	2.65E-01** (3.222)	2.91E-01*** (3.538)	2.75E-01*** (4.838)	2.65E-01*** (4.687)
Market Characteristics	2nd QUARTER _dummy	-4.24E-02* (-2.073)	-3.98E-02• (-1.825)	-3.92E-03 (-0.209)	-4.24E-03 (-0.229)	-3.82E-04 (-0.288)	-2.15E-04 (-0.012)	-5.91E-04 (-0.033)	4.81E-03 (0.264)
	3rd QUARTER _dummy	-1.26E-01*** (-5.655)	-1.21E-01*** (-4.994)	-2.56E-02 (-1.207)	-2.78E-02 (-1.325)	-2.91E-02 (-1.481)	-2.64E-02 (-1.257)	-2.87E-02 (-1.378)	-1.66E-02 (-0.793)
	4th QUARTER _dummy	-2.17E-01*** (-9.177)	-1.99E-01*** (-7.243)	-3.84E-02 (-1.571)	-4.01E-02• (-1.656)	-4.14E-02• (-1.789)	-4.06E-02• (-1.674)	-4.03E-02• (-1.710)	-3.52E-02 (-1.467)
Selling Factors related to Foreclosure Status on the Property	DISTRESSED SALE _dummy	-3.82E-01*** (-20.623)	-	-2.27E-01*** (-10.654)	-2.34E-01*** (-11.105)	-2.28E-01*** (-10.814)	-2.34E-01*** (-11.047)	-2.28E-01*** (-12.136)	-2.18E-01*** (-11.574)
	RENTER _dummy	-3.88E-02* (-2.064)	-	1.31E-02 (0.663)	1.30E-02 (0.664)	1.35E-02 (0.671)	1.16E-02 (0.592)	1.24E-02 (0.549)	1.43E-02 (0.638)
	INT_D-S AND RENTER	-	-	-1.08E-01** (-2.777)	-1.04E-01** (-2.697)	-1.08E-01** (-2.767)	-1.06E-01** (-2.738)	-1.09E-01** (-2.716)	-1.05E-01* (-2.572)
	CASH SALE _dummy	-1.39E-01*** (-7.601)	-	-6.24E-02** (-3.094)	-6.91E-02*** (-3.473)	-6.30E-02** (-3.133)	-6.87E-02*** (-3.440)	-6.28E-02** (-2.664)	-6.10E-02** (-2.617)
	INT_D-S AND CASH SALE	-	-	-1.75E-01*** (-4.769)	-1.64E-01*** (-4.501)	-1.72E-01*** (-4.726)	-1.63E-01*** (-4.472)	-1.67E-01*** (-4.092)	-1.60E-01*** (-3.972)

Table 5.35. Continued.

Vector	Independent Variable	Model 1 OLS1 _Prev _Direct	Model 2 OLS2_Prev _Spillover	Model 3 OLS3_Prev_B oth Effects	Model 4 ML_Spatial _Error	Model 5 ML_Spatial _Lag	Model 6 GMM_Error _SAR	Model 7 GMM_2SLS _HAC	Model 8 GMM_2SLS _HAC_Quad
Neighboring SFH Foreclosures within 3 rings	SFH_FC_1R_C	-	-	-1.29E-02* (-2.006)	-1.25E-02* (-1.974)	-1.30E-02* (-2.022)	-1.33E-02* (-2.097)	-1.31E-02· (-1.802)	-2.21E-02* (-1.999)
	SFH_FC_1R_C2	-	-	-	-	-	-	-	1.78E-03 (1.015)
	SFH_FC_2R_C	-	-	-6.53E-03* (-2.112)	-5.80E-03· (-1.894)	-5.82E-03· (-1.847)	-5.58E-03· (-1.821)	-5.60E-03· (-1.670)	-8.44E-04 (-0.158)
	SFH_FC_2R_C2	-	-	-	-	-	-	-	-3.26E-04 (-1.192)
	SFH_FC_3R_C	-	-	-1.48E-02*** (-8.713)	-1.42E-02*** (-8.448)	-1.43E-02*** (-8.472)	-1.40E-02*** (-8.278)	-1.38E-02*** (-6.553)	-2.20E-02*** (-7.978)
	SFH_FC_3R_C2	-	-	-	-	-	-	-	2.47E-04*** (4.363)
Neighboring Condo Foreclosures within 3 rings	CON_FC_1R_C	-	-2.53E-02*** (-14.916)	-1.19E-02*** (-7.574)	-1.19E-02*** (-7.638)	-1.19E-02*** (-7.649)	-1.21E-02*** (-7.714)	-1.21E-02*** (-7.355)	-1.94E-02*** (-6.501)
	CON_FC_1R_C2	-	-	-	-	-	-	-	2.65E-04*** (3.716)
	CON_FC_2R_C	-	-4.02E-03 (-1.631)	-3.36E-03 (-1.574)	-3.37E-03 (-1.595)	-3.30E-03 (-1.547)	-3.32E-03 (-1.569)	-3.27E-03 (-1.340)	1.11E-02 (1.565)
	CON_FC_2R_C2	-	-	-	-	-	-	-	-7.17E-04* (-2.074)
	CON_FC_3R_C	-	-2.06E-03 (-0.799)	-7.77E-03*** (-3.468)	-7.78E-03*** (-3.497)	-7.76E-03*** (-3.492)	-7.70E-03*** (-3.461)	-8.04E-03** (-3.048)	-1.36E-02*** (-3.431)
	CON_FC_3R_C2	-	-	-	-	-	-	-	2.91E-04· (1.893)
Adjusted R-squared		0.578	0.523	0.652	-	-	-	-	-
Log likelihood		-691.8	-814.5	-495.4	-487.4	-487.1	-	-	-
AIC (Akaike information criterion)		1411.7	1657.1	1034.9	1022.9	1022.3	-	-	-
J-B test on normality of errors		98.6***	91.2***	80.5***	-	-	-	-	-
B-P test for heteroskedasticity		239.0***	160.6***	257.3***	-	-	-	-	-
K-B test for heteroskedasticity		166.4***	115.5***	180.3***	-	-	-	-	-

Notes. **N= 2,003**. *t* values (OLSs and GMM_2SLS_HACs) or *z* values (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using a rook contiguity weight. A GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and 10-nearest neighbors spatial weights (Kelejian and Prucha, 1999). A GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and 10-nearest neighbors spatial weights (Kelejian and Prucha, 2007, 2010).

5.2.7 Estimation Results of Vectors

This part presents the estimation results of vectors among different categories for each data set, comparing those in housing boom and bust cycles as well as different housing types. Major categories associated with foreclosure will be discussed in the final section.

The data were segmented into two time periods, a housing boom year (2005) and a housing bust year (2008) and two types of housing samples, single family homes and condos. Thus, a total of four sample data sets were constructed and analytical tools for three OLS models (Models 1 through 3), two ML Spatial models (Models 4 and 5), and three GMM models (Models 6 through 8) were tested for each sample data set. All models were estimated to examine differences in the coefficients across time. However, the following discussion of results for the four different data sets mainly focuses on the six models (OLS3_Both Effects [Model3] thorough GMM_2SLS_HAC_Quadtratic model [Model 8]) with full explanatory variables among the eight analytical models.

5.2.7.1 Housing Physical Characteristics

Single family home samples

A study of the effects of housing characteristics on single family housing prices would show useful information, even though it is not the primary purpose of this study. Each variable was simultaneously evaluated in both hedonic models and spatial hedonic models.

Structural characteristics relate to the characteristics of a house itself, such as lot size, age of the building in years, size of main living area, number of stories, the presence of a garage, and the presence of a swimming pool. In general, these variables, except for the story dummy, are positively related to the single family housing prices.

Structural coefficient estimates are of the expected sign and are generally consistent across models. Thus, larger acreage of lot size, larger square footage of living area, presence of a garage, and presence of a swimming pool contributed positively to housing value, while older houses had lower values, all else constant.

Because the dependent variable was log transformed, coefficients of the independent variables would be interpreted differently based on the form of the variables (Asteriou and Hall, 2007). First, when the independent variable was log transformed as well, the coefficient of the variable should be interpreted as elasticity. For instance, in the variable of the main living area in the GMM_2SLS_HAC_Quadratic model (Model 8) for 2005 single family home samples, a 1% increase of the total main living area of a single family house led to an average sale price increase of 0.62%.

Second, when the independent variable was not transformed, the coefficient of the variable should be interpreted as a relative change in dependent variables on an absolute change in the dependent variable. For example, in the home age variable of GMM_2SLS_HAC_Quadratic model (Model 8) for 2005 single family home samples, a year increased in the age of the home resulted in a 0.43% drop in the sale price.

Finally, when the independent variable was an untransformed dummy variable, in the semi-logarithmic equation the interpretation of the dummy variable coefficients involves the use of the formula: $100*(e^{\beta}-l)$, where β is the dummy variable coefficient

(Halvorsen and Palmquist, 1980). This formula derives the percentage effect on the price of the presence of the factor represented by the dummy variable. For example, in the garage dummy variable of the GMM_2SLS_HAC_Quadratic model for 2005 single family home samples, the true portion change would be 4.94% (100 * (exp(0.0482) -1)) = 4.94). Hence, the expected sale price for a house with a garage was 4.94% higher than the sale price for a house that doesn't have a garage.

Coefficients of the independent variables in housing characteristics would be based on these three different ways of interpretation based on the form of the variable.

First, lot size as a transformed continuous variable would be interpreted as follows:

For single family home price samples in the 2005 housing boom year, each additional square foot of lot size increased the selling price by about 0.18% for OLS3 Both Effects, 0.19% for ML Spatial Error, 0.18% for ML Spatial Lag, 0.19% for GMM SAR Error, 0.18% for GMM 2SLS HAC, and 0.17% for GMM 2SLS HAC Quadratic models, respectively.

For single family home price samples in the 2008 housing bust year, each additional square foot of lot size increased the selling price by about 0.19% for OLS3 Both Effects, 0.19% for ML Spatial Error, 0.18% for ML Spatial Lag, 0.18% for GMM SAR Error, 0.18% for GMM 2SLS HAC, and 0.15% for GMM 2SLS HAC Quadratic models, respectively.

Second, the home sale price is supposed to decrease as the building age increases. However, heteroskedasticity is often found in a cross sectional context because of the nature of the data sets. Goodman and Thibodeau (1995) found that housing depreciation is nonlinear and dwelling age-induced heteroskedasticity is prevalent in hedonic house price equations.

Previous studies (Lin, Rosenblatt, and Yao, 2009; Rogers and Winter, 2009; Schuetz, Been, and Ellen, 2008) included an age square in their hedonic regression models to control nonlinear effects for building age. Not controlling for the nonlinear effects of age causes heteroskedasticity in the model's residuals. A positive sign for the square of age reflects diminishing marginal effects of value depreciation. Thus, this study added the quadratic term of age in the hedonic model. The coefficients of building age as an untransformed continuous variable would be interpreted as follows:

For single family home price samples in the 2005 housing boom year, a year increase in building age as an untransformed continuous variable dropped the sale price by -0.43% for OLS3 Both Effects, -0.45% for ML Spatial Error, -0.45% for ML Spatial Lag, -0.45% for GMM SAR Error, -0.45% for GMM 2SLS HAC, and -0.43% for GMM 2SLS HAC Quadratic models, respectively.

However, for single family home price samples in the 2005 housing boom year, a year increase in squared-age as an untransformed continuous variable diminished the sale price by 0.0045% for OLS3 Both Effects, 0.0048% for ML Spatial Error, 0.0052% for ML Spatial Lag, 0.0048% for GMM SAR Error, 0.0054% for GMM 2SLS HAC, and 0.0050% for GMM 2SLS HAC Quadratic models, respectively.

For single family home price samples in the 2008 housing bust year, a year increase in building age as an untransformed continuous variable dropped the sale price by -0.45% for OLS3 Both Effects, -0.44% for ML Spatial Error, -0.44% for ML Spatial Lag, -0.44% for GMM SAR Error, -0.43% for GMM 2SLS HAC, and -0.45% for GMM 2SLS HAC Quadratic models, respectively.

However, for single family home price samples in the 2008 bust, a year increase in squared-age as an untransformed continuous variable diminished the sale price by 0.0042% for OLS3 Both Effects, 0.0042% for ML Spatial Error, 0.0047% for ML Spatial Lag, 0.0043% for GMM SAR Error, 0.0048% for GMM 2SLS HAC, and 0.0049% for GMM 2SLS HAC Quadratic models, respectively.

Third, main living area in the home as a transformed continuous variable would be interpreted as follows:

For single family home price samples in the 2005 housing boom year, each additional square foot of interior living space increased the selling price by about 0.67% for OLS3 Both Effects, 0.65% for ML Spatial Error, 0.64% for ML Spatial Lag, 0.65% for GMM SAR Error, 0.64% for GMM 2SLS HAC, and 0.62% for GMM 2SLS HAC Quadratic models, respectively.

For single family home price samples in the 2008 housing bust year, each additional square foot of interior living space increased the selling price by about 0.75% for OLS3 Both Effects, 0.73% for ML Spatial Error, 0.73% for ML Spatial Lag, 0.73% for GMM SAR Error, 0.72% for GMM 2SLS HAC, and 0.69% for GMM 2SLS HAC Quadratic models, respectively.

Fourth, two stories as a dummy variable would be interpreted as follows:

For single family home price samples in the 2005 housing boom year, two-story houses had an added selling price of about 0.38% for OLS3 Both Effects, 0.17% for ML Spatial Error, 0.24% for ML Spatial Lag, 0.13% for GMM SAR Error, 0.22% for GMM 2SLS HAC, and 1.44% for GMM 2SLS HAC Quadratic models, respectively, compared to one-story houses. However, they are not statistically significant.

For single family home price samples in the 2008 housing bust year, two-story houses dropped selling prices about -2.22% for OLS3 Both Effects, -2.05% for ML Spatial Error, -2.21% for ML Spatial Lag, -2.06% for GMM SAR Error, -2.26% for GMM 2SLS HAC, and -1.98% for GMM 2SLS HAC Quadratic models, respectively, compared to one-story houses. This seems to reflect that home buyers prefer to one story house in a housing bust year (2008).

Fifth, the presence of a garage as a dummy variable would be interpreted as follows:

For single family home price samples in the 2005 housing boom year, a garage added to the selling price about 5.32% for OLS3 Both Effects, 5.18% for ML Spatial Error, 5.07% for ML Spatial Lag, 5.16% for GMM SAR Error, 4.99% for GMM 2SLS HAC, and 4.93% for GMM 2SLS HAC Quadratic models, respectively.

For single family home price samples in the 2008 housing bust year, a garage added to the selling price about 7.86% for OLS3 Both Effects, 7.30% for ML Spatial Error, 7.17% for ML Spatial Lag, 7.32% for GMM SAR Error, 7.09% for GMM 2SLS HAC, and 6.66% for GMM 2SLS HAC Quadratic models, respectively.

Table 5.36. Estimated Marginal Impacts of Housing Physical Characteristics on Existing Single Family Home Prices.

The Result of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)								
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
LN_LOT SIZE	2.24E-01*** (44.765)	1.82E-01*** (39.785)	1.81E-01*** (39.991)	1.87E-01*** (42.720)	1.81E-01*** (43.158)	1.88E-01*** (43.128)	1.82E-01*** (32.481)	1.74E-01*** (31.664)
AGE	-6.72E-03*** (-56.846)	-4.45E-03*** (-40.425)	-4.30E-03*** (-39.035)	-4.45E-03*** (-39.185)	-4.48E-03*** (-43.208)	-4.47E-03*** (-39.181)	-4.52E-03*** (-34.774)	-4.27E-03*** (-33.631)
AGE_2	8.07E-05*** (46.909)	4.63E-05*** (28.840)	4.50E-05*** (28.127)	4.77E-05*** (29.019)	5.23E-05*** (34.626)	4.79E-05*** (29.051)	5.36E-05*** (25.474)	5.04E-05*** (24.475)
LN_LIVING AREA	7.71E-01*** (118.947)	6.78E-01*** (113.549)	6.74E-01*** (113.690)	6.53E-01*** (113.440)	6.44E-01*** (119.127)	6.52E-01*** (113.700)	6.41E-01*** (94.612)	6.23E-01*** (93.682)
STORY_dummy	2.22E-03 (1.012)	4.11E-03* (2.077)	3.77E-03• (1.918)	1.69E-03 (0.898)	2.42E-03* (2.211)	1.29E-03 (0.691)	2.16E-03 (1.216)	1.04E-03 (0.591)
GARAGE_dummy	6.20E-02*** (25.943)	5.31E-02*** (24.538)	5.19E-02*** (24.165)	5.05E-02*** (24.812)	4.94E-02*** (25.127)	5.03E-02*** (24.823)	4.87E-02*** (20.536)	4.82E-02*** (20.730)
POOL_dummy	5.42E-02*** (34.997)	4.84E-02*** (34.554)	4.67E-02*** (33.543)	4.36E-02*** (33.071)	4.20E-02*** (31.880)	4.29E-02*** (32.613)	4.13E-02*** (29.594)	4.09E-02*** (30.118)
N	30,815	30,815	30,815	30,815	30,815	30,815	30,815	30,815

The Result of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2008)								
Independent Variable	**OLS1_Prev_ Direct (Model 1)**	**OLS2_Prev_ Spillover (Model 2)**	**OLS3_Prev _Both (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
LN_LOT SIZE	2.80E-01*** (24.310)	1.58E-01*** (14.155)	1.93E-01*** (19.623)	1.88E-01*** (19.373)	1.78E-01*** (18.797)	1.84E-01*** (19.060)	1.75E-01*** (15.989)	1.54E-01*** (14.761)
AGE	-3.73E-03*** (-14.238)	-5.70E-03*** (-22.521)	-4.48E-03*** (-19.958)	-4.42E-03*** (-19.507)	-4.35E-03*** (-20.027)	-4.41E-03*** (-19.424)	-4.33E-03*** (-15.310)	-4.54E-03*** (-16.455)
AGE_2	4.29E-05*** (11.872)	5.29E-05*** (15.198)	4.17E-05*** (13.583)	4.24E-05*** (13.635)	4.72E-05*** (15.850)	4.32E-05*** (13.839)	4.82E-05*** (11.081)	4.92E-05*** (11.523)
LN_LIVING AREA	8.84E-01*** (61.532)	7.73E-01*** (55.323)	7.49E-01*** (60.939)	7.33E-01*** (60.474)	7.25E-01*** (60.909)	7.29E-01*** (60.378)	7.22E-01*** (52.050)	6.91E-01*** (51.915)
STORY_dummy	-3.36E-02*** (-7.402)	-2.05E-02*** (-4.678)	-2.25E-02*** (-5.853)	-2.07E-02*** (-5.497)	-2.23E-02*** (-5.912)	-2.09E-02*** (-5.585)	-2.29E-02*** (-7.089)	-2.00E-02*** (-6.538)
GARAGE_dummy	8.57E-02*** (15.674)	8.96E-02*** (17.058)	7.57E-02*** (16.414)	7.05E-02*** (15.646)	6.92E-02*** (15.641)	7.06E-02*** (15.762)	6.85E-02*** (11.643)	6.45E-02*** (11.249)
POOL_dummy	5.65E-02*** (16.936)	4.26E-02*** (13.231)	3.86E-02*** (13.659)	3.60E-02*** (13.054)	3.40E-02*** (12.422)	3.58E-02*** (13.065)	3.32E-02*** (12.538)	2.98E-02*** (11.872)
N	12,885	12,885	12,885	12,885	12,885	12,885	12,885	12,885

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses.
Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1.

Sixth, the presence of a swimming pool as a dummy variable would be interpreted as follows:

For single family home price samples in the 2005 housing boom year, a swimming pool on the ground added to the selling price about 4.78% for OLS3 Both Effects, 4.46% for ML Spatial Error, 4.29% for ML Spatial Lag, 4.38% for GMM SAR Error, 4.22% for GMM 2SLS HAC, and 4.17% for GMM 2SLS HAC Quadratic models, respectively.

For single family home price samples in the 2008 housing bust year, a swimming pool on the ground added to the selling price about 3.94% for OLS3 Both Effects, 3.67% for ML Spatial Error, 3.46% for ML Spatial Lag, 3.64% for GMM SAR Error, 3.38% for GMM 2SLS HAC, and 3.02% for GMM 2SLS HAC Quadratic models, respectively.

Regression results for housing physical characteristics of single family homes for all models are shown in Table 5.36.

Condo samples

Since the dependent variable was log transformed, coefficients on the independent variables in housing characteristics would be based on three different ways of interpretation based on the form of the variable (Asteriou and Hall, 2007). First, when the independent variable was log transformed as well, the coefficient of the variable should be interpreted as elastic. Second, when the independent variable was not transformed, the coefficient of the variable should be interpreted as a relative change in dependent variables on an absolute change in the dependent variable. Third, when the independent variable was an untransformed dummy variable, in the semi-logarithmic equation the interpretation of the dummy variable coefficients involves the use of the formula: 100*(e^{β}-l), where β is the dummy variable coefficient (Halvorsen and Palmquist, 1980).

First, lot size as a transformed continuous variable would be interpreted as follows:

For condo samples in the 2005 housing boom year, each additional square foot of lot size increased the selling price by about 0.031% for OLS3 Both Effects, 0.053% for ML Spatial Error, 0.021% for ML Spatial Lag, 0.054% for GMM SAR Error, 0.024% for GMM 2SLS HAC, and 0.031% for GMM 2SLS HAC Quadratic models, respectively.

For condo price samples in the a 2008 housing bust year, each additional square foot of lot size increased the selling price by about 0.023% for OLS3 Both Effects, 0.024% for ML Spatial Error, 0.025% for ML Spatial Lag, 0.018% for GMM SAR Error, 0.023% for GMM 2SLS HAC, and 0.024% for GMM 2SLS HAC Quadratic models, respectively. However, it was not statistically significant in a 2008 housing bust year.

Second, the coefficients of the building age as an untransformed continuous variable would be interpreted as follows:

For condo samples in the 2005 housing boom year, a year increase in building age as an untransformed continuous variable dropped the sale price by -2.04% for OLS3 Both Effects, -1.82% for ML Spatial Error, -1.45% for ML Spatial Lag, -1.69% for GMM SAR Error, -1.72% for GMM 2SLS HAC, and -1.56% for GMM 2SLS HAC Quadratic models, respectively.

However, For condo price samples in the 2005 housing boom year, a year increase in squared-age as an untransformed continuous variable diminished the sale price by 0.012% for OLS3 Both Effects, 0.0085% for ML Spatial Error, 0.0057% for ML Spatial Lag, 0.0066% for GMM SAR Error, 0.0086% for GMM 2SLS HAC, and 0.0058% for GMM 2SLS HAC Quadratic models, respectively.

For condo price samples in the 2008 housing boom year, a year increase in building age as an untransformed continuous variable dropped the sale price by -2.08% for OLS3 Both Effects, -2.08% for ML Spatial Error, -2.05% for ML Spatial Lag, -2.09% for GMM SAR Error, -2.02% for GMM 2SLS HAC, and -2.00% for GMM 2SLS HAC Quadratic models, respectively.

However, For condo price samples in the 2008 housing bust year, a year increase in squared-age as an untransformed continuous variable diminished the sale price by 0.0016% for OLS3 Both Effects, 0.0156% for ML Spatial Error, 0.0153% for ML Spatial Lag, 0.0155% for GMM SAR Error, 0.0146% for GMM 2SLS HAC, and 0.0146% for GMM 2SLS HAC Quadratic models, respectively.

Third, main living area in the home as a transformed continuous variable would be interpreted as follows:

For condo price sample in the 2005 housing boom year, each additional square foot of interior living space increased the selling price about 0.94% for OLS3 Both Effects, 0.90% for ML Spatial Error, 0.86% for ML Spatial Lag, 0.89% for GMM SAR Error, 0.90% for GMM 2SLS HAC, and 0.89% for GMM 2SLS HAC Quadratic models, respectively.

For condo price samples in the 2008 housing bust year, each additional square foot of interior living space increased the selling price about 0.94% for OLS3 Both Effects, 0.94% for ML Spatial Error, 0.94% for ML Spatial Lag, 0.93% for GMM SAR Error, 0.93% for GMM 2SLS HAC, and 0.93% for GMM 2SLS HAC Quadratic models, respectively.

Fourth, multi-floor and semi-detached homes as a dummy variable would be interpreted as follows:

For condo price samples in the 2005 housing boom year, the selling price for multi-floor and semi-detached condos dropped by about -12.37% for OLS3 Both Effects, -9.79% for ML Spatial Error, -10.42% for ML Spatial Lag, -9.61% for GMM SAR Error, -11.57% for GMM 2SLS HAC, and -10.95% GMM 2SLS HAC Quadratic models, respectively, compared to non-multi-floor condos.

For condo price samples in the 2008 housing bust year, the selling price for multi-floor and semi-detached homes in a townhouse or condominium complex dropped by about -19.83% for OLS3 Both Effects, -19.83% for ML Spatial Error, -19.82% for ML Spatial Lag, -19.34% for GMM SAR Error, -19.34% for GMM 2SLS HAC, and -18.62% GMM 2SLS HAC Quadratic models compared to non-multi-floor condos.

Fifth, the presence of a garage as a dummy variable would be interpreted as follows:

For condo price samples in the a 2005 housing boom year, a garage was not statistically significant to the selling price in OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC, and GMM 2SLS HAC Quadratic models, respectively.

For condo price samples in the 2008 housing bust year, a garage added to the selling price about 11.29% for OLS3 Both Effects, 10.47% for ML Spatial Error, 10.08% for ML Spatial Lag, 9.99% for GMM SAR Error, 9.20% for GMM 2SLS HAC, and 10.04% for GMM 2SLS HAC Quadratic models, respectively.

Sixth, the presence of a swimming pool as a dummy variable would be interpreted as follows:

For condo price samples in the 2005 housing boom year, a swimming pool on the ground added to the selling price about 28.27% for OLS3 Both Effects, 23.74% for ML Spatial Error, 31.61% for ML Spatial Lag, 23.24% for GMM SAR Error, 30.34% for GMM 2SLS HAC, and 28.53% for GMM 2SLS HAC Quadratic models, respectively.

For condo price samples in the 2008 housing bust year, a swimming pool on the ground added to the selling price about 32.27% for OLS3 Both Effects, 32.70% for ML Spatial Error, 30.34% for ML Spatial Lag, 33.78% for GMM SAR Error, 31.65% for GMM 2SLS HAC, and 30.34% for GMM 2SLS HAC Quadratic models, respectively.

Regression results for housing physical characteristics of condo for all models are shown in Table 5.37.

Table 5.37. Estimated Marginal Impacts of Housing Physical Characteristics on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)								
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
LN_LOT SIZE	-2.22E-02* (-2.434)	1.08E-02 (1.245)	3.09E-02*** (3.770)	5.26E-02*** (6.046)	2.09E-02** (2.669)	5.37E-02*** (6.134)	2.42E-02* (2.529)	3.06E-02** (3.210)
AGE	-3.39E-02*** (-22.643)	-2.70E-02*** (-18.899)	-2.04E-02*** (-14.985)	-1.82E-02*** (-12.003)	-1.45E-02*** (-15.451)	-1.69E-02*** (-10.997)	-1.72E-02*** (-9.988)	-1.56E-02*** (-8.812)
AGE_2	3.64E-04*** (12.051)	2.33E-04*** (8.078)	1.23E-04*** (4.503)	8.46E-05** (2.850)	5.72E-05*** (3.291)	6.61E-05* (2.2027)	8.56E-05* (2.364)	5.77E-05 (1.550)
LN_LIVING AREA	1.10E+00*** (49.790)	1.01E+00*** (48.320)	9.38E-01*** (47.375)	8.99E-01*** (46.509)	8.60E-01*** (48.513)	8.93E-01*** (46.400)	9.01E-01*** (39.288)	8.92E-01*** (38.746)
STORY_dummy	-2.42E-01*** (-23.814)	-1.45E-01*** (-14.318)	-1.32E-01*** (-13.873)	-1.03E-01*** (-10.999)	-1.10E-01*** (-12.538)	-1.01E-01*** (-10.765)	-1.23E-01*** (-11.096)	-1.16E-01*** (-10.428)
GARAGE_dummy	8.94E-02*** (6.320)	5.43E-02*** (4.044)	-7.45E-03 (-0.580)	-3.25E-03 (-0.264)	-1.08E-03 (-1.190)	-1.46E-03 (-0.120)	-1.07E-02 (-0.584)	-2.61E-03 (-0.140)
POOL_dummy	2.89E-01*** (4.885)	2.68E-01*** (4.814)	2.49E-01*** (4.784)	2.13E-01*** (4.676)	2.75E-01*** (5.661)	2.09E-01*** (4.617)	2.65E-01*** (6.674)	2.51E-01*** (6.384)
N	6,205	6,205	6,205	6,205	6,205	6,205	6,205	6,205
The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)								
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
LN_LOT SIZE	-5.41E-02** (-2.745)	-4.60E-02* (-2.181)	-2.27E-02 (-1.244)	-2.42E-02 (-1.318)	-2.51E-02 (-1.412)	-1.82E-02 (-0.992)	-2.32E-02 (-1.287)	-2.38E-02 (-1.331)
AGE	-2.17E-02*** (-10.558)	-2.47E-02*** (-11.178)	-2.08E-02*** (-10.915)	-2.08E-02*** (-10.904)	-2.05E-02*** (-10.833)	-2.09E-02*** (-10.964)	-2.02E-02*** (-11.592)	-2.00E-02*** (-11.226)
AGE_2	1.69E-04*** (4.084)	1.97E-04*** (4.423)	1.60E-04*** (4.201)	1.55E-04*** (4.053)	1.53E-04*** (4.043)	1.55E-04*** (4.071)	1.46E-04*** (4.032)	1.46E-04*** (3.970)
LN_LIVING AREA	1.02E+00*** (24.921)	9.80E-01*** (22.620)	9.42E-01*** (25.212)	9.43E-01*** (25.256)	9.40E-01*** (25.505)	9.34E-01*** (25.027)	9.33E-01*** (24.925)	9.30E-01*** (25.099)
STORY_dummy	-2.84E-01*** (-13.531)	-2.93E-01*** (-13.029)	-2.21E-01*** (-11.280)	-2.21E-01*** (-11.248)	-2.21E-01*** (-11.429)	-2.15E-01*** (-10.969)	-2.15E-01*** (-10.837)	-2.06E-01*** (-10.468)
GARAGE_dummy	1.15E-01*** (4.972)	6.74E-02** (2.749)	1.07E-01*** (5.001)	9.96E-02*** (4.668)	9.61E-02*** (4.533)	9.52E-02*** (4.449)	8.80E-02*** (3.511)	9.57E-02*** (3.757)
POOL_dummy	3.37E-01*** (3.699)	3.12E-01** (3.220)	2.79E-01*** (3.362)	2.83E-01*** (3.453)	2.65E-01** (3.222)	2.91E-01*** (3.538)	2.75E-01*** (4.838)	2.65E-01*** (4.687)
N	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003

Notes. t value (OLSs and GMM_2SLS_HACs) or z value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses.
Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

5.2.7.2 Housing Market Characteristics

As the overall performances of all models are discussed in a prior section, the interpretations of GMM_2SLS-HAC Quadratic models (Model 8) would be the most conservative results. In doing so, discussion of the results for housing market characteristics mainly focus on the GMM_2SLS_HAC_Quadratic models. For the remaining models for each data sample, the variables will only be discussed if there is a substantial variation from the GMM_2SLS_HAC_Quadratic model (Model 8). Variables in the category of the market characteristics include dummy variables for the quarter in which the property sold. The quarter dummy variables are included to capture the expected differences in housing prices between the first and second, third, and fourth quarters.

The first quarter is the omitted dummy variable. There are no sign expectations in any of the time-related variables because both supply and demand for housing will change during each period. First, the quarter as a dummy variable for single family home price sample in a 2005 housing boom year would be interpreted as follows:

For single family home price samples in the 2005 housing boom year (see Table 5.38, upper section), the housing selling price in the GMM_2SLS_HAC_Quadratic model (Model 8) increased about 5.50% in the second quarter, 9.77% in the third quarter, and 11.85% in the fourth quarter, respectively, compared to the first quarter. It indicated overall trends of increasing house prices during a 2005 housing boom year.

Table 5.38. Estimated Marginal Impacts of Housing Market Characteristics on Existing Single Family Home Prices.

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)								
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
2nd QUARTER _dummy	5.20E-02*** (28.987)	5.21E-02*** (32.057)	5.28E-02*** (32.744)	5.26E-02*** (34.658)	5.29E-02*** (34.566)	5.24E-02*** (34.672)	5.27E-02*** (34.241)	5.35E-02*** (35.607)
3rd QUARTER _dummy	8.66E-02*** (48.099)	8.96E-02*** (55.003)	9.05E-02*** (55.980)	9.21E-02*** (60.439)	9.11E-02*** (59.344)	9.19E-02*** (60.598)	9.11E-02*** (59.888)	9.32E-02*** (62.509)
4th QUARTER _dummy	1.02E-01*** (53.319)	1.08E-01*** (62.520)	1.10E-01*** (64.019)	1.11E-01*** (68.246)	1.10E-01*** (67.310)	1.10E-01*** (68.320)	1.10E-01*** (67.903)	1.12E-01*** (70.600)
N	30,815	30,815	30,815	30,815	30,815	30,815	30,815	30,815

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2008)								
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
2nd QUARTER _dummy	-2.64E-02*** (-6.089)	-1.60E-02*** (-3.833)	-5.73E-03 (-1.559)	-7.85E-03* (-2.189)	-9.24E-03** (-2.604)	-8.09E-03* (-2.271)	-9.58E-03** (-2.866)	2.27E-03 (0.694)
3rd QUARTER _dummy	-8.56E-02*** (-19.993)	-5.68E-02*** (-13.656)	-3.63E-02*** (-9.841)	-3.82E-02*** (-10.639)	-4.12E-02*** (-11.575)	-3.83E-02*** (-10.730)	-4.19E-02*** (-12.116)	-2.38E-02*** (-7.016)
4th QUARTER _dummy	-1.59E-01*** (-35.238)	-1.19E-01*** (-26.613)	-7.27E-02*** (-18.101)	-7.67E-02*** (-19.529)	-8.24E-02*** (-21.283)	-7.74E-02*** (-19.778)	-8.39E-02*** (-20.922)	-7.33E-02*** (-18.921)
N	12,885	12,885	12,885	12,885	12,885	12,885	12,885	12,885

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses.
Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

For single family home price samples in the 2008 housing bust year (see Table 5.38, lower section), the housing selling prices in the GMM_2SLS_HAC_Quadratic model (Model 8) increased about 0.23% in the second quarter than the first quarter, but it is not statistically significant. It decreased -2.35% in the third quarter and -7.06% in the fourth quarter compared to the first quarter. It indicated overall trends of decreasing single family home prices during a 2008 housing bust year.

For condo price samples in the 2005 housing boom year (see Table 5.39, upper section), the house selling prices in the GMM_2SLS_HAC_Quadratic model (Model 8) increased about 13.77% in the second quarter, 28.15% in the third quarter, 41.76% in the fourth quarter compared to the first quarter. It indicated an overall trend of increasing housing prices during a 2005 housing boom year.

For condo samples in the 2008 housing bust year (see Table 5.39, lower section), the housing selling prices in the GMM_2SLS_HAC_Quadratic model (Model 8) increased about 4.93% in the second quarter compared to the first quarter, but it was not statistically significant. It decreased -15.30% in the third quarter and -29.67% in fourth quarter, respectively, compared to the first quarter. However, they were also not statistically significant.

Table 5.39. Estimated Marginal Impacts of Housing Market Characteristics on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)

Independent Variable	OLS1_Prev _Direct (Model 1)	OLS2_Prev _Spillover (Model 2)	OLS3_Prev _Both (Model 3)	ML_Spatial _Error (Model 4)	ML_Spatial _Lag (Model 5)	GMM_SAR _Error (Model 6)	GMM_2SLS _HAC (Model 7)	GMM_2SLS _HAC_Quad (Model 8)
2nd QUARTER _dummy	1.07E-01*** (9.406)	1.20E-01*** (11.141)	1.32E-01*** (13.114)	1.29E-01*** (14.649)	1.21E-01*** (12.909)	1.33E-01*** (15.079)	1.28E-01*** (12.846)	1.29E-01*** (12.972)
3rd QUARTER _dummy	1.91E-01*** (16.217)	2.12E-01*** (19.084)	2.51E-01*** (23.916)	2.50E-01*** (26.997)	2.37E-01*** (24.223)	2.52E-01*** (27.503)	2.45E-01*** (24.366)	2.48E-01*** (24.789)
4th QUARTER _dummy	3.02E-01*** (24.644)	3.33E-01*** (28.746)	3.62E-01*** (33.208)	3.55E-01*** (36.438)	3.39E-01*** (33.467)	3.51E-01*** (36.359)	3.51E-01*** (32.221)	3.49E-01*** (32.450)
N	6,205	6,205	6,205	6,205	6,205	6,205	6,205	6,205

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)

Independent Variable	OLS1_Prev _Direct (Model 1)	OLS2_Prev _Spillover (Model 2)	OLS3_Prev _Both (Model 3)	ML_Spatial _Error (Model 4)	ML_Spatial _Lag (Model 5)	GMM_SAR _Error (Model 6)	GMM_2SLS _HAC (Model 7)	GMM_2SLS _HAC_Quad (Model 8)
2nd QUARTER _dummy	-4.24E-02* (-2.073)	-3.98E-02• (-1.825)	-3.92E-03 (-0.209)	-4.24E-03 (-0.229)	-3.82E-04 (-0.288)	-2.15E-04 (-0.012)	-5.91E-04 (-0.033)	4.81E-03 (0.264)
3rd QUARTER _dummy	-1.26E-01*** (-5.655)	-1.21E-01*** (-4.994)	-2.56E-02 (-1.207)	-2.78E-02 (-1.325)	-2.91E-02 (-1.481)	-2.64E-02 (-1.257)	-2.87E-02 (-1.378)	-1.66E-02 (-0.793)
4th QUARTER _dummy	-2.17E-01*** (-9.177)	-1.99E-01*** (-7.243)	-3.84E-02 (-1.571)	-4.01E-02• (-1.656)	-4.14E-02• (-1.789)	-4.06E-02• (-1.674)	-4.03E-02• (-1.710)	-3.52E-02 (-1.467)
N	2,003	2,003	2,003	2,003	2,003	2,003	2,003	2,003

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses.
Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1.

5.2.7.3 Discount of Distressed Home Sales Associated with Foreclosure

Discount of distressed single family home sales associated with foreclosure

One of the methodological goals of this study is to estimate the effects of residential foreclosures on nearby home prices and to separate this estimate into the part due to direct foreclosure effects associated with property levels and the part due to indirect foreclosure effects associated with neighboring residential foreclosures as a negative neighborhood externality.

As typical home sales, this study limits traditional home sales to arm's length transactions, which have never been under foreclosure status in the two years prior to the sale transactions.

As distressed sales related to the foreclosure process, this study is limited to home sales that had at least one foreclosure filing in the two years prior to the sale transaction for 2005 and 2008 housing samples in the Phoenix area.

To compare distressed home sales related to the foreclosure to typical home sales, this study used dummy variables to distinguish the distressed sales related to the foreclosure in the hedonic model. In Table 5.40, the dummy, DISTRESSED SALE, indicates the impact of previous foreclosure status on home prices.

For 2005 single family home sale samples throughout the study area (see Table 5.40, upper section), the average sale price of a single family home that faced a foreclosure in the two years prior to sale and sold later were discounted about -4.93 % for OLS1 Prev Direct, -1.83% for OLS3 Both Effects, -1.19% for ML Spatial Error, -0.04% for ML Spatial Lag, -0.03% for GMM SAR Error, -0.24% for GMM 2SLS HAC, and -0.22% for GMM 2SLS HAC Quadratic models compared to the sale prices of typical homes. Two results of the OLS models were statistically significant but the others were not.

For 2008 single family home sale samples throughout the study area (see Table 5.40, lower section), the average sale price of single family home that faced a foreclosure in the two years prior to sale and sold later were discounted about -14.96 % for OLS1 Prev Direct, -9.08% for OLS3 Both Effects, -8.91% for ML Spatial Error, -5.23% for ML Spatial Lag, -8.60% for GMM SAR Error, -4.29% for GMM 2SLS HAC, and -3.42% for GMM 2SLS HAC Quadratic models compared to the sale price of typical homes.

Table 5.40. Estimated Marginal Impacts of Distressed Sales Associated with Foreclosure on Existing Single Family Home Prices.

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
DISTRESSED SALE _dummy	-5.06E-02*** (-20.276)	-1.85E-02*** (-7.111)	-1.20E-02 (-0.841)	3.55E-05 (NA)	-2.59E-04 (-0.098)	-2.42E-03 (-0.955)	-2.19E-03 (-0.897)
N	30,815	30,815	30,815	30,815	30,815	30,815	30,815
The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2008)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
DISTRESSED SALE _dummy	-1.62E-01*** (-54.879)	-9.53E-02*** (-33.634)	-9.33E-02*** (-27.434)	-5.37E-02*** (-17.485)	-8.99E-02*** (-24.800)	-4.38E-02*** (-13.642)	-3.48E-02*** (-11.187)
N	12,885	12,885	12,885	12,885	12,885	12,885	12,885
Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS2_Prev_Spillover model (model 2) doesn't have variables of selling factors related to foreclosure status and is not presented in this table.							

Discount of distressed condo sales associated with foreclosure

To compare distressed condo sales related to the foreclosure to typical (non-distressed) condo sales, this study used dummy variables to distinguish the distressed sales related to the foreclosure in the hedonic model. In Table 5.41, the dummy, DISTRESSED SALE, indicates the impact of previous foreclosure status on the condo sale price.

For 2005 condo price samples (see Table 5.41, upper section) throughout the study area, the average sale price of condos that had a foreclosure filing in the two years prior to sale and sold later were discounted about -14.02% for OLS1 Prev Direct, -4.76% for OLS3 Both Effects, -3.73% for ML Spatial Error, -1.41% for ML Spatial Lag, -2.24% for GMM SAR Error, -4.41% for GMM 2SLS HAC, and -3.69% for GMM 2SLS HAC Quadratic models compared to the sale price of typical condos.

For 2008 condo price samples (see Table 5.41, lower section) throughout the study area, the average sale price of condos that had a foreclosure filing in the two years prior to sale and sold later were discounted about -31.75% for OLS1 Prev Direct, -20.31% for OLS3 Both Effects, -20.86% for ML Spatial Error, -20.39% for ML Spatial Lag, -20.86% for GMM SAR Error, -20.39% for GMM 2SLS HAC, and -19.59% for GMM 2SLS HAC Quadratic models compared to the sale price of typical condos.

The results indicated that the discount of condos that faced a foreclosure in two years prior to sale and sold later in 2008 was much larger than that in 2005. This indicated that the value depreciation by foreclosure activity in the 2008 housing bust year was much greater than that of the 2005 housing boom year.

Table 5.41. Estimated Marginal Impacts of Distressed Sales Associated with Foreclosure on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
DISTRESSED SALE _dummy	-1.51E-01*** (-7.368)	-4.88E-02* (-2.262)	-1.42E-02 (-0.763)	-3.80E-02• (-1.806)	-2.27E-02 (-1.226)	-4.51E-02* (-2.555)	-3.76E-02* (-2.153)
N	6,205	6,205	6,205	6,205	6,205	6,205	6,205
The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
DISTRESSED SALE _dummy	-3.82E-01*** (-20.623)	-2.27E-01*** (-10.654)	-2.34E-01*** (-11.105)	-2.28E-01*** (-10.814)	-2.34E-01*** (-11.047)	-2.28E-01*** (-12.136)	-2.18E-01*** (-11.574)
N	2,003	2,003	2,003	2,003	2,003	2,003	2,003

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. OLS2_Prev_Spillover model (model 2) doesn't have variables of selling factors related to foreclosure status and is not presented in this table.

5.2.7.4 Discount for Renter Occupied Homes

Discount for renter occupied single family homes

In Table 5.42, the dummy, RENTER, indicates the effect of renter occupancy status on home sale prices. The negative and significant coefficient suggests that the marginal impact of the property sale price has a discount.

For 2005 single family home samples (see Table 5.42, upper section), renter occupied home had a discount of about -2.24% for OLS1 Prev Direct, -2.33% for OLS3 Both Effects, -2.18% for ML Spatial Error, -2.16% for ML Spatial Lag, -2.19% for GMM SAR Error, -2.19% for GMM 2SLS HAC, and -2.12% for GMM 2SLS HAC Quadratic models, respectively.

For 2008 single family homes samples (see Table 5.42, lower section), renter occupied home had a discount of about -6.79% for OLS1 Prev Direct, -6.54% for OLS3 Both Effects, -6.22% for ML Spatial Error, -6.42% for ML Spatial Lag, -6.19% for GMM SAR Error, -6.28% for GMM 2SLS HAC, and -5.78% for GMM 2SLS HAC Quadratic models, respectively.

This study also investigated the effect of renter occupancy status on distressed home sales associated with foreclosure using the interaction term. In Table 5.42, the interaction term, INT_D-S AND RENTER, is the interaction dummy variable denoting single family homes that faced a foreclosure in the two years prior to sale and sold later under renter occupied status.

Table 5.42. Estimated Marginal Impacts of Renter Occupancy on Existing Single Family Home Prices.

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
RENTER _dummy	-2.27E-02*** (-12.477)	-2.36E-02*** (-13.726)	-2.20E-02*** (-13.612)	-2.19E-02*** (-13.514)	-2.21E-02*** (-13.707)	-2.21E-02*** (-13.416)	-2.14E-02*** (-13.220)
INT_D-S AND RENTER	-	-1.16E-02* (-2.068)	-9.83E-03• (-1.865)	-1.19E-02* (-2.114)	-1.09E-02* (-2.068)	-1.18E-02* (-2.173)	-1.09E-02* (-2.059)
N	30,815	30,815	30,815	30,815	30,815	30,815	30,815
The Results of Analytical Models (Dependent Variable: LN_ Single Family Home Sale Prices in 2008)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
RENTER _dummy	-7.02E-02*** (-16.619)	-6.76E-02*** (-11.312)	-6.42E-02*** (-10.989)	-6.39E-02*** (-10.805)	-6.45E-02*** (11.092)	-6.49E-02*** (-7.791)	-5.95E-02*** (-7.320)
INT_D-S AND RENTER	-	2.04E-02** (2.751)	1.57E-02* (2.168)	1.88E-02* (2.541)	1.60E-02* (2.220)	2.02E-02* (2.105)	1.60E-02• (1.727)
N	12,885	12,885	12,885	12,885	12,885	12,885	12,885
Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.							

For 2005 single family homes samples (see Table 5.42, upper section), the price of renter occupied homes that faced a foreclosure in the two years prior to sale and sold later (distressed sale) decreased about -1.15% for OLS3 Both Effects, -0.989% for ML Spatial Error, -1.18% for ML Spatial Lag, -1.08% for GMM SAR Error, and -1.19% for GMM 2SLS HAC, -1.08% for GMM 2SLS HAC Quadratic models compared to owner occupied home sale prices.

For 2008 single family home samples (see Table 5.42, lower section), the price of renter occupied home that faced a foreclosure in the two years prior to sale and sold later (distressed sale) was a little higher at about 2.06% for OLS3 Both Effects, 1.58% for ML Spatial Error, 1.90% for ML Spatial Lag, 1.61% for GMM SAR Error, 2.04% for GMM 2SLS HAC, and 1.61% for GMM 2SLS HAC Quadratic models compared to owner occupied home sale prices. These interesting findings seem to suggest that renter occupied and distressed single family home sales associated with foreclosure don't have any discount compared to owner occupied and distressed single family home sale prices in a bad housing market (2008).

Discount for renter occupied condos

In Table 5.43, the dummy, RENTER, indicates the effect of renter occupancy on condo prices. The negative and significant coefficient suggests that the marginal impact of property sale price has a discount.

For 2005 condo samples (see Table 5.43, upper section), renter occupied condo had a discount of about -6.84% for OLS1 Prev Direct, -4.83% for OLS3 Both Effects, -

4.20% for ML Spatial Error, -4.32% for ML Spatial Lag, -4.39% for GMM SAR Error, -4.81% for GMM 2SLS HAC, and -5.49% for GMM 2SLS HAC Quadratic models, respectively.

For 2008 condo samples (see Table 5.43, lower section), renter occupied condo had a discount of about -3.72% in OLS1 Prev Direct. But it was not statistically significant in OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC, and GMM 2SLS HAC Quadratic models, respectively.

Table 5.43. Estimated Marginal Impacts of Renter Occupancy on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
RENTER _dummy	-7.08E-02*** (-7.163)	-4.95E-02*** (-5.520)	-4.30E-02*** (-5.446)	-4.49E-02*** (-5.343)	-4.42E-02*** (-5.654)	-4.93E-02*** (-5.161)	-5.65E-02*** (-5.938)
INT_D-S AND RENTER	-	-1.98E-02 (-0.456)	-4.14E-02 (-1.091)	-2.01E-02 (-0.429)	-2.91E-02 (-0.780)	-1.76E-02 (-0.474)	-6.60E-03 (-0.178)
N	6,205	6,205	6,205	6,205	6,205	6,205	6,205
The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
RENTER _dummy	-3.88E-02* (-2.064)	1.31E-02 (0.663)	1.30E-02 (0.664)	1.35E-02 (0.671)	1.16E-02 (0.592)	1.24E-02 (0.549)	1.43E-02 (0.638)
INT_D-S AND RENTER	-	-1.08E-01** (-2.777)	-1.04E-01** (-2.697)	-1.08E-01** (-2.767)	-1.06E-01** (-2.738)	-1.09E-01** (-2.716)	-1.05E-01* (-2.572)
N	2,003	2,003	2,003	2,003	2,003	2,003	2,003
Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.							

This study also investigated the effect of renter occupancy status on the price of distressed condos associated with foreclosure using the interactive dummy variable. In

Table 5.43, the interaction term, INT_D-S AND RENTER, is the interaction dummy variable denoting condo units that faced foreclosure in the two years prior to sale and sold later (distressed sale) under renter occupied status.

For 2005 condo samples (see Table 5.43, upper section), the price of renter occupied condo that faced a foreclosure in the two years prior to sale and sold later (distressed sale) was not statistically significant for this interaction term in OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC, and GMM 2SLS HAC Quadratic models, respectively.

For 2008 condo samples (Table 5.43, lower section), the price of renter occupied condo that faced a foreclosure in the two years prior to sale and sold later (distressed sale) was less about -10.23% for OLS3 Both Effects, -9.88% for ML Spatial Error, -10.24% for ML Spatial Lag, -10.06% for GMM SAR Error, -10.32% for GMM 2SLS HAC, and -9.98% for GMM 2SLS HAC Quadratic models than owner occupied condo sale prices, respectively.

Generally, the results indicated that renter occupied condos had a discount compared to owner occupied condos in 2005. However, it was not statistically significant in 2008. Furthermore, renter occupied home that faced a foreclosure in the two years prior to sale and sold later (distressed sale) had larger discount than owner occupied and distressed condo sales in 2008.

5.2.7.5 Discount for Cash Transactions

Single family home samples

In Table 5.44, the dummy, CASH SALE, indicates the impact of cash transactions on home sale prices. The negative and significant coefficient suggests that the marginal impact of the property sale price has a discount.

For 2005 single family home samples (see Table 5.44, upper section), home sold by cash transaction had a discount of about -1.09% for OLS1 Prev Direct, -1.07% for OLS3 Both Effects, -1.39% for ML Spatial Error, -1.32% for ML Spatial Lag, -1.41% for GMM SAR Error, -1.33% for GMM 2SLS HAC, and -1.52% for GMM 2SLS HAC Quadratic models, respectively.

For 2008 single family home samples (see Table 5.44, lower section), home sold by cash transaction had a discount of about -11.75% for OLS1 Prev Direct, -7.21% for OLS3 Both Effects, -7.13% for ML Spatial Error, -7.21% for ML Spatial Lag, -7.02% for GMM SAR Error, -7.11% for GMM 2SLS HAC, and -7.51% for GMM 2SLS HAC Quadratic models, respectively.

This study also investigated the effect of cash transactions on distressed single family home prices associated with foreclosure using the interactive dummy variable. In Table 5.44, the interaction term, INT_D-S AND CASH SALE, is the interactive dummy variable denoting single family units that have been foreclosed in the two years prior to sale and sold later (distressed sales) by cash transactions.

Table 5.44. Estimated Marginal Impacts of Cash Transactions on Existing Single Family Home Prices.

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CASH SALE _dummy	-1.10E-03 (-0.424)	-1.08E-02*** (-4.443)	-1.40E-02*** (-6.107)	-1.33E-02*** (-15.011)	-1.42E-02*** (-6.241)	-1.34E-02*** (-4.707)	-1.53E-02*** (-5.528)
INT_D-S AND CASH SALE	-	-4.61E-03 (-0.551)	-5.12E-03 (-0.648)	-5.70E-03 (-0.736)	-4.27E-03 (-0.542)	-4.55E-03 (-0.503)	-2.51E-03 (-0.279)
N	30,815	30,815	30,815	30,815	30,815	30,815	30,815

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2008)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CASH SALE _dummy	-1.25E-01*** (-33.563)	-7.48E-02*** (-14.381)	-7.40E-02*** (-14.601)	-7.48E-02*** (-14.841)	-7.28E-02*** (-14.435)	-7.38E-02*** (-9.988)	-7.81E-02*** (-10.909)
INT_D-S AND CASH SALE	-	-5.13E-02*** (-7.923)	-4.97E-02*** (-7.859)	-4.96E-02*** (-7.874)	-5.11E-02*** (-8.132)	-5.07E-02*** (-5.886)	-4.68E-02*** (-5.631)
N	12,885	12,885	12,885	12,885	12,885	12,885	

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.

For 2005 single family home samples (see Table 5.44, upper section), the sale price of single family home that faced a foreclosure in the two years prior to sale and sold later (distressed sale) by a cash transaction was not statistically significant in OLS3_Both_Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC, GMM 2SLS HAC Quadratic models, respectively.

For 2008 single family home samples (see Table 5.44, lower section), the sale price of single family home that faced a foreclosure in the two years prior to sale and sold later (distressed sale) by a cash transaction was lower by about -5.00% for OLS3 Both Effects, -4.85% for ML Spatial Error, -4.84% for ML Spatial Lag, -4.98% for GMM SAR Error, -4.94% for GMM 2SLS HAC, and -4.74% for GMM 2SLS HAC

Quadratic models than homes sold with mortgage financing.

Condo samples

In Table 5.45, the dummy, CASH SALE, indicates the impact of cash transactions on condo prices. The negative and significant coefficient indicated that the marginal impact on condo price had a discount.

For 2005 condo samples (see Table 5.45, upper section), condo sold by a cash transaction had discounts of about -2.47% for OLS1 Prev Direct, -3.48% for OLS3 Both Effects, -3.83% for ML Spatial Error, -3.45% for ML Spatial Lag, -3.79% for GMM SAR Error, -3.45% for GMM 2SLS HAC, and -4.06% for GMM 2SLS HAC Quadratic models, respectively.

For 2008 condo samples (see Table 5.45, lower section), condo sold by a cash transaction had discounts of about -12.98% for OLS1 Prev Direct, -6.04% for OLS3 Both Effects, -6.68% for ML Spatial Error, -6.11% for ML Spatial Lag, -6.64% for GMM SAR Error, -6.09% for GMM 2SLS HAC, and -5.92% for GMM 2SLS HAC Quadratic models, respectively.

This study also investigated the effect of cash transactions on the price of condos associated with foreclosure using the interaction term. In Table 5.45, the interaction term, INT_D-S AND CASH SALE, is the interactive dummy variable denoting condo units that had been foreclosed in the two years prior to sale and sold later (distressed sales) by cash transactions.

For 2005 condo samples (see Table 5.45, upper section), the sale price of condo that faced a foreclosure in the two years prior to sale and sold later (distressed sale) by a cash transaction was not statistically significant in OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC, GMM 2SLS HAC Quadratic models, respectively.

Table 5.45. Estimated Marginal Impacts of Cash Transactions on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CASH SALE _dummy	-2.50E-02* (-2.140)	-3.54E-02*** (-3.367)	-3.91E-02*** (-4.262)	-3.51E-02*** (-3.532)	-3.86E-02*** (-4.235)	-3.51E-02** (-2.946)	-4.14E-02*** (-3.516)
INT_D-S AND CASH SALE	-	-6.23E-02 (-1.181)	-6.46E-02 (-1.420)	-5.96E-02 (-1.126)	-7.11E-02 (-1.573)	-6.74E-02 (-1.412)	-5.23E-02 (-1.103)
N	6,205	6,205	6,205	6,205	6,205	6,205	6,205

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)							
Independent Variable	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CASH SALE _dummy	-1.39E-01*** (-7.601)	-6.24E-02** (-3.094)	-6.91E-02*** (-3.473)	-6.30E-02** (-3.133)	-6.87E-02*** (-3.440)	-6.28E-02** (-2.664)	-6.10E-02** (-2.617)
INT_D-S AND CASH SALE	-	-1.75E-01*** (-4.769)	-1.64E-01*** (-4.501)	-1.72E-01*** (-4.726)	-1.63E-01*** (-4.472)	-1.67E-01*** (-4.092)	-1.60E-01*** (-3.972)
N	2,003	2,003	2,003	2,003	2,003	2,003	2,003

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.

For 2008 condo samples (see Table 5.45, lower section), the sale price of condo that faced a foreclosure in the two years prior to sale and sold later (distressed sale) by a cash transaction was lower by about -16.05% for OLS3 Both Effects, -15.12% for ML Spatial Error, -15.80% for ML Spatial Lag, -15.04% for GMM SAR Error, -15.38% for GMM 2SLS HAC, and -14.81% for GMM 2SLS HAC Quadratic models compared to condos sold with mortgage financing.

The results indicated that condos sold by cash transactions had a discount compared to condos sold through mortgage financing in 2005 and 2008. Condos that faced a foreclosure in the two years prior to sale and sold later (distressed sale) by cash transactions also had a much larger discount than those sold through mortgage financing in 2008.

5.2.7.6 Distance Effects of Neighboring Foreclosures on Existing Home Prices

Distance effects of neighboring single family home foreclosures on existing single family home prices

For 2005 single family home samples, results (Table 5.46, upper section) indicated that a foreclosure on existing sale prices of single family homes within 500 feet created a negative spillover effect of approximately -1.32% for OLS2 Prev Spillover, -1.22% for OLS3 Both Effects, -1.07% for ML Spatial Error, -1.00% for ML Spatial Lag, -1.04% for GMM SAR Error, and -0.96% for GMM 2SLS HAC model, respectively. This negative impact diminished by distance and fell to -1.02% for OLS2 Prev Spillover, -1.04% for OLS3 Both Effects, -0.88% for ML Spatial Error, -0.82% for ML Spatial Lag, -0.86% for GMM SAR Error, and -0.79% for GMM 2SLS HAC models at a distance of 501-1000 feet, respectively. This negative impact was similar to those of the 501-1000 foot rings at a distance of 1001-1500 feet. It was about -1.08% for OLS2 Prev Spillover, -1.09% for OLS3 Both Effects, -0.87% for ML Spatial Error, -0.84% for ML Spatial Lag, -0.83% for GMM SAR Error, and -0.83% for GMM 2SLS HAC models at a distance of

1001-1500 feet, respectively.

Table 5.46. Estimated Marginal Impacts of Neighboring Single Family Home Foreclosures on Existing Single Family Home Prices.

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)							
Independent Variable	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
SFH_FC_1R_C [500 feet]	-1.32E-02*** (-27.473)	-1.22E-02*** (-25.214)	-1.07E-02*** (-22.957)	-1.00E-02*** (-22.578)	-1.04E-02*** (-22.307)	-9.63E-03*** (-21.853)	-2.12E-02*** (-22.072)
SFH_FC_1R_C2 [500 feet]	-	-	-	-	-	-	2.75E-03*** (15.318)
SFH_FC_2R_C [501-1000 feet]	-1.02E-02*** (-31.040)	-1.04E-02*** (-31.714)	-8.84E-03*** (-27.982)	-8.18E-03*** (-26.479)	-8.59E-03*** (-27.322)	-7.91E-03*** (-26.733)	-2.02E-02*** (-29.147)
SFH_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-	1.71E-03*** (22.093)
SFH_FC_3R_C [1001-1500 feet]	-1.08E-02*** (-42.112)	-1.09E-02*** (-42.826)	-8.65E-03*** (-34.880)	-8.42E-03*** (-34.894)	-8.32E-03*** (-33.652)	-8.14E-03*** (-33.473)	-1.86E-02*** (-32.683)
SFH_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	-	1.11E-03*** (23.167)
N	30,815	30,815	30,815	30,815	30,815	30,815	30,815

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2008)							
Independent Variable	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
SFH_FC_1R_C [500 feet]	-1.07E-02*** (-26.403)	-7.58E-03*** (-21.095)	-7.06E-03*** (-19.869)	-6.20E-03*** (-17.679)	-6.93E-03*** (-19.611)	-5.96E-03*** (-17.347)	-1.49E-02*** (-20.366)
SFH_FC_1R_C2 [500 feet]	-	-	-	-	-	-	3.96E-04*** (15.223)
SFH_FC_2R_C [501-1000 feet]	-3.12E-03*** (-11.138)	-2.89E-03*** (-11.741)	-2.67E-03*** (-11.090)	-2.38E-03*** (-9.933)	-2.63E-03*** (-10.955)	-2.33E-03*** (-9.882)	-7.24E-03*** (-15.187)
SFH_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-	1.20E-04*** (12.272)
SFH_FC_3R_C [1001-1500 feet]	-3.05E-03*** (-16.370)	-2.41E-03*** (-14.688)	-2.30E-03*** (-14.205)	-2.07E-03*** (-12.927)	-2.25E-03*** (-13.952)	-1.95E-03*** (-11.576)	-4.49E-03*** (-13.398)
SFH_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	-	4.56E-05*** (9.433)
N	12,885	12,885	12,885	12,885	12,885	12,885	12,885

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '・' 0.1. C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. OLS1_Prev_Direct model (model 1) doesn't have neighboring foreclosure variables and is not presented in this table.

For 2008 single family home samples, results (Table 5.46, lower section) indicated that a foreclosure on existing sale prices of single family homes within 500 feet created a negative spillover effect of approximately -1.07% for OLS2 Prev Spillover, -0.76% for OLS3 Both Effects, -0.71% for ML Spatial Error, -0.62% for ML Spatial Lag, -0.69% for GMM SAR Error, -0.60% for GMM 2SLS HAC models, respectively. This negative impact diminished by distance and fell to -0.31% for OLS2 Prev Spillover, -0.29% for OLS3 Both Effects, -0.27% for ML Spatial Error, -0.24% for ML Spatial Lag, -0.26% for GMM SAR Error, and -0.23% for GMM 2SLS HAC models at a distance of 501-1000 feet. This negative impact diminished by distance and fell to -0.31% for OLS2 Prev Spillover, -0.24% for OLS3 Both Effects,, -0.23% for ML Spatial Error, -0.21% for ML Spatial Lag, -0.23% for GMM SAR Error, and -0.20% for GMM 2SLS HAC models at a distance of 1001-1500 feet.

Distance effects of neighboring single family home foreclosures on existing condo prices

For 2005 condo samples, results (see table on page 214 [Table 5.47], upper section) indicated that the negative spillover effect of a foreclosure of single family home on existing condo sale prices within 500 feet was not statistically significant in OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, and GMM 2SLS HAC models, respectively. This insignificance of the other types of foreclosure coefficients on existing condo prices within 500 feet seems to reflect the small degree of variation in the number of different types of foreclosures in those intervals. However, a foreclosure of single family home on existing condo sale prices within 501-1000 feet created a negative spillover effect of approximately -1.86% for OLS3 Both Effects, -1.85% for ML Spatial Error, -1.51% for ML Spatial Lag, -1.81% for GMM SAR Error, and -1.66% for GMM 2SLS HAC models, respectively. This negative impact was similar to those of 501-1000 foot rings at a distance of 1001-1500 feet. It was about -2.28% for OLS3 Both Effects, -1.65% for ML Spatial Error, -1.37% for ML Spatial Lag, -1.60% for GMM SAR Error, and -1.86% for GMM 2SLS HAC models, respectively.

For 2008 condo samples, results (see Table 5.47, lower section) indicated that a foreclosure of single family home on existing condo sale prices within 500 feet created a negative spillover effect of approximately -1.29% for OLS3 Both Effects, -1.25% for ML Spatial Error, -1.30% for ML Spatial Lag, -1.33% for GMM SAR Error, and -1.31% for GMM 2SLS HAC models, respectively. This negative impact diminished by distance and fell to approximately -0.65% for OLS3 Both Effects, -0.58% for ML Spatial Error, -0.58% for ML Spatial Lag, -0.56% for GMM SAR Error, and -0.56% for GMM 2SLS HAC models at a distance of 501-1000 feet, respectively. However, this negative impact intensified to -1.48% for OLS3 Both Effects, -1.42% for ML Spatial Error, -1.43% for ML Spatial Lag, -1.40% for GMM SAR Error, and -1.38% for GMM 2SLS HAC models at a distance of 1001-1500 feet, respectively.

Table 5.47. Estimated Marginal Impacts of Neighboring Single Family Home Foreclosures on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_ Condo Sale Prices in 2005)						
Independent Variable	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
SFH_FC_1R_C [500 feet]	-9.13E-04 (-0.204)	4.66E-03 (1.098)	2.32E-03 (NA)	6.12E-03 (1.451)	2.75E-04 (0.055)	5.96E-03 (0.573)
SFH_FC_1R_C2 [500 feet]	-	-	-	-	-	-1.09E-03 (-0.406)
SFH_FC_2R_C [501-1000 feet]	-1.84E-02*** (-8.483)	-1.85E-02*** (-8.892)	-1.51E-02*** (-7.786)	-1.81E-02*** (-8.844)	-1.66E-02*** (-6.770)	-2.10E-02*** (-4.635)
SFH_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	6.16E-04 (1.560)
SFH_FC_3R_C [1001-1500 feet]	-2.28E-02*** (-16.041)	-1.65E-02*** (-11.563)	-1.37E-02*** (-10.562)	-1.60E-02*** (-11.250)	-1.86E-02*** (-9.604)	-3.87E-02*** (-10.620)
SFH_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	1.59E-03*** (6.347)
N	6,205	6,205	6,205	6,205	6,205	6,205

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)						
Independent Variable	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
SFH_FC_1R_C [500 feet]	-1.29E-02* (-2.006)	-1.25E-02* (-1.974)	-1.30E-02* (-2.022)	-1.33E-02* (-2.097)	-1.31E-02• (-1.802)	-2.21E-02* (-1.999)
SFH_FC_1R_C2 [500 feet]	-	-	-	-	-	1.78E-03 (1.015)
SFH_FC_2R_C [501-1000 feet]	-6.53E-03* (-2.112)	-5.80E-03• (-1.894)	-5.82E-03• (-1.847)	-5.58E-03• (-1.821)	-5.60E-03• (-1.670)	-8.44E-04 (-0.158)
SFH_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-3.26E-04 (-1.192)
SFH_FC_3R_C [1001-1500 feet]	-1.48E-02*** (-8.713)	-1.42E-02*** (-8.448)	-1.43E-02*** (-8.472)	-1.40E-02*** (-8.278)	-1.38E-02*** (-6.553)	-2.20E-02*** (-7.978)
SFH_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	2.47E-04*** (4.363)
N	2,003	2,003	2,003	2,003	2,003	2,003

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. OLS1_Prev_Direct model (model 1) and OLS2_Prev_Spillover model (model 2) don't have neighboring SFH foreclosure variables for condo samples and are not presented in this table.

Distance effects of neighboring condo foreclosures on existing single family home prices

For 2005 single family home samples (see Table 5.48, upper section), results indicated that a neighboring condo foreclosure on the existing single family home prices within 500 feet created a negative spillover effect of approximately -0.31% for OLS3 Both Effects, -0.33% for ML Spatial Error, -0.21% for ML Spatial Lag, -0.32% for GMM SAR Error, and -0.23% for GMM 2SLS HAC models, respectively. However, it was not statistically significant in the GMM 2SLS HAC model. This negative impact intensified to -0.35% for OLS3 Both Effects, -0.37% for ML Spatial Error, -0.34% for ML Spatial Lag, -0.38% for GMM SAR Error, and -0.33% for GMM 2SLS HAC models at a distance of 501-1000 feet, respectively. This negative impact again intensified to -0.44% for OLS3 Both Effects, -0.41% for ML Spatial Error, -0.40% for ML Spatial Lag, -0.41% for GMM SAR Error, and -0.41% for GMM 2SLS HAC models at a distance of 1001-1500 feet, respectively. Thus, the impact of a neighboring condo foreclosure on the existing single family home prices was flat at about -0.3 to -0.4% at a distance of 1001-1500 feet.

Table 5.48. Estimated Marginal Impacts of Neighboring Condo Foreclosures on Existing Single Family Home Prices.

The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2005)						
Independent Variable	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CON_FC_1R_C [500 feet]	-3.14E-03• (-1.779)	-3.33E-03* (-1.967)	-2.13E-03• (-1.722)	-3.20E-03• (-1.899)	-2.28E-03 (-1.378)	-3.07E-03 (-0.918)
CON_FC_1R_C2 [500 feet]	-	-	-	-	-	2.73E-04 (0.392)
CON_FC_2R_C [501-1000 feet]	-3.48E-03*** (-4.022)	-3.71E-03*** (-4.499)	-3.44E-03*** (-4.343)	-3.79E-03*** (-4.613)	-3.31E-03*** (-3.989)	9.63E-05 (0.062)
CON_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-5.10E-04* (-2.407)
CON_FC_3R_C [1001-1500 feet]	-4.41E-03*** (-7.263)	-4.06E-03*** (-6.944)	-3.96E-03*** (-6.936)	-4.12E-03*** (-7.080)	-4.06E-03*** (-7.053)	-1.65E-03 (-1.532)
CON_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	-3.08E-04* (-2.166)
N	30,815	30,815	30,815	30,815	30,815	30,815
The Results of Analytical Models (Dependent Variable: LN_Single Family Home Sale Prices in 2008)						
Independent Variable	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CON_FC_1R_C [500 feet]	-2.03E-03 (-1.130)	-1.74E-03 (-0.999)	-1.27E-03 (-0.514)	-1.95E-03 (-1.123)	-1.58E-03 (-0.865)	-1.68E-03 (-0.482)
CON_FC_1R_C2 [500 feet]	-	-	-	-	-	-3.15E-05 (-0.120)
CON_FC_2R_C [501-1000 feet]	-2.23E-03** (-2.790)	-2.05E-03** (-2.641)	-2.02E-03** (-2.662)	-1.97E-03* (-2.539)	-1.74E-03• (-1.874)	7.59E-04 (0.576)
CON_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-1.47E-04* (-2.460)
CON_FC_3R_C [1001-1500 feet]	-3.53E-04 (-0.663)	-2.75E-04 (-0.527)	-1.34E-04 (NA)	-3.81E-04 (-0.734)	-6.19E-05 (-0.096)	-3.08E-04 (-0.297)
CON_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	1.83E-05 (0.343)
N	12,885	12,885	12,885	12,885	12,885	12,885

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. OLS1_Prev_Direct model (model 1) and OLS2_Prev_Spillover model (model 2) don't have neighboring condo foreclosure variables for single family home samples and are not presented in this table.

For 2008 single family home samples, results (see Table 5.48, lower section) indicated that the negative spillover effect of a condo foreclosure on existing sale prices of single family homes within 500 feet was not statistically significant in OLS3 Both

Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC models, respectively. This insignificance of a condo foreclosure on the existing single family home prices within 500 feet seems to reflect the small degree of variation in the number of condo foreclosures in those intervals. This negative impact was about -0.22% for OLS3 Both Effects, -0.21% for ML Spatial Error, -0.20% for ML Spatial Lag, -0.20%, for GMM SAR Error and -0.17% for GMM 2SLS HAC models at a distance of 501-1000 feet, respectively. However, it was not statistically significant in OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, GMM 2SLS HAC models at a distance of 1001-1500 feet, respectively.

Distance effects of neighboring condo foreclosures on existing condo prices

For 2005 condo samples, results (see Table 5.49, upper section) indicated that a neighboring condo foreclosure on the existing condo sale prices within 500 feet created a negative spillover effect of approximately -3.96% for OLS1 Prev Direct, -2.86% for OLS3 Both Effects, -2.64% for ML Spatial Error, -2.32% for ML Spatial Lag, -2.63% for GMM SAR Error, and -2.58% for GMM 2SLS HAC models, respectively. This negative impact diminished by distance and falls to -0.49% for OLS1 Prev Direct, -1.16% for OLS3 Both Effects, -1.18% for ML Spatial Error, -0.88% for ML Spatial Lag, -1.26% for GMM SAR Error, and -1.04% for GMM 2SLS HAC models at a distance of 501-1000 feet, respectively. However, this negative impact intensified to -2.34% for OLS1 Prev Direct, -2.68% for OLS3 Both Effects, -2.52% for ML Spatial Error, -2.26% for ML Spatial Lag, -2.43% for GMM SAR Error, and -2.48% for GMM 2SLS HAC models at a distance of 1001-1500 feet, respectively.

Table 5.49. Estimated Marginal Impacts of Neighboring Condo Foreclosures on Existing Condo Prices.

The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)							
Independent Variable	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CON_FC_1R_C [500 feet]	-3.96E-02*** (-20.604)	-2.86E-02*** (-15.376)	-2.64E-02*** (-14.641)	-2.32E-02*** (-13.283)	-2.63E-02*** (-14.700)	-2.58E-02*** (-11.785)	-3.82E-02*** (-9.777)
CON_FC_1R_C2 [500 feet]	-	-	-	-	-	-	1.34E-03*** (4.025)
CON_FC_2R_C [501-1000 feet]	-4.90E-03* (-2.507)	-1.16E-02*** (-6.209)	-1.18E-02*** (-6.531)	-8.84E-03*** (-4.932)	-1.26E-02*** (-7.065)	-1.04E-02*** (-5.143)	-1.51E-02*** (-4.332)
CON_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-	1.27E-04 (0.545)
CON_FC_3R_C [1001-1500 feet]	-2.34E-02*** (-11.381)	-2.68E-02*** (-13.776)	-2.52E-02*** (-13.866)	-2.26E-02*** (-12.720)	-2.43E-02*** (-13.522)	-2.48E-02*** (-11.531)	-2.64E-02*** (-6.370)
CON_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	-	2.68E-04 (0.855)
N	6,205	6,205	6,205	6,205	6,205	6,205	6,205
The Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)							
Independent Variable	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both_Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC_Linear (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
CON_FC_1R_C [500 feet]	-2.53E-02*** (-14.916)	-1.19E-02*** (-7.574)	-1.19E-02*** (-7.638)	-1.19E-02*** (-7.649)	-1.21E-02*** (-7.714)	-1.21E-02*** (-7.355)	-1.94E-02*** (-6.501)
CON_FC_1R_C2 [500 feet]	-	-	-	-	-	-	2.65E-04*** (3.716)
CON_FC_2R_C [501-1000 feet]	-4.02E-03 (-1.631)	-3.36E-03 (-1.574)	-3.37E-03 (-1.595)	-3.30E-03 (-1.547)	-3.32E-03 (-1.569)	-3.27E-03 (-1.340)	1.11E-02 (1.565)
CON_FC_2R_C2 [501-1000 feet]	-	-	-	-	-	-	-7.17E-04 (-2.074)
CON_FC_3R_C [1001-1500 feet]	-2.06E-03 (-0.799)	-7.77E-03*** (-3.468)	-7.78E-03*** (-3.497)	-7.76E-03*** (-3.492)	-7.70E-03*** (-3.461)	-8.04E-03** (-3.048)	-1.36E-02*** (-3.431)
CON_FC_3R_C2 [1001-1500 feet]	-	-	-	-	-	-	2.91E-04• (1.893)
N	2,003	2,003	2,003	2,003	2,003	2,003	2,003

Notes. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. OLS1_Prev_Direct model (model 1) doesn't have neighboring foreclosure variables and is not presented in this table.

For 2008 condo samples, results (see Table 5.49, lower section) indicated that a neighboring condo foreclosure on existing condo sale prices within 500 feet created a negative spillover effect of approximately -2.53% for OLS1 Prev Direct, -1.19% for OLS3 Both Effects, -1.19% for ML Spatial Error, -1.19% for ML Spatial Lag, -1.21% for GMM SAR Error, and -1.21% for GMM 2SLS HAC models, respectively. This negative impact was not statistically significant in OLS1 Prev Direct, OLS3 Both Effects, ML Spatial Error, ML Spatial Lag, GMM SAR Error, and GMM 2SLS HAC models at a distance of 1001-1500 feet, respectively. This negative impact diminished by distance and fell to -0.21% for OLS1 Prev Direct, -0.78% for OLS3 Both Effects, -0.78% for ML Spatial Error, -0.78% for ML Spatial Lag, -0.77% for GMM SAR Error, and -0.80% for GMM 2SLS HAC models at a distance of 1001-1500 feet, respectively.

The results of both types of foreclosure effects on existing home price are summarized as follows: first, the negative price impact of neighboring foreclosures was larger in close proximity. Second, these result suggested that the relationship of negative impact between the same types of foreclosures with sample housing sales was larger than those of different types of foreclosures with sample housing sales. Third, this study estimated that the marginal foreclosure impact was smaller in a housing bust year (2008) than a housing boom year (2005).

5.2.7.7 Nonlinear and Incremental Effects of Neighboring Foreclosures

Nonlinear and incremental effects of clustered neighboring foreclosures on existing single family home prices

This study uses an alternative specification that allows for quadratic terms of neighboring foreclosures to assess the nonlinearity of the marginal effects of the foreclosures. Table on page 222 (Table 5.50) presents estimates of specifications for single family home samples in the GMM_2SLS_HAC_Quadratic model (Model 8). The estimates of coefficients for neighboring single family home foreclosures, neighboring condo foreclosures, and the coefficients for the quadratic terms of each type of foreclosure are presented in the quadratic columns in table on page 222 (Table 5.50). Following results are based on the GMM_2SLS_HAC_Quadratic model (Model 8), which contains quadratic terms for neighboring foreclosures.

In table on page 222 (Table 5.50, see the column labeled "Marginal" and the row "SFH or CON_FC_R_C": # of foreclosure), the estimates presented in the rows of each SFH or CON_FC_R_C indicated that the marginal effect of a neighboring foreclosure within each ring had a negative coefficient for the increase in the number of foreclosures on a per unit basis. In comparison (see the column labeled "Quadratic" and the row "SFH or CON_FC_R_C2": # of the square of foreclosures), the rows of SFH or CON_FC_R_C2 indicated that the marginal effect of the square of foreclosures had a positive coefficient for the increase in the number of these foreclosures on a per unit basis. However, the quadratic coefficients had positive and small impact relative to the linear effect. The quadratic coefficients implied a diminishing marginal impact of foreclosures (see others; table on page 223 [Table 5.51] for 2005 single family home samples; table on page 227 [Table 5.52] for 2008 single family home samples; figure on page 224 [Figure 5.6] for 2005 single family home samples; figure on page 228 [Figure 5.7] for 2008 single family home samples). Results indicated an expected decline of the existing housing sale prices with an increase in the number of neighboring foreclosures, but the quadratic coefficients provided empirical evidence that the marginal effect of an additional neighboring foreclosure decreases as the number of neighboring foreclosures increases.

It should be noted that not all coefficients were statistically significant at the five percent level of confidence; 3 pairs of the 6 pairs were significant for 2005 and 2008 single family home samples respectively (see Table 5.50).[23]

For 2005 single family home samples (see Table 5.50; upper left section, table on page 223 [Table 5.51], and figure on page 224 [Figure 5.6]), results indicated that a foreclosure of neighboring single family home on the existing sale prices of single family home within 500 feet created a negative marginal effect of approximately -2.12% in the GMM_2SLS_HAC_Quadratic model (Model 8). However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.28% per additional unit of foreclosure in the GMM_2SLS_HAC_Quadratic model.

[23] One pair denotes the coefficient for neighboring foreclosures (SFH or CON_FC_R_C) and the coefficient for the square of neighboring foreclosures in each ring (SFH or CON_FC_R_C2).

Table 5.50. Estimates of Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Single Family Home Prices.

For GMM_2SLS_HAC_Quadratic Model (Model 8)								
Nearby FC Type	**DV: LN_Single Family Home Sale Prices in 2005**				**DV: LN_Single Family Home Sale Prices in 2008**			
	Independent Variable	**Marginal**	**Independent Variable**	**Quadratic**	**Independent Variable**	**Marginal**	**Independent Variable**	**Quadratic**
SFH Foreclosure # In Three Rings	SFH_FC_1R_C [500 ft]	-2.12E-02*** (-22.072)	SFH_FC_1R _C2	2.75E-03*** (15.318)	SFH_FC_1R_C [500 ft]	-1.49E-02*** (-20.366)	SFH_FC_1R _C2	3.96E-04*** (15.223)
	% change on one FC unit(1R)	**-2.12%**	% change per additional unit	**+0.28%**	% change on one FC unit(1R)	**-1.49%**	% change per additional unit	**+0.04%**
	Cumulative Max. FC# in1R	**4**	Cumulative Max. % in1R	**-4.1%**	Cumulative Max. FC# in1R	**19**	Cumulative Max. % in1R	**-13.95%**
	SFH_FC_2R_C [501-1000 ft]	-2.02E-02*** (-29.147)	SFH_FC_2R _C2	1.71E-03*** (22.093)	SFH_FC_2R_C [501-1000 ft]	-7.24E-03*** (-15.187)	SFH_FC_2R _C2	1.20E-04*** (12.272)
	% change on one FC unit(2R)	**-2.02%**	% change per additional unit	**+0.02%**	% change on one FC unit(2R)	**-0.72%**	% change per additional unit	**+0.01%**
	Cumulative Max. FC# in 2R	**6**	Cumulative Max. % in 2R	**-6.0%**	Cumulative Max. FC# in 2R	**30**	Cumulative Max. % in 2R	**-10.9%**
	SFH_FC_3R_C [1001-1500 ft]	-1.86E-02*** (-32.683)	SFH_FC_3R _C2	1.11E-03*** (23.167)	SFH_FC_3R_C [1001-1500 ft]	-4.49E-03*** (-13.398)	SFH_FC_3R _C2	4.56E-05*** (9.433)
	% change on one FC unit(3R)	**-1.86%**	% change per additional unit	**+0.01%**	% change on one FC unit(3R)	**-0.05%**	% change per additional unit	**+0.005%**
	Cumulative Max. FC# in 3R	**8**	Cumulative Max. % in 3R	**-7.8%**	Cumulative Max. FC# in 3R	**45**	Cumulative Max. % in 3R	**-10.1%**
Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-3.07E-03 (-0.918)	CON_FC_1R _C2	2.73E-04 (0.392)	CON_FC_1R_C [500 ft]	-1.68E-03 (-0.482)	CON_FC_1R _C2	-3.15E-05 (-0.120)
	% change on one FC unit(1R)	-0.31%	% change(1R)	+0.03%	% change on one FC unit(1R)	-0.17%	% change(1R)	-0.00%
	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-
	CON_FC_2R_C [501-1000 ft]	9.63E-05 (0.062)	CON_FC_2R _C2	-5.10E-04* (-2.407)	CON_FC_2R_C [501-1000 ft]	7.59E-04 (0.576)	CON_FC_2R _C2	-1.47E-04* (-2.460)
	% change on one FC unit(2R)	0.00%	% change(2R)	-0.05%	% change on one FC unit(2R)	+0.08%	% change(2R)	-0.01%
	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-
	CON_FC_3R_C [1001-1500 ft]	-1.65E-03 (-1.532)	CON_FC_3R _C2	-3.08E-04* (-2.166)	CON_FC_3R_C [1001-1500 ft]	-3.08E-04 (-0.297)	CON_FC_3R _C2	1.83E-05 (0.343)
	% change on one FC unit(3R)	-0.02%	% change(3R)	-0.03%	% change on one FC unit(3R)	-0.03%	% change(3R)	0.00%
	Cumulative Max. FC# in 3R	-	Cumulative Max. % in 3R	-	Cumulative Max. FC# in 3R	-	Cumulative Max. % in 3R	-

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2). C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. Cumulative maximum % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})). Cumulative maximum N is counted until marginal coefficient per additional unit is zero. R1: 500 foot ring, R2: 501-1000 foot ring, R3: 1001-1500 foot ring.

Table 5.51. Calculation of Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home Foreclosures on Existing Single Family Home Prices in a 2005 Housing Boom Year.

R1: 0-500 feet (SFH Foreclosure)			**R2: 501-1000 feet (SFH Foreclosure)**			**R3: 1001-1500 feet (SFH Foreclosure)**		
Counts of Foreclosures (C*i*)	Marginal impact (coefficient) change for additional foreclosure counts	Cumulative Sum: Cumulative Foreclosure Impact on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosure on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosure on Nearby Home Prices
0	0	**0**	**0**	0	**0**	**0**	0	**0**
1	-0.0185	**-0.0185**	**1**	-0.01849	**-0.01849**	**1**	-0.01751	**-0.01751**
2	-0.0130	**-0.0315**	**2**	-0.01507	**-0.03356**	**2**	-0.01529	**-0.0328**
3	-0.0075	**-0.0390**	**3**	-0.01165	**-0.04521**	**3**	-0.01307	**-0.04587**
4	-0.0020	**-0.0410**	**4**	-0.00823	**-0.05344**	**4**	-0.01085	**-0.05672**
5	0.0035	**-**	**5**	-0.00481	**-0.05825**	**5**	-0.00863	**-0.06535**
-	**-**	**-**	**6**	-0.00139	**-0.05964**	**6**	-0.00641	**-0.07176**
-	**-**	**-**	7	0.00203	**-**	**7**	-0.00419	**-0.07595**
-	**-**	**-**	**-**	**-**	**-**	**8**	-0.00197	**-0.07792**
-	**-**	**-**	**-**	**-**	**-**	9	0.00025	-
-	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**
Cumulative Max. N = 4		**Cumulative Max. % = -4.1%**	**Cumulative Max. N = 6**		**Cumulative Max. % = -6.0%**	**Cumulative Max. N= 8**		**Cumulative Max. % = -7.8%**

Notes. Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × $(C_i^2 - C_{i-1}^2)$.
C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings.
Cumulative maximum N is counted until marginal coefficient per additional foreclosure unit is zero.
Cumulative maximum % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})).

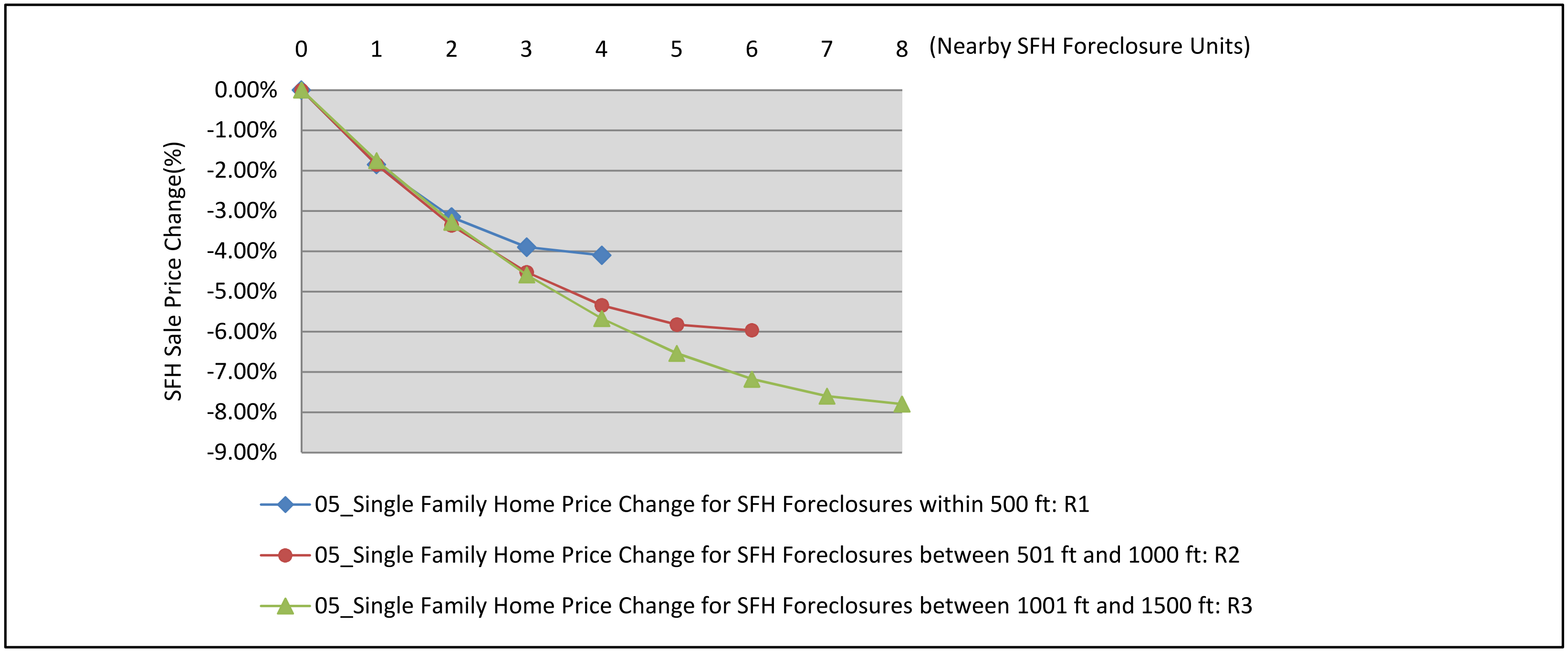

Figure 5.6. Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home Foreclosures on Existing Single Family Home Prices in a 2005 Housing Boom Year.

For 2005 single family home samples within 501-1000 feet, a foreclosure of neighboring single family home on the existing sale prices of single family home created a negative marginal effect of approximately -2.02% in the GMM_2SLS_HAC_Quadratic model (Model 8). However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.02% per additional unit of foreclosure in the GMM_2SLS_HAC_Quadratic model (Model 8).

For 2005 single family home samples within 1001-1500 feet, a foreclosure of neighboring single family home on the existing sale prices of single family home created a negative marginal effect of approximately -1.86% in the GMM_2SLS_HAC_Quadratic model (Model 8). However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.01% per additional unit of foreclosure in the GMM_2SLS_HAC_Quadratic model (Model 8).

The nonlinearity tests of the 3 pairs of neighboring condo foreclosures were not statistically significant in the GMM_2SLS_HAC_Quadratic model (Model 8) (see table on page 222 [Table 5.50], right section).

For 2008 single family home samples (see table on page 222 [Table 5.50]; upper right section, table on page 227 [Table 5.52], and figure on page 228 [Figure 5.7]), results indicated that a foreclosure of neighboring single family home on the existing sale prices of single family home within 500 feet created a negative marginal effect of approximately -1.49% in the GMM_2SLS_HAC_Quadratic model (Model 8). However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.04% per additional unit of foreclosure in the GMM

2SLS_HAC_Quadratic model (Model 8).

For 2008 single family home samples within 501-1000 feet, a foreclosure of neighboring single family home on the existing sale prices of single family home created a negative marginal effect of approximately -0.72% in the GMM_2SLS_HAC_Quadratic model (Model 8). However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.01% per additional unit of foreclosure in the GMM_2SLS_HAC_Quadratic model (Model 8).

For 2008 single family home samples within 1001-1500 feet, a foreclosure of neighboring single family home on the existing sale prices of single family home created a negative marginal effect of approximately -0.05% in the GMM_2SLS_HAC_Quadratic model (Model 8). However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.005% per additional unit of foreclosure in the GMM_2SLS_HAC_Quadratic model (Model 8).

The nonlinearity tests of 3 pairs of neighboring condo foreclosures on existing single family home prices were not statistically significant in the GMM 2SLS_HAC_Quadratic model (see table on page 222 [Table 5.50], lower right section). These results for 2005 and 2008 single family home samples implied that additional marginal foreclosure impacts in each ring was relatively larger in the 2005 housing boom year than the 2008 housing buster year. However, the incremental (cumulative) neighboring foreclosure impacts in 2008 were much larger than the 2005 housing boom year within the same ring because of the high density of foreclosure in the neighborhood during a housing bust year (2008).

Table 5.52. Calculation of Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home Foreclosures on Existing Single Family Home Prices in a 2008 Housing Bust Year.

R1: 0-500 feet (SFH Foreclosure)			**R2: 501-1000 feet (SFH Foreclosure)**			**R3: 1001-1500 feet (SFH Foreclosure)**		
Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosure on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosure on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosure on Nearby Home Prices
0	0	**0**	**0**	0	**0**	**0**	0	**0**
1	-0.01454	**-0.01454**	**1**	-0.00712	**-0.00712**	**1**	-0.00444	**-0.00444**
2	-0.01374	**-0.02828**	**2**	-0.00688	**-0.01400**	**2**	-0.00434	**-0.00878**
3	-0.01294	**-0.04122**	**3**	-0.00664	**-0.02064**	**3**	-0.00424	**-0.01302**
4	-0.01214	**-0.05336**	**4**	-0.0064	**-0.02704**	**4**	-0.00414	**-0.01716**
5	-0.01134	**-0.06470**	**5**	-0.00616	**-0.03320**	**5**	-0.00404	**-0.02120**
:	:	**:**	**:**	:	**:**	**:**	:	**:**
:	:	**:**	**:**	:	**:**	**:**	:	**:**
18	-0.00094	**-0.13932**	**18**	-0.00304	**-0.09144**	**18**	-0.00274	**-0.06462**
19	-0.00014	**-0.13946**	**19**	-0.00280	**-0.09424**	**19**	-0.00264	**-0.06726**
20	0.00066	**-**	**20**	-0.00256	**-0.09680**	**20**	-0.00254	**-0.06980**
-	-	**-**	**:**	:	**:**	**:**	:	**:**
-	-	**-**	**:**	:	**:**	**:**	:	**:**
-	-	**-**	**30**	-0.00016	**-0.10920**	**30**	-0.00154	**-0.08970**
-	-	**-**	31	0.00008	**-**	**31**	-0.00144	**-0.09114**
-	-	**-**	**-**	-	**-**	**:**	:	**:**
-	-	**-**	**-**	-	**-**	**45**	-0.00004	**-0.1008**
-	-	**-**	**-**	-	**-**	46	0.00006	**-**
Cumulative Max. N = 19		**Cumulative Max. % = -13.95%**	**Cumulative Max. N = 30**		**Cumulative Max. % = -10.9%**	**Cumulative Max. N= 45**		**Cumulative Max. % = -10.1%**

Notes. Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2).
C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings.
Cumulative maximum N is counted until marginal coefficient per additional foreclosure unit is zero.
Cumulative maximum % = $\sum_{i=0}^{n} ai$, a*i* =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})).

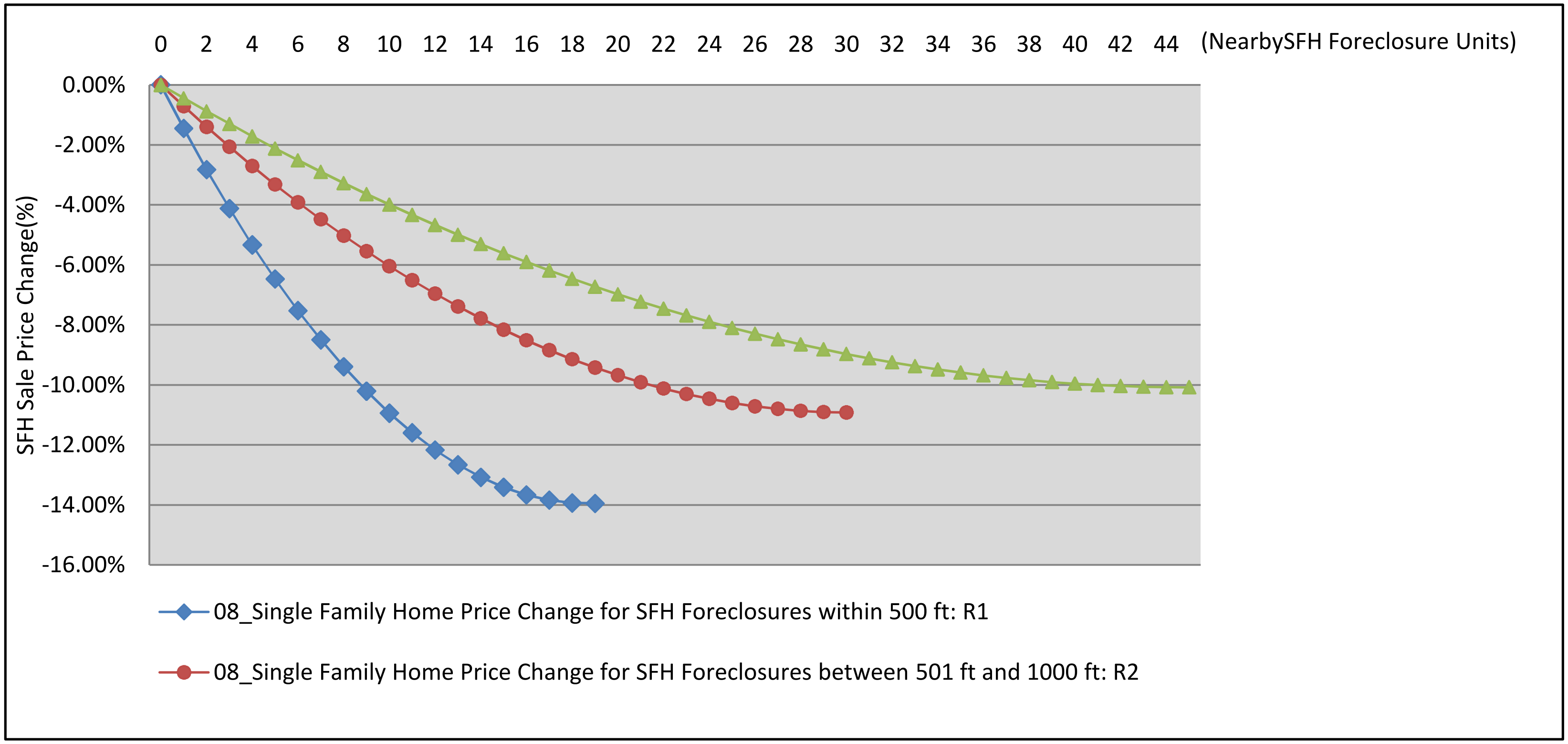

Figure 5.7. Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home Foreclosures on Existing Single Family Home Prices in a 2008 Housing Bust Year.

Nonlinear and incremental effects of clustered neighboring foreclosures on existing condo prices

Results illustrated in Table 5.53 indicated an expected decline of the neighboring sale prices with an increase in the number of foreclosures, but the quadratic coefficients provided empirical evidence that the marginal effects of an additional neighboring foreclosure decreased as the number of neighboring foreclosures increased. It should be noted that not all coefficients were statistically significant at the 5% or better level of confidence, but 2 pairs of the 6 pairs were significant for 2005 and 3 pairs of the 6 pairs were significant for 2008 condo samples. In Table 5.53 (see the column labeled "Marginal" and the row of "SFH or CON_FC_R_C": # of foreclosure), the estimates presented in the rows of each SFH or CON_FC_R_C revealed that the marginal effects of a neighboring foreclosure within each ring had a negative coefficient for the increase in the number of foreclosures (on a per unit basis). In comparison (see the column labeled "Quadratic" and the row of "SFH or CON_FC_R_C2": # of the square of foreclosures), the rows of SFH or CON_FC_R_C2 revealed that the marginal effects of the square of foreclosures had a positive coefficient for the increased number of these foreclosures (on a per unit basis).

Table 5.53. Estimates of Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices.

For GMM_2SLS_HAC_Quadratic Model (Model 8)								
Nearby FC Type	**DV: LN_ Condo Sale Prices in 2005**				**DV: LN_ Condo Sale Prices in 2008**			
	Independent Variable	**Marginal**	**Independent Variable**	**Quadratic**	**Independent Variable**	**Marginal**	**Independent Variable**	**Quadratic**
SFH Foreclosure # In Three Rings	SFH_FC_1R_C [500 ft]	5.96E-03 (0.573)	SFH_FC_1R _C2	-1.09E-03 (-0.406)	SFH_FC_1R_C [500 ft]	-2.21E-02* (-1.999)	SFH_FC_1R _C2	1.78E-03 (1.015)
	% change on one FC unit(1R)	+0.60%	% change per additional unit	-0.11%	% change on one FC unit(1R)	-2.22%	% change per additional unit	+0.18%
	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-
	SFH_FC_2R_C [501-1000 ft]	-2.10E-02*** (-4.635)	SFH_FC_2R _C2	6.16E-04 (1.560)	SFH_FC_2R_C [501-1000 ft]	-8.44E-04 (-0.158)	SFH_FC_2R _C2	-3.26E-04 (-1.192)
	% change on one FC unit(2R)	-2.10%	% change per additional unit	+0.06%	% change on one FC unit(2R)	-0.08%	% change per additional unit	-0.03%
	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-
	SFH_FC_3R_C [1001-1500 ft]	-3.87E-02*** (-10.620)	SFH_FC_3R _C2	1.59E-03*** (6.347)	SFH_FC_3R_C [1001-1500 ft]	-2.20E-02*** (-7.978)	SFH_FC_3R _C2	2.47E-04*** (4.363)
	% change on one FC unit(3R)	**-3.87%**	% change per additional unit	**+0.02%**	% change on one FC unit(3R)	**-2.20%**	% change per additional unit	**+0.02%**
	Cumulative Max. FC# in 3R	**12**	Cumulative Max. % in 3R	**-23.56%**	Cumulative Max. FC# in 3R	**44**	Cumulative Max. % in 3R	**-48.36%**
Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-3.82E-02*** (-9.777)	CON_FC_1R _C2	1.34E-03*** (4.025)	CON_FC_1R_C [500 ft]	-1.94E-02*** (-6.501)	CON_FC_1R _C2	2.65E-04*** (3.716)
	% change on one FC unit(1R)	**-3.83%**	% change(1R)	**+0.13%**	% change on one FC unit(1R)	**-1.94%**	% change(1R)	**+0.03%**
	Cumulative Max. FC# in1R	**14**	Cumulative Max. % in1R	**-27.26%**	Cumulative Max. FC# in1R	**37**	Cumulative Max. % in1R	**-36.30%**
	CON_FC_2R_C [501-1000 ft]	-1.51E-02*** (-4.332)	CON_FC_2R _C2	1.27E-04 (0.545)	CON_FC_2R_C [501-1000 ft]	1.11E-02 (1.565)	CON_FC_2R _C2	-7.17E-04* (-2.074)
	% change on one FC unit(2R)	-1.51%	% change(2R)	+0.01%	% change on one FC unit(2R)	+1.11%	% change(2R)	-0.07%
	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-
	CON_FC_3R_C [1001-1500 ft]	-2.64E-02*** (-6.370)	CON_FC_3R _C2	2.68E-04 (0.855)	CON_FC_3R_C [1001-1500 ft]	-1.36E-02*** (-3.431)	CON_FC_3R _C2	2.91E-04• (1.893)
	% change on one FC unit(3R)	-2.64%	% change(3R)	+0.03%	% change on one FC unit(3R)	**-1.36%**	% change(3R)	**+0.03%**
	Cumulative Max. FC# in 3R	-	Cumulative Max. % in 3R	-	Cumulative Max. FC# in 3R	**23**	Cumulative Max. % in 3R	**-15.94%**

Notes. Dependent variable: log (sale price for each housing type). N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1.
Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2).
C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. Cumulative maximum % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})). Cumulative maximum N is counted until marginal coefficient per additional unit is zero. R1: 500 foot ring, R2: 501-1000 foot ring, R3: 1001-1500 foot ring.

For 2005 condo samples (see Table 5.53; upper left, Table 5.54, and figure on page 233 [Figure 5.8]), results indicated that the negative spillover effect of a foreclosure of neighboring single family home on existing condo sale prices were not statistically significant within 500 feet and 501-1000 feet in the GMM_2SLS_HAC_Quadratic model. Again, this insignificance of the foreclosures of single family homes on existing condo prices within 500 feet and 501-1000 feet seems to reflect the small degree of variation in the number of different types of foreclosure in those intervals. However, a foreclosure of neighboring single family home on existing condo sale prices within 1001-1500 feet created a negative marginal effect of approximately -3.87% in the GMM_2SLS_HAC_Quadratic model. However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.02% per additional unit of single family home foreclosures in the GMM_2SLS_HAC_Quadratic model.

For 2005 condo samples within 500 feet (see Table 5.53; lower left, Table 5.54, and figure on page 233 [Figure 5.8]), a foreclosure of neighboring condo on existing condo sale prices created a negative marginal effect of approximately -3.83% in the GMM_2SLS_HAC_Quadratic model. However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.13% in GMM_2SLS_HAC_Quadratic model (Model 8). However, the impacts of a neighboring condo foreclosure on existing condo sale prices beyond 1000 feet were not statistically significant in the GMM 2SLS_HAC_Quadratic model.

Table 5.54. Calculation of Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices in a 2005 Housing Boom Year.

R1: 0-500 feet (Condo Foreclosure)			**R2: 501-1000 feet**			**R3: 1001-1500 feet (SFH Foreclosure)**		
Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosures on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosures on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosures on Nearby Home Prices
0	0	**0**	-	-	-	**0**	0	**0**
1	-0.03689	**-0.03689**	-	-	-	**1**	-0.03712	**-0.03712**
2	-0.07110	**-0.07110**	-	-	-	**2**	-0.03394	**-0.07106**
3	-0.10263	**-0.10263**	-	-	-	**3**	-0.03076	**-0.10182**
4	-0.13148	**-0.13148**	-	-	-	**4**	-0.02758	**-0.12940**
5	-0.15765	**-0.15765**	-	-	-	**5**	-0.02440	**-0.15380**
:	:	**:**	:	:	:	**:**	:	**:**
:	:	**:**	:	:	:	**:**	:	**:**
9	-0.01545	**-0.23553**	-	-	-	**9**	-0.01168	**-0.21960**
10	-0.01277	**-0.24830**	-	-	-	**10**	-0.00850	**-0.22810**
11	-0.01009	**-0.25839**	-	-	-	**11**	-0.00532	**-0.23342**
12	-0.00741	**-0.26580**	-	-	-	**12**	-0.00214	**-0.23556**
13	-0.00473	**-0.27053**	-	-	-	13	0.00104	-
14	-0.00205	**-0.27258**	-	-	-	-	-	-
15	0.00063		-	-	-	-	-	-
Cumulative Max. N = 14		**Cumulative Max. % = -27.26%**	-		-	**Cumulative Max. N = 12**		**Cumulative Max. % = -23.56%**

Notes. Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2).
C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings.
Cumulative maximum N is counted until marginal coefficient per additional foreclosure unit is zero.
Cumulative maximum % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})).

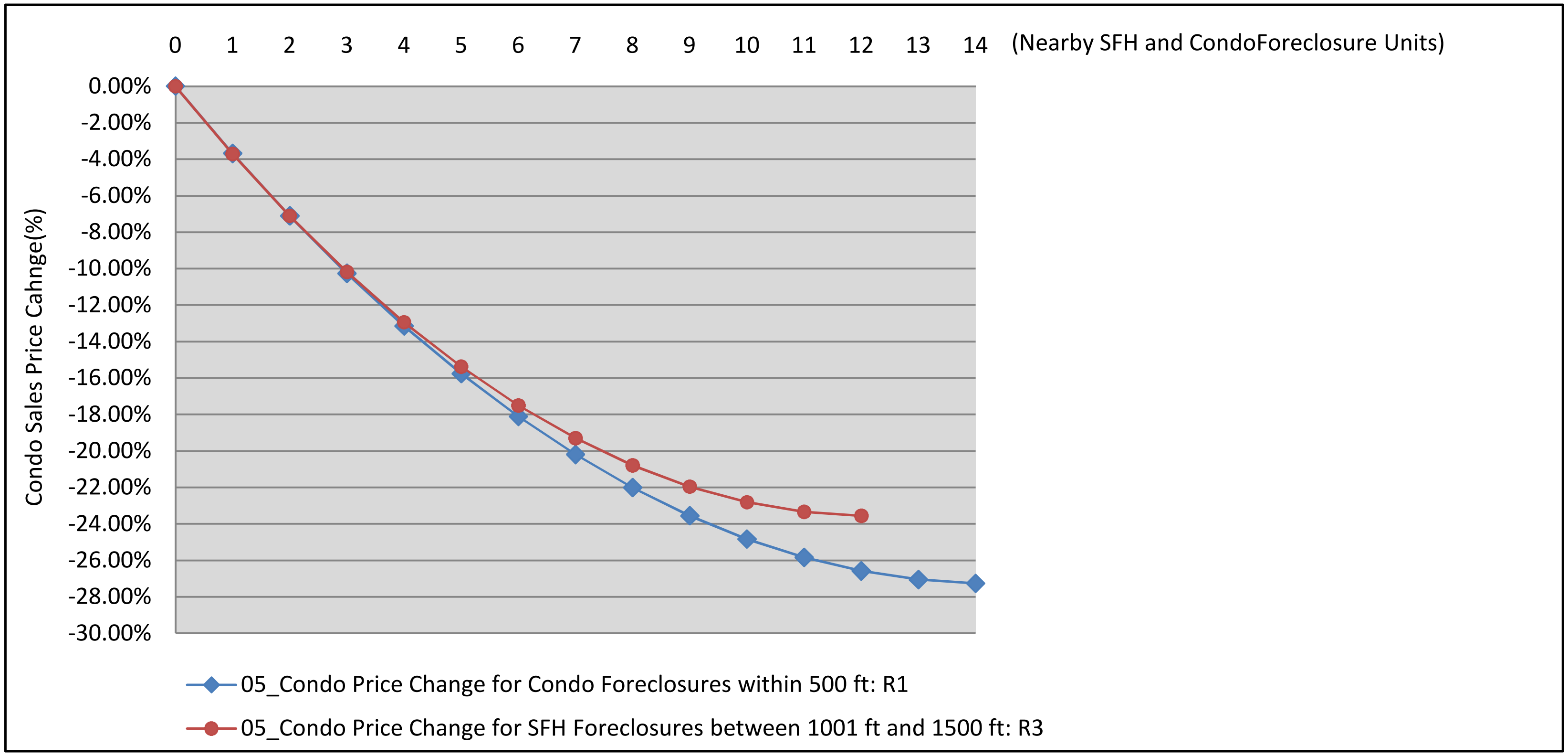

Figure 5.8. Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices in a 2005 Housing Boom Year.

For 2008 condo samples (see table on page 230 [Table 5.53]; upper right, Table 5.55, and figure on page 236 [Figure 5.9]), results indicated that the negative spillover effect of a neighboring single family home foreclosure on existing condo sale prices within 500 feet and 501-1000 feet were not statistically significant in the GMM_2SLS_HAC_Quadratic model. However, a foreclosure of neighboring single family home on existing condo sale prices within 1001-1500 feet created a negative marginal effect of approximately -2.20% in the GMM_2SLS_HAC_Quadratic model. However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.02% per additional unit of single family home foreclosures.

For 2008 condo samples within 500 feet (see table on page 230 [Table 5.53]; lower right, Table 5.55, and figure on page 236 [Figure 5.9]), a foreclosure of neighboring condo on the existing condo sale prices created a negative marginal effect of approximately -1.94% in the GMM_2SLS_HAC_Quadratic model. However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.03%. However, the impact of a neighboring condo foreclosure on the existing condo sale prices within 501-1000 feet was not statistically significant in the GMM_2SLS_HAC_Quadratic model. Again, a foreclosure of neighboring condo on the existing condo sale prices within 1001-1500 feet created a negative marginal effect of approximately -1.36% in the GMM_2SLS_HAC_Quadratic model. However, through the square of foreclosures as untransformed continuous variables, this negative impact diminished by 0.03%.

Table 5.55. Calculation of Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices in a 2008 Housing Bust Year.

R1: 0-500 feet (Condo Foreclosure)			**R3: 1001-1500 feet (Condo Foreclosure)**			**R3: 1001-1500 feet (SFH Foreclosure)**		
Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosures on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosures on Nearby Home Prices	Counts of Foreclosures (C*i*)	Marginal Impact (coefficient) Change for Additional Foreclosure Counts	Cumulative Sum: Cumulative Impact of Foreclosures on Nearby Home Prices
0	0	**0**	**0**	0	**0**	**0**	0	**0**
1	-0.01917	**-0.01917**	**1**	-0.01331	**-0.01331**	**1**	-0.02174	**-0.02174**
2	-0.01865	**-0.03782**	**2**	-0.01273	**-0.02604**	**2**	-0.02124	**-0.04298**
:	**:**	**:**	**:**	**:**	**:**	**:**	**:**	**:**
16	-0.01137	**-0.24432**	**16**	-0.00461	**-0.14336**	**16**	-0.01424	**-0.28784**
17	-0.01085	**-0.25517**	**17**	-0.00403	**-0.14739**	**17**	-0.01374	**-0.30158**
:	**:**	**:**	**:**	**:**	**:**	**:**	**:**	**:**
23	-0.00773	**-0.30935**	**23**	-0.00055	**-0.15939**	**23**	-0.01074	**-0.37352**
24	-0.00721	**-0.31656**	24	0.00003	**-**	**24**	-0.01024	**-0.38376**
25	-0.00669	**-0.32325**	**-**	**-**	**-**	**25**	-0.00974	**-0.3935**
:	**:**	**:**	**-**	**-**	**-**	**:**	**:**	**:**
37	-0.00045	**-0.36297**	**-**	**-**	**-**	**37**	-0.00374	**-0.47138**
38	0.00007	**-**	**-**	**-**	**-**	**38**	-0.00324	**-0.47462**
-	**-**	**-**	**-**	**-**	**-**	**:**	**:**	**:**
-	**-**	**-**	**-**	**-**	**-**	**44**	-0.00024	**-0.48356**
-	**-**	**-**	**-**	**-**	**-**	45	0.00026	**-**
Cumulative Max. N = 37		**Cumulative Max. % = -36.30%**	**Cumulative Max. N = 23**		**Cumulative Max. % = -15.94%**	**Cumulative Max. N = 44**		**Cumulative Max. % = -48.36%**

Notes. Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2).
C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings.
Cumulative maximum N is counted until marginal coefficient per additional foreclosure unit is zero.
Cumulative maximum % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})).
Both condo and SFH foreclosure impact are not significant in R2 rings.

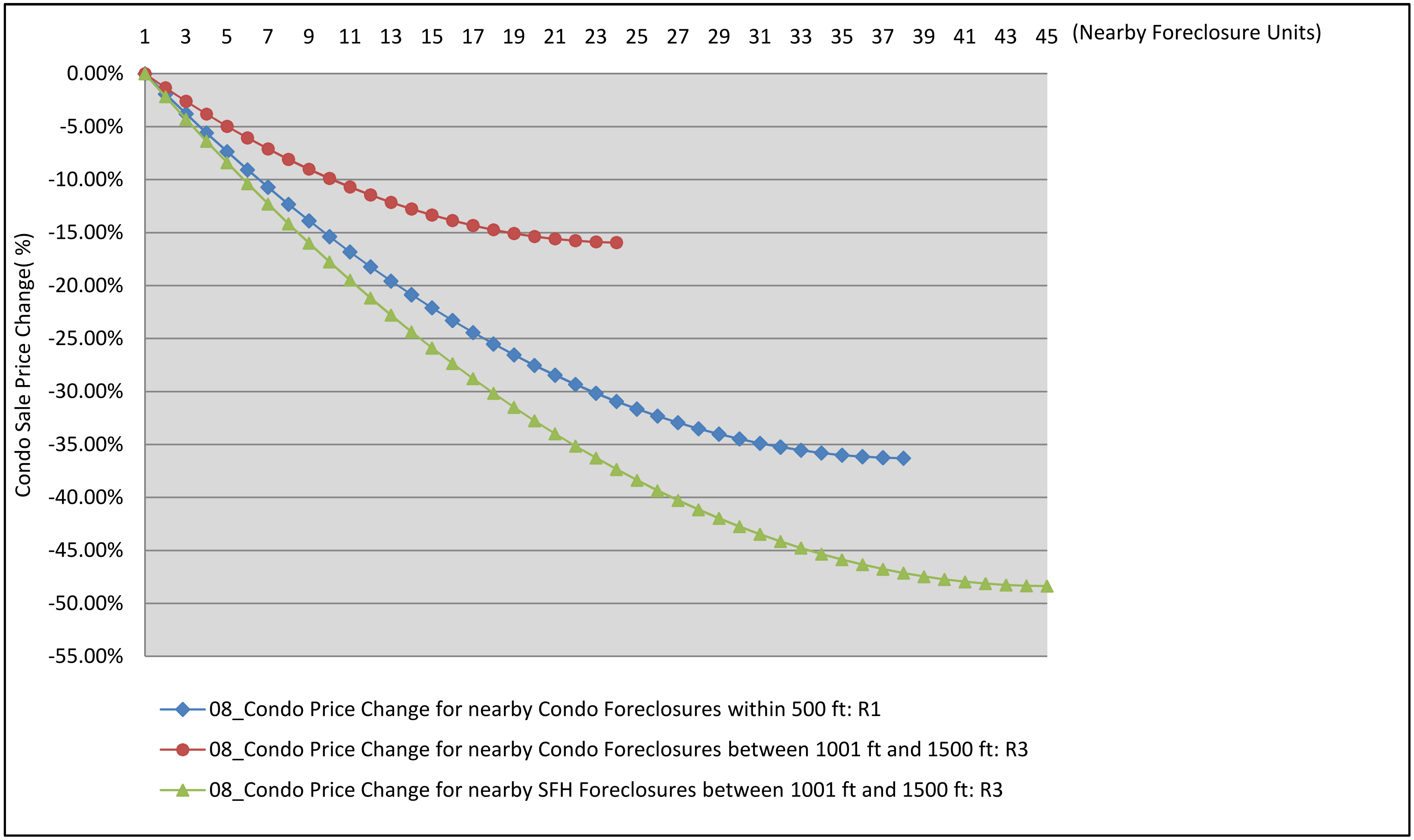

Figure 5.9. Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices in a 2008 Housing Bust Year.

6. FINDINGS AND CONCLUSIONS

6.1 Findings and Discussions

6.1.1 Summary of Modeling Procedures

The estimations of hedonic price parameters (OLS regression estimators) are assuming independent observations. When spatial autocorrelation, or spatial dependency, is expected to exist within data, hedonic model estimation using OLS may lead to misleading inferences from the model. Spatial dependencies affect hedonic studies either from structural relationships among the observations (lagged dependency) or among the error terms (Anselin, 1988).

A typical example in housing market research is housing price. The housing prices in a neighborhood will affect or be affected by the housing prices in adjacent neighborhoods. Spatial econometric techniques such as spatial autoregressive analysis have been developed to address this concern (Anselin, 1998; Basu and Thibodeau, 1998; Can, 1990, 1992; Can and Megboluge, 1997; Dubin, Pace, and Thibodeau, 1999; Gillen, Thibodeau, and Wachter, 2001; Kelejian and Prucha, 1998; Pace, Barry, and Sirmans, 1998; Pace and LeSage, 2004; among others).

Two types of alternatives that incorporate spatial dependence in the model explicitly are the spatial lag model and the spatial error model (see Anselin, 1988; Anselin and Hudak, 1992; Smirnov and Anselin, 2001 for detailed discussions). The Lagrange Multiplier (LM) test is used for selection of the type of spatial model that best fits the data through robust form.

By incorporating the spatial autocorrelation in model construction, these models tend to eliminate the spatial effects on the coefficients. Comparing the traditional hedonic price function of the ordinary lease squares (OLSs) models (Models 1-3), the improvement of the maximum likelihood (ML) spatial error and lag models (Models 4 and 5) can be attributed to the use of spatial autocorrelation that is ignored by the traditional OLS models. Although the estimations of parametric ML spatial lag or error model is most commonly based on the maximum likelihood principle, large sample sizes like housing sales data causes significant estimation problems in the maximum likelihood (ML) approach (Anselin 1988; Dubin, 1988). One of the most promising methods of estimating these models to overcome large spatial problems is the estimation of generalized method of moments (GMM) developed by Kelejian and Prucha (1998, 1999).

The GMM_SAR model (Model 6) is an error spatially autoregressive model estimated via generalized method of moments (GMM). While maximum likelihood (ML) approach is the best available estimator within the classical statistics approach, this dependence on the probability distribution can become a weakness for two main reasons: computational infeasibility for large data set and restrictions on the normal distribution of the data (Bell, 2000). In contrast, the GMM estimation is based on population moment conditions. The GMM model does not specify the complete distribution.

Using an actual micro-level housing data set for this study, the maximum likelihood (ML) estimator was not computationally feasible in this case. On the other hand, the GMM approach allowed introducing more flexibility into the structure of the spatial weight matrix quite easily. This study presents the generalized moments (GM) estimator developed by Kelejian and Prucha (1998, 1999) which is computationally simple irrespective of the sample size. However, the results of the maximum likelihood (ML) estimation are compared with the generalized moments (GM) estimator.

The spatial patterns are richer than those implied by either the spatial lag or error models (Kelejian and Prucha, 1998). Unfortunately, endogeneity (reverse causation) is generally a common problem in the real world. As for this study, foreclosures lead to a decline in neighborhood property values. The reverse may also be true. Falling property values may lead to an increase in foreclosures because, if house prices drop dramatically, the borrower may owe more than the house is worth, which may cause more borrowers to default on their mortgages. If both of these inferences are true, this would cause an undesirable feedback loop between property values and foreclosure. Such correlation (reverse causation or endogeneity) may occur when there are relevant explanatory variables which are omitted from the model, or when the covariates are subject to measurement error. In this situation, ordinary linear regression (OLS) generally produces biased and inconsistent estimates (Anselin, 2006).

When endogeneity violates the assumption of ordinary least squares (OLS) regression, two-stage least-squares regression (2SLS) using instrumental variables is the most common suggested alternative (Anselin, 1988; Kelejian and Prucha, 1998, 1999, 2004; Lee, 2003, 2006). The new endogenous variables in 2SLS replace the problematic causal variables. In this study, the endogeneity of the spatially lagged dependent variable is accounted for using the spatially lagged exogenous variables as instruments.

In addition, to account for heteroskedasticity and remaining spatial autocorrelation, the most appropriate specification is to use the heteroskedasticity and autocorrelation consistent (HAC) estimator of the standard errors. Recently, Kelejian and Prucha (2010) provided results concerning the joint asymptotic distribution of instrument and GMM estimators in the regression model. Piras (2010) supports the validity of this alternative implementation through the "sphet" package in R software.[24] Their results provide test of the joint hypothesis if no spatial spillovers originated from the endogenous variables or from the disturbances.

Finally, this study suggests an estimation procedure for cross-sectional spatial models that contain spatially lagged dependent variables as well as control for spatially autocorrelated error terms. The results of two GMM_2SLS_HAC models for this study also provide an assessment of the effect of addressing endogeneity and spatial dependence in combination. Therefore, this study gives empirical results for large micro-level samples with GMM methods. Figure 6.1 shows the model decision process.

[24] Sphet developed by Piras (2010) is a package for estimating and testing a variety of spatial models with heteroskedastic innovations in R software.

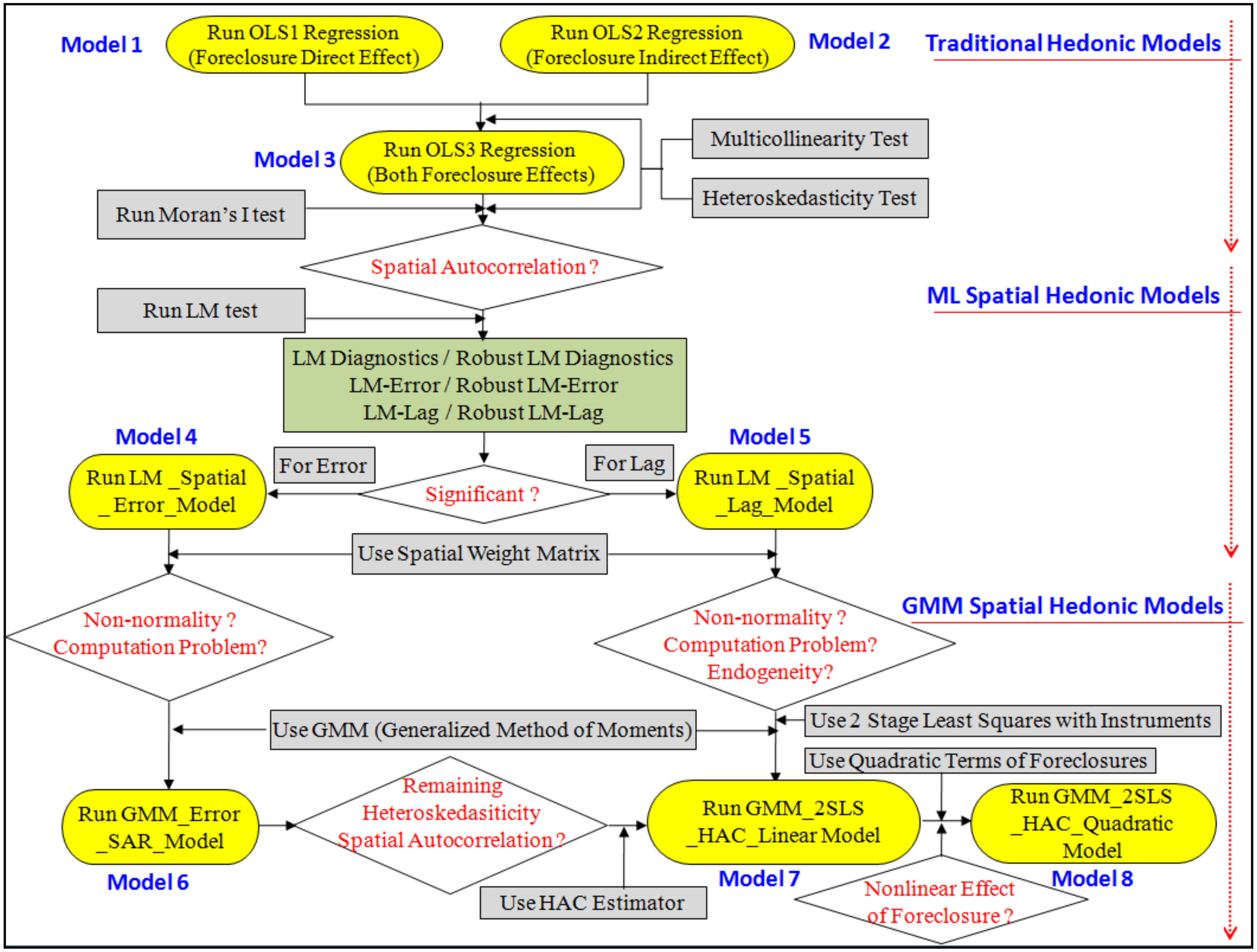

Figure 6.1. Model Decision Process.

6.1.2 Spatial Dependence in Cross-Sectional Housing Sales Data

6.1.2.1 Hypothesis 1: Existence of Spatial Dependence on Housing Prices

The first hypothesis of this study is the following: *Ho*: absence of spatial dependence and *Ha*: presence of spatial dependence based on spatial characteristics of housing price data.

A number of statistical tests are used to detect the presence of spatial autocorrelation from a least-squares model. Among the methods, maximum likelihood (ML) techniques are commonly used to estimate the autocorrelation parameters and the regression coefficients. A commonly adopted two-stage modeling strategy begins by estimating a simple spatial regression model. As the first stage of the model, Moran's I provides diagnostics for the existence of spatial dependence in the models.

Based on the results of Moran's I test, Table 6.1 (for the OLS3_Prev_Both Effects model) indicated that the value was estimated by 0.157 for the 2005 single family home samples, 0.099 for the 2008 single family home samples, 0.299 for the 2005 condo samples, and 0.054 for the 2008 condo samples, respectively. They were highly significant at a 0.001 level of confidence. Then the Lagrange Multiplier (LM) test can be used as a guide to choose the better alternative model through comparison between the two LM diagnostics (Anselin, 2005). The Lagrange Multiplier (LM) test is based on the least-squares residuals and calculations involving the spatial weight matrix (Anselin, 1988).

Table 6.1. Diagnostics of Spatial Dependence and Model Specification Tests.

Weight Type		**Single Family Home Sale Samples**		**Condo Sale Samples**	
	Diagnostics	**Housing Boom _2005**	**Housing Bust _2008**	**Housing Boom _2005**	**Housing Bust _2008**
Contiguity-Based Spatial Weights (Test: Rook-Based Contiguity)	**Moran's I**	0.157***	0.0988***	0.299***	0.054***
	LM_Lag[1]	3210.1***	977.7***	917.5***	18.04***
	R_LM_lag[2]	1336.2***	617.4***	51.80***	4.02*
	LM_Error[3]	2218.7***	366.3***	1605.4***	16.77***
	R_LM_Error[4]	344.8***	6.00***	739.6***	2.75·
Distance-Based Spatial Weight (Test: *K=10* Nearest Neighbors)	**Moran's I**	0.149***	0.0943***	0.292***	0.377***
	LM_Lag[1]	4279.7***	1258.9***	1149.8***	20.85***
	R_LM_lag[2]	1660.2***	723.49***	44.78***	6.89**
	LM_Error[3]	3859.90***	641.07***	3188.7***	17.07***
	R_LM_Error[4]	1240.75***	105.63***	2083.7***	3.10·

Notes. Moran's I is the Moran's test adapted to OLS residuals (Cliff and Ord, 1981). 1. LM_Lag is the Lagrange Multiplier test for spatially lagged endogenous variables. 2. R_LM_Lag is its robust version. 3. LM_Error is the Lagrange Multiplier test for residual spatial autocorrelation. 4. R_ LM_Error is its robust version (Anselin, 2005).
Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

Tables on pages 245-246 (Tables 6.2 through 6.5) show the model performances for each housing sample in 2005 and 2008. As a result, the OLS's goodness-of-fit, R^2, which is based on the decomposition of the total sum of squares, is no longer applicable. Likelihood function based goodness-of-fit statistics, mainly log-likelihood and Akaike Information Criterion (AIC), are used to measure the spatial model's goodness-of-fit (Anselin, 1992). Moreover, these statistics are directly comparable to those of the OLS estimators. The model with the highest LIK or lowest AIC is considered as the better model (Anselin, 1992).

However, large sample sizes like housing sales data causes significant estimation problems in the maximum likelihood (ML) approach (Anselin, 1988; Dubin, 1988; Kelejian and Prucha, 1998, 1999). One of the most promising methods of estimating these models to overcome large spatial problems is the estimation of generalized moments (GM) technique developed by Kelejian and Prucha (1998, 1999).

The GMM_SAR_Error model (Model 6) indicated a strong positive and significant spatial autoregressive coefficient of disturbance terms, suggesting significant spatial autocorrelation of error terms in the maximum likelihood (ML) spatial error model. On the other hand, the GMM_2SLS_HAC model (Model 7) indicated a strong positive and significant spatial autoregressive coefficient of lagged terms, suggesting a great spatial similarity in given housing prices and neighboring home selling prices.

First, let's examine the estimates for the spatial parameters. The lambda (λ) estimates of the spatial error model by maximum likelihood (ML) and by the general method of moments (GMM) are comparable. For example, lambda was 0.3872 in the ML_Spatial_Error model (Model 4) and 0.4411 in the GMM_SAR_Error model (Model 6) for 2005 single family home samples (see Table 6.2). It appears that the spatial econometric estimates confirm the effects of the significant explanatory variables and that a significant positive spatial autocorrelation of the errors is found. Since the estimation of lambda (λ) by generalized methods of moments (GMM) does not depend on the assumption of normally distributed error terms, it is not possible to conduct a *t*-

test of the significance of this coefficient. Thus, we include "(non-parametric)" in place of the *t*-statistics for lambda (λ) in Tables 6.2 through 6.5. However, it relies on the results of the specification tests discussed earlier for evidence of the presence of spatial autocorrelation through the Lagrange Multiplier (LM) test. The significance of incorporating the spatial errors is consistent with the notion that some unobserved variables, such as neighborhood externality and environmental factors that have been undertaken in the Phoenix area, vary across houses.

Table 6.2. The Model Performances for 2005 Single Family Home Samples.

	Results of Analytical Models (Dependent Variable: LN_ Single Family Home Sale Prices in 2005)							
	OLS1_Prev _Direct (Model 1)	**OLS1_Prev _Spillover (Model 2)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
Spatial Parameter _Rho_lag	-	-	-	-	0.251*** (57.004)	-	0.287*** (44.9978)	0.273*** (43.8928)
Spatial Parameter _Lambda_error	-	-	-	0.387*** (52.093)	-	0.441 (non-parametric)	-	-
Adjusted R-squared	0.661	0.723	0.727	-	-	-	-	-
LIK	23740.1	26821.0	27080.2	28086.2	28451.3	-	-	-
AIC	-47452.1	-53613.9	-54116.4	-56124.0	-56855.0	-	-	-
JB Test	468.3***	874.8***	880.6***	-	-	-	-	-
BP Test	2791.8***	2590.5***	2821.5***	Sig.*** [a]	Sig.*** [a]	-	-	-
KB Test	2225.7***	1833.7***	1995.5***	-	-	-	-	-

Notes. N = 30,815. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007, 2010). LIK: the value of the maximum likelihood function. AIC: Akaike information criterion. JB Test: Jarque-Berra test on normality of error. BP test: Breusch-Pagan test for heteroskedasticity. KB test: Koenker-Bassett test for heteroskedasticity. a. Sig.*** was tested by GeoDa Software and other tests were conducted through R software.

Table 6.3. The Model Performances for 2008 Single Family Home Samples.

	Results of Analytical Models (Dependent Variable: LN_ Single Family Home Sale Prices in 2008)							
	OLS1_Prev _Direct (Model 1)	**OLS1_Prev _Spillover (Model 2)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Qua d (Model 8)**
Spatial Parameter _Rho_lag	-	-	-	-	0.219*** (31.734)	-	0.264*** (26.894)	0.197*** (20.581)
Spatial Parameter _Lambda_error	-	-	-	0.262*** (18.336)	-	0.342 (non-parametric)	-	-
Adjusted R-squared	0.699	0.722	0.786	-	-	-	-	-
LIK	5724.2	6236.0	7931.2	8102.8	8363.8	-	-	-
AIC	-11420.4	-12443.9	-15818.3	-16158.0	-16680.0	-	-	-
JB Test	693.8***	1399.4***	2919.2***	-	-	-	-	-
BP Test	1396.6***	1920.7***	2391.6***	Sig.*** [a]	Sig.*** [a]	-	-	-
KB Test	890.6***	1096.6***	1114.3***	-	-	-	-	-

Notes. N = 12,885. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

Table 6.4. The Model Performances for 2005 Condo Samples.

	Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2005)							
	OLS1_Prev _Direct (Model 1)	**OLS1_Prev _Spillover (Model 2)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
Spatial Parameter _Rho_lag	-	-	-	-	0.316*** (29.477)	-	0.157*** (7.451)	0.138*** (6.456)
Spatial Parameter _Lambda_error	-	-	-	0.536*** (38.186)	-	0.616 (non-parametric)	-	-
Adjusted R-squared	0.588	0.635	0.680	-	-	-	-	-
LIK	-1703.8	-1333.3	-913.1	-349.1	-526.2	-	-	-
AIC	3435.6	2694.7	1870.3	746.2	1100.5	-	-	-
JB Test	489.5***	766.4***	1149.6***	-	-	-	-	-
BP Test	656.6***	580.5***	863.2***	Sig.*** [a]	Sig.*** [a]	-	-	-
KB Test	411.4***	314.9***	428.1***	-	-	-	-	-

Notes. N = 6,205. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007, 2010). LIK: the value of the maximum likelihood function. AIC: Akaike information criterion. JB Test: Jarque-Berra test on normality of error. BP test: Breusch-Pagan test for heteroskedasticity. KB test: Koenker-Bassett test for heteroskedasticity. a. Sig.*** was tested by GeoDa Software and other tests were conducted through R software.

Table 6.5. The Model Performances for 2008 Condo Samples.

	Results of Analytical Models (Dependent Variable: LN_Condo Sale Prices in 2008)							
	OLS1_Prev _Direct (Model 1)	**OLS1_Prev _Spillover (Model 2)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
Spatial Parameter _Rho_lag	-	-	-	-	0.099*** (4.305)	-	0.184*** (5.279)	0.163*** (4.774)
Spatial Parameter _Lambda_error	-	-	-	0.145*** (4.343)	-	0.193 (non-parametric)	-	-
Adjusted R-squared	0.578	0.523	0.652	-	-	-	-	-
LIK	-691.8	-814.5	-495.4	-487.4	-487.1	-	-	-
AIC	1411.7	1657.1	1034.9	1022.9	1022.3	-	-	-
JB Test	98.6***	91.2***	80.5***	-	-	-	-	-
BP Test	239.0***	160.6***	257.3***	Sig.*** [a]	Sig.*** [a]	-	-	-
KB Test	166.4***	115.5***	180.3***	-	-	-	-	-

Notes. N = 2,003. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.

A closer consideration of the results seems to suggest that the primary difference is due to accounting for spatial dependence or (and) endogeneity. It becomes possible to distinguish the spatial effects from the total effect through inclusion of the spatial lag or error term.

Most of all, this study investigated the endogeneity issue and expanded the model specifications to account for the endogeneity of neighboring housing characteristics using 2SLS estimators. It also corrected the model specification form of heteroskedasticity and remaining spatial autocorrelation by using the HAC correction form. In particular, this study considers spatial hedonic models via general method of moments (GMM) for better performance and predictive accuracy, accounting for spatial dependence and endogeneity as well as spatial heteroskedasticity. Thus, discussion of analytical results for four different data sets mainly focuses on the GMM

2SLS_HAC_Quadratic model (Model 8) as the most conservative approach among the eight analytical models. For the remaining models for each data sample, the variables will only be discussed if there is a substantial variation from the GMM 2SLS_HAC_Quadratic model.

The spatially lagged dependent variable was positive and significant in the GMM_2SLS_HAC_Quadratic estimation, with a spatial coefficient parameter estimate of 0.273 for 2005 single family home prices (see Table 6.2). This implies that if the weighted average of all other house sale prices increases by 1%, the sale price of a sample house on average in 2005 increased by 0.27%. Single family home samples had a spatial coefficient parameter of 0.197 for lagged dependence in 2008. Condo samples had a spatial coefficient parameter of 0.138 and 0.168 for lagged dependence in 2005 and 2008, respectively.

The spatial autoregressive coefficients illustrated in Tables 6.2 through 6.5 are dependent on housing types and cycles. All estimated coefficients were highly significant, with slightly higher magnitudes for the spatial autoregressive parameter for housing samples in 2005 compared to 2008.

The largest estimates of spatial autoregressive lag coefficients are consistent for 2005 single family home samples and the smallest for 2008 condo samples in the GMM_2SLS_HAC_Quadratic model. On the other hand, the largest estimates of spatial autoregressive error coefficients are consistent for 2005 condo samples and the smallest for 2008 condo samples in the GMM_2SLS_HAC_Quadratic model.

6.1.3 Direct Foreclosure Effects on Existing Home Prices in Different Housing Types and Housing Cycles

6.1.3.1 Hypothesis 2: Discount for Distressed Sales Associated with Foreclosure

One of the main methodological goals of this study is to estimate the effects of residential mortgage foreclosures on existing home prices and to separate these estimates into the part due to direct foreclosure effect associated with property level and the part due to indirect foreclosure effects associated with neighboring residential foreclosures as a negative neighborhood externality.

Table 6.6 shows the comparison of the coefficients of the discount for distressed sales associated with foreclosure in a housing boom year (2005) and a housing bust year (2008).

As eight analytical models are adopted in this study, the discussion starts with how direct foreclosure effects (discount for distressed sales) is changed in each model, accounting for the spatial effects such as spatial dependence and endogeneity as well as spatial heteroskedasticity. For the OLS_Prev_Direct model (Model 1), the sale price of a single family home associated with foreclosure implied a -14.96 % discount in a housing bust year (2008). When all variables of the OLS1_Pre_Direct model plus indirect foreclosure variables were added to OLS3_Prev_Both_Effects model (Model 3), the discount of direct foreclosure effect dropped to about -14.96 % in the OLS1_Pre_Direct model to -9.08 % in the OLS3_Prev_Both_Effects model. Thus, controlling for indirect foreclosure variables reduced the discount for sales associated with direct foreclosure effects.

Table 6.6. Estimated Marginal Impacts of Distressed Sales Associated with Foreclosures.

Housing Type	Housing Cycle	Independent Variable	Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Cycle (Housing Boom vs. Bust)						
		DISTRESSED SALE _dummy	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Coefficient	-5.06E-02*** (-20.276)	-1.85E-02*** (-7.111)	-1.20E-02 (-0.841)	3.55E-05 (NA)	-2.59E-04 (-0.098)	-2.42E-03 (-0.955)	-2.19E-03 (-0.897)
		% Pr change :100×(e^{β}-1)	**-4.93%**	**-1.83%**	-1.19%	-0.04%	-0.03%	-0.24%	-0.22% (-$560)
	2008 (Bust)	Coefficient	-1.62E-01*** (-54.879)	-9.53E-02*** (-33.634)	-9.33E-02*** (-27.434)	-5.37E-02*** (-17.485)	-8.99E-02*** (-24.800)	-4.38E-02*** (-13.642)	-3.48E-02*** (-11.187)
		% Pr change :100×(e^{β}-1)	**-14.96%**	**-9.08%**	**-8.91%**	**-5.23%**	**-8.60%**	**-4.29%**	**-3.42% (-$6,800)**
D.V.: Condo Sale Prices	2005 (Boom)	Coefficient	-1.51E-01*** (-7.368)	-4.88E-02* (-2.262)	-1.42E-02 (-0.763)	-3.80E-02· (-1.806)	-2.27E-02 (-1.226)	-4.51E-02* (-2.555)	-3.76E-02* (-2.153)
		% Pr change :100×(e^{β}-1)	**-14.02%**	**-4.76%**	-1.41%	**-3.73%**	-2.24%	**-4.41%**	**-3.69% (-$5,600)**
	2008 (Bust)	Coefficient	-3.82E-01*** (-20.623)	-2.27E-01*** (-10.654)	-2.34E-01*** (-11.105)	-2.28E-01*** (-10.814)	-2.34E-01*** (-11.047)	-2.28E-01*** (-12.136)	-2.18E-01*** (-11.574)
		% Pr change :100×(e^{β}-1)	**-31.75%**	**-20.31%**	**-20.86%**	**-20.39%**	**-20.86%**	**-20.39%**	**-19.59% (-$32,000)**

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error model were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors was used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). The OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.

When controlling for the spatial dependence in the ML_Spatial_Error model (Model 4), the ML_Spatial_Lag model (Model 5), and the GMM_SAR Error model (Model 6), the discount of direct foreclosure effect dropped to about -8.91%, -5.23%, and -8.60%, respectively. Last, when controlling for the spatial dependence and endogeneity as well as spatial heteroskedasticity in the GMM_2SLS_HAC (Model 7) and the GMM_2SLS_HAC_Quadratic model (Model 8), the discount of direct foreclosure effect dropped to about -4.29% and -3.42%, respectively. The following discussion is based on the results of the GMM_2SLS_HAC_Quadratic model as the most conservative model.

The results of the GMM_2SLS_HAC_Quadratic model shown in Table 6.6 (lower section) demonstrated that the sale price was about -3.42% (-$6,800) lower for single family homes that faced foreclosures in the two years prior to sale and sold later during 2008 throughout the study area. However, it was not statistically significant for single family homes in 2005 (see Table 6.6, upper section).

The sale price was about -3.69% (-$5,600) lower for condos that faced foreclosures in the two years prior to the sale transaction and sold later in 2005 throughout the study area (see Table 6.6, lower section).

The discount for distressed condo sales that faced foreclosure in the two years prior to sale and sold later during 2008 was about -19.59% (-$32,000), compared to typical condo sales (see Table 6.6, lower section).

This indicated that the value depreciation by foreclosure was larger for the condo samples than that of single family homes, especially during a housing bust year (2008). This also indicated that small and affordable house types such as condos or townhomes had a larger price-depressing impact from foreclosures in a housing bust year (2008).

6.1.3.2 Hypothesis 3: Discount for Renter Occupancy in Full Sale Samples

We would expect owner or renter occupancy status to have an effect on home sale prices. The following discussion is based on the GMM_2SLS_HAC_Quadratic model (Model 8) as the most conservative approach. In Table 6.7, RENTER dummy indicates the impact on the sale price of a renter occupied home. The negative and significant coefficient suggests that the marginal impact of property sale prices creates a discount on the price of renter occupied homes.

It indicated that renter occupied properties among all samples in 2005 and 2008, except condo samples in 2008, decreased sale prices. Renter occupied single family homes had -2.12% and -5.78% discounts in 2005 and 2008 respectively, not controlling for previous foreclosure status (see Table 6.7, upper section). Considering that the average sale price of single family homes throughout the study area was about $256,000 in 2005 and was about $200,000 in 2008, that was a discount of -$5,400 (-2.12%) and -$12,000 (-5.78%) for renter occupied single family home sales, respectively.

Renter occupied condos had a -5.49% discount in 2005. Considering that the average sale price of condos throughout the study area was about $153,000 in 2005, this was a discount of -$8,400 (-5.49%) for renter occupied condos. However, the estimated discount for renter occupied condos was not statistically significant in 2008.

Consistent with the previous findings, this suggests that the expected depreciation level is negatively associated with renter occupancy status on properties.

Table 6.7. Estimated Marginal Impacts of Renter Occupancy in Full Sale Samples for Each Housing Type.

Housing Type	Housing Cycle	Independent Variable	Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Cycle (Housing Boom vs. Bust)						
		RENTER _dummy	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Coefficient	-2.27E-02*** (-12.477)	-2.36E-02*** (-13.726)	-2.20E-02*** (-13.612)	-2.19E-02*** (-13.514)	-2.21E-02*** (-13.707)	-2.21E-02*** (-13.416)	-2.14E-02*** (-13.220)
		% Pr change :100×(e^{β}-1)	**-2.24%**	**-2.33%**	**-2.18%**	**-2.16%**	**-2.18%**	**-2.18%**	**-2.12% (-$5,400)**
	2008 (Bust)	Coefficient	-7.02E-02*** (-16.619)	-6.76E-02*** (-11.312)	-6.42E-02*** (-10.989)	-6.39E-02*** (-10.805)	-6.45E-02*** (-11.092)	-6.49E-02*** (-7.791)	-5.95E-02*** (-7.320)
		% Pr change :100×(e^{β}-1)	**-6.78%**	**-6.54%**	**-6.22%**	**-6.19%**	**-6.42%**	**-6.28%**	**-5.78% (-$12,000)**
D.V.: Condo Sale Prices	2005 (Boom)	Coefficient	-7.08E-02*** (-7.163)	-4.95E-02*** (-5.520)	-4.30E-02*** (-5.446)	-4.49E-02*** (-5.343)	-4.42E-02*** (-5.654)	-4.93E-02*** (-5.161)	-5.65E-02*** (-5.938)
		% Pr change :100×(e^{β}-1)	**-6.84%**	**-4.83%**	**-4.20%**	**-4.39%**	**-4.32%**	**-4.81%**	**-5.49% (-$8,400)**
	2008 (Bust)	Coefficient	-3.88E-02* (-2.064)	1.31E-02 (-0.663)	1.30E-02 (-0.664)	1.35E-02 (0.671)	1.16E-02 (-0.592)	1.24E-02 (-0.549)	1.43E-02 (-0.638)
		% Pr change :100×(e^{β}-1)	**-3.72%**	1.32%	1.31%	1.36%	1.67%	1.25%	1.44%

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. The ML Spatial Lag and Error model were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). The OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.

6.1.3.3 Hypothesis 4: Discount for Renter Occupancy in Distressed Sale Samples

This hypothesis tests the foreclosure discount through the inclusion of interaction terms between the indicator of distressed housing sales and renter occupancy status. A coefficient on an interaction term indicates the relationship between a distressed home's sales price associated with foreclosure and renter occupancy status as the relevant interacted variable such that a negative (positive) coefficient is associated with a larger (smaller) discount.

In Table 6.8, the interaction term, INT_D-S AND RENTER, is the interactive dummy variable denoting units that have foreclosed in the two years prior to sale and sold later under renter occupancy status. It indicates the impact on distressed sales associated with foreclosure under renter occupied status.

The following discussion is based on the GMM_2SLS_HAC_Quadratic model (Model 8) as the most conservative model. In Table 6.8 (upper section), the interaction illustrates that the prices for renter occupied single family homes that faced foreclosure in the two years prior to sale and sold later in 2005 were lower by about 1.08% than the sale prices of owner occupied homes. However, the renter occupied single family homes that had faced foreclosure in the two years prior to sale and sold later in 2008 were higher by about 1.61% compared to the sale prices of owner occupied homes.

For the condo samples (see Table 6.8, lower section), the interaction illustrates that renter occupied condos that faced a foreclosure in the two years prior to sale and sold later in 2008 were still lower by about -9.98% compared to owner occupied condo prices. However, the interaction was statistically insignificant for the condo samples in 2005.

Table 6.8. Estimated Marginal Impacts of Interaction between Distressed Home Sales Associated with Foreclosure and Renter Occupancy.

Housing Type	Housing Cycle	Independent Variable	Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Cycle (Housing Boom vs. Bust)					
		INT_D-S AND RENTER	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Coefficient	-1.16E-02* (2.068)	-9.83E-03• (1.865)	-1.19E-02* (-2.114)	-1.09E-02* (2.068)	-1.18E-02* (2.173)	-1.09E-02* (2.059)
		% Pr change :100×(e^{β}-1)	**-1.15%**	**-0.98%**	**-1.18%**	**-1.08%**	**-1.17%**	**-1.08%**
	2008 (Bust)	Coefficient	2.04E-02** (2.751)	1.57E-02* (2.168)	1.88E-02* (2.541)	1.60E-02* (2.220)	2.02E-02* (2.105)	1.60E-02• (1.727)
		% Pr change :100×(e^{β}-1)	**2.06%**	**1.58%**	**1.90%**	**1.61%**	**2.04%**	**1.61%**
D.V.: Condo Sale Prices	2005 (Boom)	Coefficient	-1.98E-02 (-0.456)	-4.14E-02 (-1.091)	-2.01E-02 (-0.429)	-2.91E-02 (-0.780)	-1.76E-02 (-0.474)	-6.60E-03 (-0.178)
		% Pr change :100×(e^{β}-1)	-1.96%	-4.05%	-1.99%	-2.87%	-1.74%	-0.66%
	2008 (Bust)	Coefficient	-1.08E-01** (-2.777)	-1.04E-01** (-2.697)	-1.08E-01** (-2.767)	-1.06E-01** (-2.738)	-1.09E-01** (-2.716)	-1.05E-01* (-2.572)
		% Pr change :100×(e^{β}-1)	**-10.23%**	**-9.88%**	**-10.24%**	**-10.06%**	**-10.32%**	**-9.98%**

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '•' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). The OLS1_Prev_Direct model (model 1) doesn't have an INT_D-S AND RENTER variable and the OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status. They are not presented in this table.

In comparison, the price impact for renter occupancy (see Table 6.9, upper section), renter occupied homes in the 2005 full single family home samples, not controlling for previous foreclosure, implied a -2.12% discount in GMM_2SLS_HAC_Quadratic model. On the other hand, the renter occupied single family homes among distressed sales associated with foreclosure had more discount (-

1.08%) than owner occupied homes in 2005 (see Table 6.9, upper section). Considering that the average sale price of a single family home throughout the study area was about $256,000 in 2005, distressed single family home sales with renter occupancy status had a discount of -3.2%, which is about an -$8,200 discount (see Table 6.9, upper section).

The renter occupied homes in 2008 full single family home samples, not controlling for previous foreclosure status, had a -5.78% discount (see Table 6.9, upper section). On the other hand, the renter occupied and distressed single family home sales associated with foreclosure were a little higher (+1.61%) than owner occupied homes in GMM_2SLS_HAC_Quadratic model (see Table 6.9, upper section). However, considering that the average sale price of a single family home throughout the study area was about $200,000 in 2008, distressed and renter occupied single family homes still had a discount of -4.62%, which is about -$9,200 (see Table 6.9, upper section).

The renter occupied condo sales had a -5.49 % discount during a 2005 housing boom year (see Table 6.9; lower section). The renter occupied condos among distressed sales associated with foreclosure had little discount (-0.66%) compared to owner occupied condos in GMM_2SLS_HAC_Quadratic model (see Table 6.9, lower section). However, the discount of distressed renter condos (-6.15%) was not statistically significant for 2005 condo samples (see Table 6.9, upper section).

Table 6.9. Estimated Marginal Impacts of Renter Occupancy in Distressed Home Sales Associated with Foreclosure.

Housing Type	**Housing Cycle**	**Marginal Impact (Discount) for Renter Occupancy Status in Distressed Home Sales**	**Results of Analytical Models by Housing Type (SFH vs. Condo) and Cycle (Housing Boom vs. Bust)**					
			OLS3_Prev _Both Effects (Model 3)	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Discount for Renter Occupancy in Full Sample + Interaction Effect Between Distressed Sale and Renter Occupancy Status	**-2.33%** **-1.15%**	**-2.18%** **-0.98%**	**-2.16%** **-1.18%**	**-2.18%** **-1.08%**	**-2.18%** **-1.17%**	**-2.12%** **-1.08%**
		= Discount for Renter Occupancy in Distressed Home Sale	**-3.48%**	**-3.16%**	**-3.34%**	**-3.26%**	**-3.35%**	**-3.20%** **(-$8,200)**
	2008 (Bust)	Discount for Renter Occupancy in Full Sample + Interaction Effect Between Distressed Sale and Renter Occupancy Status	**-6.54%** **+2.06%**	**-6.22%** **+1.58%**	**-6.19%** **+1.90%**	**-6.42%** **+1.61%**	**-6.28%** **+2.04%**	**-5.78%** **+1.61%**
		= Discount for Renter Occupancy in Distressed Home Sale Status	**-4.48%**	**-4.64%**	**-4.29%**	**-5.26%**	**-4.24%**	**-4.62%** **(-$9,200)**
D.V.: Condo Sale Prices	2005 (Boom)	Discount for Renter Occupancy in Full Sample + Interaction Effect Between Distressed Sale and Renter Occupancy Status	**-4.83%** -1.96%	**-4.20%** -4.05%	**-4.39%** -1.99%	**-4.32%** -2.87%	**-4.81%** -1.74%	**-5.49%** -0.66%
		= Discount for Renter Occupancy in Distressed Home Sale	-6.79%	-8.25%	-6.38	-7.19%	-6.55%	-6.15% (-$19,000)
	2008 (Bust)	Discount for Renter Occupancy in Full Sample + Interaction Effect Between Distressed Sale and Renter Occupancy Status	1.32% **-10.23%**	1.31% **-9.88%**	1.36% **-10.24%**	1.67% **-10.06%**	1.25% **-10.32%**	1.44% **-9.98%**
		= Discount for Renter Occupancy in Distressed Home Sale	**-8.91%**	**-8.75%**	**-8.88%**	**-8.39%**	**-9.07%**	**-8.54%** **(-$14,000)**

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). Based on the interaction effect, bold fonts are statistically significant. The OLS1_Prev_Direct model (model 1) doesn't have an INT_D-S AND RENTER variable and the OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status. They are not presented in this table.

The discount of renter occupied condos was not statistically significant for 2008 condo samples (see Table 6.9, lower section). However, when controlling for previous foreclosure status, distressed condo sales with renter occupancy status had a reduction in price of -9.98% compared to owner occupied condo sales in GMM 2SLS_HAC_Quadratic model (see Table 6.9, lower section). Considering that the average sale price of a condo throughout the study area was about $164,000 in 2008, distressed and renter occupied condos had a discount of about -8.54%, which is about -$14,000 (see Table 6.9, lower section).

Previous results suggested that renter occupied condo sales had a discounted price compared to owner occupied condo sales. This study suggests that if the renter occupied condo previously faced foreclosure in two years prior to sale and sold later, the discount is larger. These results seem to suggest that the larger discount of distressed and renter occupied condo sales would reflect less maintenance and/or a property vandalized since the foreclosure starts.

6.1.3.4 Hypothesis 5: Discount for Cash Transactions in Full Sale Samples

In Table 6.10, CASH SALE dummy indicates the impact on the sale price of a cash transaction. The following discussion is based on the GMM_2SLS_HAC_Quadratic model (Model 8) as the most conservative model. The negative and significant coefficient suggests that the marginal impact of property sale prices has a discount. Properties sold by cash transactions have reduced prices for full samples in 2005 and 2008. Single family homes had -1.52% and -7.51% discounts in 2005 and 2008, respectively (see Table 6.10, upper section). Considering that the average sale price of single family homes throughout the study area was about $256,000 in 2005 and was about $200,000 in 2008, a discount of -$3,900 (-1.52%) and -$15,260 (-7.51%) resulted for single family home sales through cash transactions, respectively.

Table 6.10. Estimated Marginal Impacts of Cash Transactions in Full Sale Samples of Each Housing Type.

Housing Type	Housing Cycle	Independent Variable	Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Cycle (Housing Boom vs. Bust)						
		CASH SALE _dummy	**OLS1_Prev _Direct (Model 1)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Coefficient	-1.10E-03 (-0.424)	-1.08E-02*** (-4.443)	-1.40E-02*** (-6.107)	-1.33E-02*** (-15.011)	-1.42E-02*** (-6.241)	-1.34E-02*** (-4.707)	-1.53E-02*** (-5.528)
		% Pr change :100×(e^{β}-1)	-1.09%	**-1.07%**	**-1.39%**	**-1.32%**	**-1.41%**	**-1.33%**	**-1.52%**
	2008 (Bust)	Coefficient	-1.25E-01*** (-33.563)	-7.48E-02*** (-14.381)	-7.40E-02*** (-14.601)	-7.48E-02*** (-14.841)	-7.28E-02*** (-14.435)	-7.38E-02*** (-9.988)	-7.81E-02*** (-10.909)
		% Pr change :100×(e^{β}-1)	**-11.75%**	**-7.21%**	**-7.13%**	**-7.21%**	**-7.02%**	**-7.11%**	**-7.51%**
D.V.: Condo Sale Prices	2005 (Boom)	Coefficient	-2.50E-02* (-2.140)	-3.54E-02*** (-3.367)	-3.91E-02*** (-4.262)	-3.51E-02*** (-3.532)	-3.86E-02*** (-4.235)	-3.51E-02** (-2.946)	-4.14E-02*** (-3.516)
		% Pr change :100×(e^{β}-1)	**-2.47%**	**-3.48%**	**-3.83%**	**-3.45%**	**-3.79%**	**-3.45%**	**-4.06%**
	2008 (Bust)	Coefficient	-1.39E-01*** (-7.601)	-6.24E-02** (-3.094)	-6.91E-02*** (-3.473)	-6.30E-02** (-3.133)	-6.87E-02*** (-3.440)	-6.28E-02** (-2.664)	-6.10E-02** (-2.617)
		% Pr change :100×(e^{β}-1)	**-12.98%**	**-6.04%**	**-6.68%**	**-6.11%**	**-6.64%**	**-6.09%**	**-5.92%**

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). The OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status and is not presented in this table.

The discount of -4.06% and -5.92% were estimated for 2005 and 2008 full condo samples respectively (see Table 6.10, lower section), not controlling for previous foreclosure status. Considering that the average sale price of condos throughout the study area was about $153,000 in 2005 and was about $164,000 in 2008, a discount of -$6,200 and -$9,700 resulted for condo sales through cash transactions, respectively.

Consistent with previous findings, they suggest that the expected depreciation level is negatively associated with cash sales.

6.1.3.5 Hypothesis 6: Discount for Cash Transactions in Distressed Sale Samples

This hypothesis examines the foreclosure discount through the inclusion of interaction terms between the indicator of distressed housing sales and cash transactions. A coefficient on an interaction term indicates the relationship between distressed home sale prices associated with foreclosure and cash sales as the relevant interacted variable, such that a negative (positive) coefficient is associated with a larger (smaller) discount. The following discussion is based on the GMM_2SLS_HAC_Quadratic model (Model 8) as the most conservative model.

One would expect the effects of cash transactions on distressed sale samples associated with foreclosure to be expressed through the interaction of two dummy variables: a dummy for distressed sales associated with foreclosure status on the property and a dummy for cash transactions.

The interaction term, INT_D-S AND CASH SALE, is an interaction dummy variable and denotes property units that faced foreclosure in the two years prior to sale and sold later through cash transactions. Table 6.11 (upper section) indicated that the interaction of cash transactions on the existing sale prices of single family homes that faced a foreclosure in the two years prior to sale and sold later in 2008 was lower by about -4.74% than single family homes with mortgage financing. However, it was statistically insignificant for the single family home samples in 2005.

Table 6.11. Estimated Marginal Impacts of Interaction between Distressed Home Sales Associated with Foreclosure and Cash Transactions.

Housing Type	**Housing Cycle**	**Independent Variable**	**Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Cycle (Housing Boom vs. Bust)**					
		INT_D-S AND CASH SALE	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Coefficient	-4.61E-03 (-0.551)	-5.12E-03 (-0.648)	-5.70E-03 (-0.736)	-4.27E-03 (-0.542)	-4.55E-03 (-0.503)	-2.51E-03 (-0.279)
		% Pr change :100×(e^{β}-1)	-0.45%	-0.51%	-0.57%	-0.43%	-0.45%	-0.25%
	2008 (Bust)	Coefficient	-5.13E-02*** (-7.923)	-4.97E-02*** (-7.859)	-4.96E-02*** (-7.874)	-5.11E-02*** (-8.132)	-5.07E-02*** (-5.886)	-4.68E-02*** (-5.631)
		% Pr change :100×(e^{β}-1)	**-5.00%**	**-4.85%**	**-4.84%**	**-4.98%**	**-4.94%**	**-4.74%**
D.V.: Condo Sale Prices	2005 (Boom)	Coefficient	-6.23E-02 (-1.181)	-6.46E-02 (-1.420)	-5.96E-02 (-1.126)	-7.11E-02 (-1.573)	-6.74E-02 (-1.412)	-5.23E-02 (-1.103)
		% Pr change :100×(e^{β}-1)	-6.04%	-6.25%	-5.79%	-6.86%	-6.52%	-5.10%
	2008 (Bust)	Coefficient	-1.75E-01*** (-4.769)	-1.64E-01*** (-4.501)	-1.72E-01*** (-4.726)	1.63E-01*** (-4.472)	-1.67E-01*** (-4.092)	-1.60E-01*** (-3.972)
		% Pr change :100×(e^{β}-1)	**-16.05%**	**-15.12%**	**-15.80%**	**-15.04%**	**-15.38%**	**-14.81%**

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. t value (OLSs and GMM_2SLS_HACs) or z value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error terms with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). The OLS1_Prev_Direct model (model 1) doesn't have an INT_D-S AND CASH SALE variable and the OLS2_Prev_Spillover model (model 2) doesn't have variables for of selling factors related to foreclosure status. They are not presented in this table.

The interaction of cash transactions on condo sale prices that faced a foreclosure in the two years prior to sale and sold later in 2008 was lower by about -14.81% than condos with mortgage financing (see Table 6.11, lower section). However, it was statistically insignificant for the condo samples in 2005 (see Table 6.11, lower section).

In comparison (see Table 6.12, upper section), cash transitions in the full single family home samples in 2008, not controlling for previous foreclosure status, implied a -7.51% discount. However, the cash transactions for distressed single family home sales associated with a foreclosure had a greater discount than family homes with mortgage financing in 2008 and reached a -12.25% discount (see Table 6.12, upper section). Considering that the average sale price of single family homes throughout the study area was about $256,000 in 2005, single family homes which faced foreclosure in the two years prior to sale and sold later through cash transactions had a discount of -$24,500 (-12.25%). However, it was not statistically significant in 2005 (see Table 6.12, upper section).

In comparison with cash transitions in condo samples (see Table 6.12, lower section), cash transitions in 2008 full condo samples, not controlling for previous foreclosure status, resulted in a -5.92% discount. However, the cash transactions in distressed condo sales associated with foreclosure had a greater discount than condo sales through mortgage financing in 2008 and reached a -20.73% discount (see Table 6.12, lower section).

Table 6.12. Estimated Marginal Impacts of Cash Transactions in Distressed Home Sales Associated with Foreclosure.

Housing Type	Housing Cycle	Marginal Impact (Discount) for Renter Occupancy Status in Distressed Home Sales	Results of Analytical Models by Housing Type (SFH vs. Condo) and Cycle (Housing Boom vs. Bust)					
			OLS3_Prev _Both Effects (Model 3)	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**	**GMM_2SLS _HAC_Quad (Model 8)**
D.V.: SFH Sale Prices	2005 (Boom)	Discount for Cash Transaction in Full Sample + Interaction Effect Between Distressed Sale and Cash Transaction	**-1.07%** -4.51%	**-1.39%** -4.99%	**-1.32%** -0.57%	**-1.41%** -4.18%	**-1.33%** -4.45%	**-1.52%** -0.25%
		= Discount for Cash Transaction in Distressed Home Sale	-5.58%	-6.38%	-1.89%	-5.59%	-5.78%	-1.77%
	2008 (Bust)	Discount for Cash Transaction in Full Sample + Interaction Effect Between Distressed Sale and Cash Transaction	**-7.21%** **-5.00%**	**-7.13%** **-4.85%**	**-7.21%** **-4.84%**	**-7.02%** **-4.98%**	**-7.11%** **-4.94%**	**-7.51%** **-4.74%**
		= Discount for Cash Transaction in Distressed Home Sale	**-12.21%**	**-11.98%**	**-12.05%**	**-12.00%**	**-12.05%**	**-12.25%** **(-$24,500)**
D.V.: Condo Sale Prices	2005 (Boom)	Discount for Cash Transaction in Full Sample + Interaction Effect Between Distressed Sale and Cash Transaction	**-3.48%** -6.04%	**-3.83%** -6.25%	**-3.45%** -5.79%	**-3.79%** -6.86%	**-3.45%** -6.52%	**-4.06%** -5.10%
		= Discount for Cash Transaction in Distressed Home Sale	-9.52%	-10.08%	-9.24%	-10.65%	-9.97%	-9.16%
	2008 (Bust)	Discount for Cash Transaction in Full Sample + Interaction Effect Between Distressed Sale and Cash Transaction	**-6.04%** **-16.05%**	**-6.68%** **-15.12%**	**-6.11%** **-15.80%**	**-6.64%** **-15.04%**	**-6.09%** **-15.38%**	**-5.92%** **-14.81%**
		= Discount for Cash Transaction in Distressed Home Sale	**-22.09%**	**-21.80%**	**-21.91%**	**-21.68%**	**-21.47%**	**-20.73%** **(-34,000)**

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. *t* value (OLSs and GMM_2SLS_HACs) or *z* value (ML Spatial Lag; ML Spatial Error; GMM_SAR_Error) are given in parentheses. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. OLS is Ordinary Least Squares. Prev (Both) denotes simple previous models for direct or (and) spillover effects of foreclosure. ML Spatial Lag and Error models were used to control for spatial lag terms and error terms with spatial parameters ρ and λ, respectively, using rook contiguity weight. The GMM_SAR_Error (Spatial Simultaneous Autoregressive Error model by GMM) procedure was used to control for spatial error term with spatial parameter λ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 1999). The GMM_2SLS_HAC (Generalized Spatial Two Stages Least Squares with Heteroskedasticity and Spatial Autocorrelation Consistent Estimator) models with HAC standard errors were used to control for spatial lag terms with spatial parameter ρ and a 10-nearest neighbors spatial weight (Kelejian and Prucha, 2007; 2010). Based on the interaction effect, bold fonts are statistically significant. The OLS1_Prev_Direct model (model 1) doesn't have an INT_D-S AND CASH SALE variable and the OLS2_Prev_Spillover model (model 2) doesn't have variables for selling factors related to foreclosure status. They are not presented in this table.

It demonstrated that the cash transaction effect on condo sale prices was the greatest for condo units that faced foreclosure in the two years prior to sale and sold later during a 2008 housing bust year. These distressed condo sales through cash transactions had almost a three and half times discount (-20.73 %) than condos (-5.92%) sold through mortgage financing in 2008. Considering that the average sale price of condos throughout the study area was about $200,000 in 2008, condos which faced foreclosure in the two years prior to sale and sold later through cash transactions had a discount of -$34,000 (-20.73 %). However, it was not statistically significant in 2005 (see Table 6.12, lower section).

The discount through a cash transaction was larger on a distressed property than a typical sale, indicating that distressed sellers may reduce their reservation prices over time with more discounts. This discount also seems to reflect seller's pressure for an urgent sale caused by foreclosure or a distressed financial status. This result shows that the discount is larger in affordable housing types such as condos and townhomes than single family homes.

6.1.4 Spillover Effects of Neighboring Foreclosures on Existing Home Prices in Different Housing Types and Housing Cycles

6.1.4.1 Hypotheses 7 and 8: Distance Effects of Neighboring Foreclosures

Results for Hypotheses 7and 8 in the 2005 and 2008 samples (table on page 267 [Table 6.13] and table on page 268 [Table 6.14]) are consistent with previous studies (see tables on pages 46-47 [Table 2.2]) and existing theories: foreclosures closer to the house to be sold have a larger negative impact than foreclosures further away from the house to be sold. The estimates of the coefficients for neighboring single family home foreclosures and neighboring condo foreclosures are presented in table on page 267 (Table 6.13) and table on page 268 (Table 6.14). The following discussion is based on the GMM_2SLS_HAC_Linear model (Model 7).

First, it should be noted that two cases of foreclosure effects were not statistically significant within 500 feet: the foreclosure effects of condos on the 2005 single family home prices within 500 feet as well as foreclosure effects of single family homes on 2008 condo prices within 500 feet. The insignificance of the different type of foreclosure coefficients on existing housing prices within 500 feet seems to reflect the small degree of variation in the number of foreclosures in those intervals. Thus, a small number of single family home foreclosures did not significantly depress condo prices within 500 feet and vice versa. It may be associated with the characteristic that the same types of housing developments tend to be clustered closely in residential zoning.

For 2005 single family home samples (see table on page 267 [Table 6.13], upper section), results indicated that a neighboring foreclosure of single family homes on the existing sale prices of single family homes within 500 feet created a negative spillover effect of approximately -0.96% for the GMM_2SLS_HAC_Linear model (Model 7). This negative impact diminished by distance and falls to -0.79% at a distance of 501-1000 feet and to -0.81% at a distance of 1001-1500 feet. The results also indicated that a condo foreclosure on existing sale prices of single family homes within 501-1000 feet created a negative spillover effect of approximately -0.33%. This negative impact intensified a little to -0.41% at 1001-1500 feet. Thus, this impact was flat at 501-1500 feet during a 2005 housing boom year. Considering that Phoenix's average sale price for single family homes in 2005 was about $256,000, that was a price-depressing impact of -$2,500 (-0.96%) within the 500 foot ring, -$2,000 (-0.79%) within the 501-1000 foot ring, and -$2,100 (-0.81%) within the 1001-1500 foot ring per neighboring single family home foreclosure, respectively. And that was a price-depressing impact of -$850 (-0.33%) within the 501-1000 foot ring and $1,000 (-0.41%) within the 1001-1500 foot ring per neighboring condo foreclosure, respectively.

For 2008 single family home samples (see Table 6.13, lower section), a neighboring single family home foreclosure on existing sale prices of single family homes within 500 feet created a negative spillover effect of approximately -0.60% for the GMM_2SLS_HAC_Linear model (Model 7). This negative impact diminished by distance and falls to -0.23% at a distance of 501-1000 feet and to -0.20 % at a distance of 1001-1500 feet during a 2008 housing bust year. Thus, this impact was flat at 501-1500 feet during a 2008 housing bust year. The results also indicated that a neighboring condo foreclosure on existing sale prices of single family homes within 1001-1500 feet didn't create any negative spillover effects. Considering that Phoenix's average sale price for single family homes in 2005 was about $200,000, that was a price-depressing impact of -$1,200 (-0.60%) within the 500 foot ring, -$460 (-0.23%) within the 501-1000 foot ring and -$400 (-0.20 %) within the 1001-1500 foot ring per neighboring condo foreclosure, respectively. And it was a price-depressing impact of -$340 (-0.17%) per neighboring condo foreclosure within the 501-1000 foot ring in 2008.

Table 6.13. Estimated Marginal Impacts of Neighboring Single Family Home and Condo Foreclosures on Existing Single Family Home Prices.

Housing Type	Nearby FC Type	Independent Variable	Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Housing Cycle (Housing Boom vs. Bust)					
			OLS2_Prev _Spillover (Model 2)	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**
Dependent Variable: Single Family Home Sale Prices in 2005	SFH Foreclosure # in Three Rings	SFH_FC_1R_C [500 ft]	-1.32E-02*** (-27.473)	-1.22E-02*** (-25.214)	-1.07E-02*** (-22.957)	-1.00E-02*** (-22.578)	-1.04E-02*** (-22.307)	-9.63E-03*** (-21.853)
		% change(1R)	**-1.32%**	**-1.22%**	**-1.07%**	**-1.00%**	**-1.04%**	**-0.96% (-$2,500)**
		SFH_FC_2R_C [501-1000 ft]	-1.02E-02*** (-31.040)	-1.04E-02*** (-31.714)	-8.84E-03*** (-27.982)	-8.18E-03*** (-26.479)	-8.59E-03*** (-27.322)	-7.91E-03*** (-26.733)
		% change(2R)	**-1.02%**	**-1.04%**	**-0.88%**	**-0.82%**	**-0.86%**	**-0.79% (-$2000)**
		SFH_FC_3R_C [1001-1500 ft]	-1.08E-02*** (-42.112)	-1.09E-02*** (-42.826)	-8.65E-03*** (-34.880)	-8.42E-03*** (-34.894)	-8.32E-03*** (-33.652)	-8.14E-03*** (-33.473)
		% change(3R)	**-1.08%**	**-1.09%**	**-0.87%**	**-0.84%**	**-0.83%**	**-0.81% (-$2000)**
	Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-	-3.14E-03· (-1.779)	-3.33E-03* (-1.967)	-2.13E-03· (-1.722)	-3.20E-03· (-1.899)	-2.28E-03 (-1.378)
		% change(1R)	**-**	**-0.31%**	**-0.33%**	**-0.21%**	**-0.32%**	-0.23%
		CON_FC_2R_C [501-1000 ft]	-	-3.48E-03*** (-4.022)	-3.71E-03*** (-4.499)	-3.44E-03*** (-4.343)	-3.79E-03*** (-4.613)	-3.31E-03*** (-3.989)
		% change(2R)	**-**	**-0.35%**	**-0.37%**	**-0.34%**	**-0.38%**	**-0.33% (-$850)**
		CON_FC_3R_C [1001-1500 ft]	-	-4.41E-03*** (-7.263)	-4.06E-03*** (-6.944)	-3.96E-03*** (-6.936)	-4.12E-03*** (-7.080)	-4.06E-03*** (-7.053)
		% change(3R)	**-**	**-0.44%**	**-0.41%**	**-0.40%**	**-0.41%**	**-0.41% (-$1000)**
Dependent Variable: Single Family Home Sale Prices in 2008	SFH Foreclosure # in Three Rings	SFH_FC_1R_C [500 ft]	-1.07E-02*** (-26.403)	-7.58E-03*** (-21.095)	-7.06E-03*** (-19.869)	-6.20E-03*** (-17.679)	-6.93E-03*** (-19.611)	-5.96E-03*** (-17.347)
		% change(1R)	**-1.07%**	**-0.76%**	**-0.71%**	**-0.62%**	**-0.69%**	**-0.60% (-$1,200)**
		SFH_FC_2R_C [501-1000 ft]	-3.12E-03*** (-11.138)	-2.89E-03*** (-11.741)	-2.67E-03*** (-11.090)	-2.38E-03*** (-9.933)	-2.63E-03*** (-10.955)	-2.33E-03*** (-9.882)
		% change(2R)	**-0.31%**	**-0.29%**	**-0.27%**	**-0.24%**	**-0.26%**	**-0.23% (-$460)**
		SFH_FC_3R_C [1001-1500 ft]	-3.05E-03*** (-16.370)	-2.41E-03*** (-14.688)	-2.30E-03*** (-14.205)	-2.07E-03*** (-12.927)	-2.25E-03*** (-13.952)	-1.95E-03*** (-11.576)
		% change(3R)	**-0.31%**	**-0.24%**	**-0.23%**	**-0.21%**	**-0.23%**	**-0.20% (-$400)**
	Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-	-2.03E-03 (-1.130)	-1.74E-03 (-0.999)	-1.27E-03 (-0.514)	-1.95E-03 (-1.123)	-1.58E-03 (-0.865)
		% change(1R)	**-**	-0.20%	-0.17%	-0.13%	-0.20%	-0.16%
		CON_FC_2R_C [501-1000 ft]	-	-2.23E-03** (-2.790)	-2.05E-03** (-2.641)	-2.02E-03** (-2.662)	-1.97E-03* (-2.539)	-1.74E-03· (-1.874)
		% change(2R)	**-**	**-0.22%**	**-0.21%**	**-0.20%**	**-0.20%**	**-0.17% (-$340)**
		CON_FC_3R_C [1001-1500 ft]	-	-3.53E-04 (-0.663)	-2.75E-04 (-0.527)	-1.34E-04 (NA)	-3.81E-04 (-0.734)	-6.19E-05 (-0.096)
		% change(3R)	**-**	-0.04%	-0.03%	-0.01%	-0.04%	-0.00%

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples and N = 12,885 in 2005 and 2008 respectively. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. C denotes # of neighboring foreclosures within rings. R1: 500 foot ring, R2: 501-1000 foot ring, R3: 1001-1500 foot ring.

Table 6.14. Estimated Marginal Impacts of Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices.

Housing Type	Nearby FC Type	Independent Variable	**Results of Analytical Models by Housing Type (Single Family Home vs. Condo) and Housing Cycle (Housing Boom vs. Bust)**					
		Independent Variable	**OLS2_Prev _Spillover (Model 2)**	**OLS3_Prev _Both Effects (Model 3)**	**ML_Spatial _Error (Model 4)**	**ML_Spatial _Lag (Model 5)**	**GMM_SAR _Error (Model 6)**	**GMM_2SLS _HAC (Model 7)**
Dependent Variable: Condo Sale Prices in 2005	SFH Foreclosure # in Three Rings	SFH_FC_1R_C [500 ft]	-	-9.13E-04 (-0.204)	4.66E-03 (1.098)	2.32E-03 (NA)	6.12E-03 (1.451)	2.75E-04 (0.055)
		% change(1R)	-	-0.09%	0.47%	0.23%	0.61%	0.03%
		SFH_FC_2R_C [501-1000 ft]	-	-1.84E-02*** (-8.483)	-1.85E-02*** (-8.892)	-1.51E-02*** (-7.786)	-1.81E-02*** (-8.844)	-1.66E-02*** (-6.770)
		% change(2R)	-	**-1.84%**	**-1.85%**	**-1.51%**	**-1.81%**	**-1.66% (-2,500)**
		SFH_FC_3R_C [1001-1500 ft]	-	-2.28E-02*** (-16.041)	-1.65E-02*** (-11.563)	-1.37E-02*** (-10.562)	-1.60E-02*** (-11.250)	-1.86E-02*** (-9.604)
		% change(3R)	-	**-2.28%**	**-1.65%**	**-1.37%**	**-1.60%**	**-1.86% (-$2,800)**
	Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-3.96E-02*** (-20.604)	-2.86E-02*** (-15.376)	-2.64E-02*** (-14.641)	-2.32E-02*** (-13.283)	-2.63E-02*** (-14.700)	-2.58E-02*** (-11.785)
		% change(1R)	**-3.96%**	**-2.86%**	**-2.64%**	**-2.32%**	**-2.63%**	**-2.58% (-$4,000)**
		CON_FC_2R_C [501-1000 ft]	-4.90E-03* (-2.507)	-1.16E-02*** (-6.209)	-1.18E-02*** (-6.531)	-8.84E-03*** (-4.932)	-1.26E-02*** (-7.065)	-1.04E-02*** (-5.143)
		% change(2R)	**-0.49%**	**-1.16%**	**-1.18%**	**-0.88%**	**-1.26%**	**-1.04% (-1,600)**
		CON_FC_3R_C [1001-1500 ft]	-2.34E-02*** (-11.381)	-2.68E-02*** (-13.776)	-2.52E-02*** (-13.866)	-2.26E-02*** (-12.720)	-2.43E-02*** (-13.522)	-2.48E-02*** (-11.531)
		% change(3R)	**-2.34%**	**-2.68%**	**-2.52%**	**-2.26%**	**-2.43%**	**-2.48% (-3,800)**
Dependent Variable: Condo Sale Prices in 2008	SFH Foreclosure # in Three Rings	SFH_FC_1R_C [500 ft]	-	-1.29E-02* (-2.006)	-1.25E-02* (-1.974)	-1.30E-02* (-2.022)	-1.33E-02* (-2.097)	-1.31E-02· (-1.802)
		% change(1R)	-	**-1.29%**	**-1.25%**	**-1.30%**	**-1.33%**	**-1.31% (-$2,100)**
		SFH_FC_2R_C [501-1000 ft]	-	-6.53E-03* (-2.112)	-5.80E-03· (-1.894)	-5.82E-03· (-1.847)	-5.58E-03· (-1.821)	-5.60E-03· (-1.670)
		% change(2R)	-	**-0.65%**	**-0.58%**	**-0.58%**	**-0.56%**	**-0.56% (-$900)**
		SFH_FC_3R_C [1001-1500 ft]	-	-1.48E-02*** (-8.713)	-1.42E-02*** (-8.448)	-1.43E-02*** (-8.472)	-1.40E-02*** (-8.278)	-1.38E-02*** (-6.553)
		% change(3R)	-	**-1.48%**	**-1.42%**	**-1.43%**	**-1.40%**	**-1.38% (-$2,200)**
	Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-2.53E-02*** (-14.916)	-1.19E-02*** (-7.574)	-1.19E-02*** (-7.638)	-1.19E-02*** (-7.649)	-1.21E-02*** (-7.714)	-1.21E-02*** (-7.355)
		% change(1R)	**-2.53%**	**-1.19%**	**-1.19%**	**-1.19%**	**-1.21%**	**-1.21% (-$2,000)**
		CON_FC_2R_C [501-1000 ft]	-4.02E-03 (-1.631)	-3.36E-03 (-1.574)	-3.37E-03 (-1.595)	-3.30E-03 (-1.547)	-3.32E-03 (-1.569)	-3.27E-03 (-1.340)
		% change(2R)	-0.40%	-0.34%	-0.34%	-0.33%	-0.33%	-0.33%
		CON_FC_3R_C [1001-1500 ft]	-2.06E-03 (-0.799)	-7.77E-03*** (-3.468)	-7.78E-03*** (-3.497)	-7.76E-03*** (-3.492)	-7.70E-03*** (-3.461)	-8.04E-03** (-3.048)
		% change(3R)	-0.21%	**-0.78%**	**-0.78%**	**-0.78%**	**-0.77%**	**-0.80% (-$1,300)**

Notes. Dependent variable: log (sale price for each housing type). N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1. C denotes the count of neighboring foreclosures within rings. R1: 500 foot ring, R2: 501-1000 foot ring, R3: 1001-1500 foot ring.

For 2005 condo samples (see Table 6.14, upper section), results indicated that a neighboring foreclosure of single family home on existing condo sale prices within 501-1000 feet created a negative spillover effect of approximately -1.66%. However, this negative impact intensified a little to -1.86 % at a distance of 1001-1500 feet during a 2008 housing bust year. The results also indicated that a neighboring foreclosure of condo on existing sale prices of condos within 500 feet created a negative spillover effect of approximately -2.58%. This negative impact diminished by distance, falling to -1.04 % at a distance of 501-1000 feet and this impact has intensified to -2.48 % at a distance of 1001-1500 feet. The diminishing of neighboring foreclosure impacts on the existing condo prices was not applicable to a distance of 501-1000 feet and 1001-1500 feet during a 2005 housing boom year. Considering that the average of condo prices in 2005 was about $153,000, that was a price-depressing impact of -$2,500 (-1.66%) within the 501-1000 foot ring and -$2,800 (-1.86%) within the 1001-1500 foot ring per neighboring single family home foreclosure. And that was a price-depressing impact of -$4,000 (-2.58%) within the 500 foot ring, -$1,600 (-1.04%) within the 501- 1000 foot ring and -$3,800 (-2.48%) within the 1001-1500 foot ring per neighboring condo foreclosure, respectively.

For 2008 condo samples (see Table 6.14, lower section), results indicated that a foreclosure of single family homes on existing condo sale prices within 501-1000 feet created a negative spillover effect of approximately -1.30%. This negative impact diminished by distance and dramatically fell to -0.56% at a distance of 501-1000 feet during a 2008 housing bust year. However, this negative impact intensified to -1.38 % at a distance of 1001-1500 feet. Again, the diminishing of foreclosure impact was not applicable to a distance of 501-1000 feet and 1001-1500 feet during a 2008 housing bust year. The results also indicated that a foreclosure of condo on existing condo sale prices within 500 feet created a negative spillover effect of approximately -1.21%. This negative impact was not statistically significant beyond 501-1000 feet during a 2008 housing bust year. However, this negative impact diminished by distance, falling to -0.80 % at a distance of 1001-1500 feet. Considering that the average of condo prices in 2005 was about $165,000, that was a price-depressing impact of -$2,100 (-1.31%) within the 500 foot ring, -$900 (-0.56%) within the 501-1000 foot ring, and -$2200 (-1.38%) within the 1000-1500 foot ring per neighboring single family home foreclosure, respectively. And that was a price-depressing impact of -$2,000 (-1.21%) within the 500 foot ring and -$1,300 (-0.80%) within the 1001-1500 foot ring per neighboring condo foreclosure, respectively.

Based on above results, this study highlights three points. First, negative spillover impact of foreclosures continued to fall as the distance increases; the neighboring foreclosures had a larger negative price impact in close proximity. Second, the negative spillover effects vary with the types of foreclosures. This result also indicated that the relationship of negative impact between the same types of foreclosures and housing sales was larger than those of different types of foreclosures and housing sales. Third, this study estimated that the marginal foreclosure impacts were smaller in a housing bust year (2008) than a housing boom year (2005).

For the first point, these results are similar to those found by Immergluck and

Smith (2006a) in Chicago in 2000. The study by Immergluck and Smith (2006a) found that each conventional foreclosure within an eighth of a mile of a home decreased by 0.9% on single-family home values. In the distance range between a one-eighth and one-quarter of a mile, the result was a 0.33% decline in prices with only modest spillover effects. Although the study by Immergluck and Smith (2006a) used different data sets (foreclosure sales) with this study using independent spatial rings of 1/8 mile (660 feet) and 1/4 mile (1320 feet) for measurement, the findings for price impact of foreclosures in this study are consistent with those of Immergluck and Smith (2006a).

To compare these results to previous research, the following discussion will mention only previous research with similar data sets using foreclosure filings and similar spatial rings for measurement of foreclosure effects.

For a New York case (Schuetz, Been, and Ellen, 2008), the marginal impact (by OLS) of a foreclosure filing within 250-500 feet and in 18 months was almost -0.2 % and had the same impact within 500-1000 feet and 1000-1500 feet from 2000 through 2005.

For the Cleveland case (Mikelbank, 2008), the marginal impact of a foreclosure filing for one year was almost -1.6 % within 250-500 feet and -1.1 % within 750-1000 feet in a 2006 sample for the ML Spatial Error model.

For the Dallas case (Leonard and Murdoch, 2009), the marginal impact of a foreclosure filing for two years (from 2005 through 2007) was almost -0.3% within 500 feet and -0.1% within 500-1000 and 1000-1500 feet for the GMM Spatial Error model.

In summary, this study indicated that negative impacts of a foreclosure filing in each distance ring were larger than those of New York and Dallas but smaller than those of Cleveland, suffering from a longer term housing downturn. However, the regression results are comparatively consistent with the evidence that foreclosures in close proximity within spatial rings had larger negative impacts on sale prices. As Rogers and Winter (2009) point out, some differences of the variance for foreclosure effects in results could be due to the models employed and/or to the different housing markets at different points in time. Thus, the test of the seventh and eighth hypothesis is pointing out the importance of sequential analysis at different time points and within different housing markets.

For the second point, in the context of the literature of foreclosure spillovers, spillover impacts vary with the types of foreclosures. This result indicates that condo foreclosures have a negative impact on existing sale prices of single family homes and vice versa. These are unique findings that have not been studied in previous research. But obviously, the findings could be a result of the Phoenix case; a cyclic housing market suffering from a current housing crisis. Consequently it should be verified through an examination of other markets in further study.

For the third point, Lin, Rosenblatt, and Yao (2009) estimated that marginal neighboring foreclosure impacts were the greatest during housing bust years (2006-2007) with higher price declines than in the relatively stable years (2000-2002). However, Rogers and Winter (2009) found that the marginal impact of a foreclosure for the prior year within 200 yards (600 feet) was almost 0.7 % from 2000 through 2002, but by 2008 the marginal impact decreased by about half. Their estimate of the marginal foreclosure impact was smaller in bad markets (2006 and 2007). The results of this study are also consistent with the findings of Rogers and Winter (2009): the decline of impact size was about half at 500 feet or over half beyond 500 feet (see tables on pages 267-268 [Table 6.13 and Table 6.14]). It seems to be associated with the density level of neighboring foreclosures. The results of the following hypotheses will discuss this density issue.

6.1.4.2 Hypotheses 9 and 10: Nonlinear and Incremental Effects of Neighboring Foreclosures

This study uses an alternative specification that allows quadratic terms for the counts of neighboring foreclosures in each spatial ring to assess the nonlinearity of the marginal effects of the foreclosures. Table 6.15 and Table 6.16 present estimates of specifications which are similar to those presented in table on page 267 (Table 6.13) and table on page 268 (Table 6.14) except quadratic terms of neighboring foreclosures included in each distance-based ring. Table 6.15 presents the results of single family home samples. Table 6.16 presents the results of condo samples. The estimates of the coefficients for neighboring single family home foreclosures, neighboring condo foreclosures, and quadratic terms of each type of neighboring foreclosures are presented in Table 6.15 and Table 6.16. The following discussion is based on the GMM_2SLS_HAC_Quadratic model as the most conservative model.

Table 6.15. Estimates of Nonlinear and Clustered Impacts by Neighboring Single Family Home and Condo Foreclosures on Existing Single Family Home Prices.

For GMM_2SLS_HAC_Quadratic Model (Model 8)								
Nearby FC Type	DV: LN_Single Family Home Sale Prices in 2005				DV: LN_Single Family Home Sale Prices in 2008			
	Independent Variable	**Marginal**	**Independent Variable**	**Quadratic**	**Independent Variable**	**Marginal**	**Independent Variable**	**Quadratic**
SFH Foreclosure # In Three Rings	SFH_FC_1R_C [500 ft]	-2.12E-02*** (-22.072)	SFH_FC_1R_C2	2.75E-03*** (15.318)	SFH_FC_1R_C [500 ft]	-1.49E-02*** (-20.366)	SFH_FC_1R_C2	3.96E-04*** (15.223)
	% change on one FC unit(1R)	**-.2.12%**	% change per additional unit	**+0.28%**	% change on one FC unit(1R)	**-1.49%**	% change per additional unit	**+0.04%**
	Cumulative Max. FC# in1R	**4**	Cumulative Max. % in1R	**-4.1% (-$10,000)**	Cumulative Max. FC# in1R	**19**	Cumulative Max. % in1R	**-13.95% (-$28,000)**
	SFH_FC_2R_C [501-1000 ft]	-2.02E-02*** (-29.147)	SFH_FC_2R_C2	1.71E-03*** (22.093)	SFH_FC_2R_C [501-1000 ft]	-7.24E-03*** (-15.187)	SFH_FC_2R_C2	1.20E-04*** (12.272)
	% change on one FC unit(2R)	**-2.02%**	% change per additional unit	**+0.02%**	% change on one FC unit(2R)	**-0.72%**	% change per additional unit	**+0.01%**
	Cumulative Max. FC# in 2R	**6**	Cumulative Max. % in 2R	**-6.0% (-$15,000)**	Cumulative Max. FC# in 2R	**30**	Cumulative Max. % in 2R	**-10.9% (-$22,000)**
	SFH_FC_3R_C [1001-1500 ft]	-1.86E-02*** (-32.683)	SFH_FC_3R_C2	1.11E-03*** (23.167)	SFH_FC_3R_C [1001-1500 ft]	-4.49E-03*** (-13.398)	SFH_FC_3R_C2	4.56E-05*** (9.433)
	% change on one FC unit(3R)	**-1.86%**	% change per additional unit	**+0.01%**	% change on one FC unit(3R)	**-0.05%**	% change per additional unit	**+0.005%**
	Cumulative Max. FC# in 3R	**8**	Cumulative Max. % in 3R	**-7.8% (-$20,000)**	Cumulative Max. FC# in 3R	**45**	Cumulative Max. % in 3R	**-10.1% (-$20,000)**
Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-3.07E-03 (-0.918)	CON_FC_1R_C2	2.73E-04 (0.392)	CON_FC_1R_C [500 ft]	-1.68E-03 (-0.482)	CON_FC_1R_C2	-3.15E-05 (-0.120)
	% change on one FC unit(1R)	-0.31%	% change(1R)	+0.03%	% change on one FC unit(1R)	-0.17%	% change(1R)	-0.00%
	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-
	CON_FC_2R_C [501-1000 ft]	9.63E-05 (0.062)	CON_FC_2R_C2	-5.10E-04* (-2.407)	CON_FC_2R_C [501-1000 ft]	7.59E-04 (0.576)	CON_FC_2R_C2	-1.47E-04* (-2.460)
	% change on one FC unit(2R)	0.00%	% change(2R)	-0.05%	% change on one FC unit(2R)	+0.08%	% change(2R)	-0.01%
	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-
	CON_FC_3R_C [1001-1500 ft]	-1.65E-03 (-1.532)	CON_FC_3R_C2	-3.08E-04* (-2.166)	CON_FC_3R_C [1001-1500 ft]	-3.08E-04 (-0.297)	CON_FC_3R_C2	1.83E-05 (0.343)
	% change on one FC unit(3R)	-0.02%	% change(3R)	-0.03%	% change on one FC unit(3R)	-0.03%	% change(3R)	0.00%
	Cumulative Max. FC# in 3R	-	Cumulative Max. % in 3R	-	Cumulative Max. FC# in 3R	-	Cumulative Max. % in 3R	-

Notes. Dependent variable: log (sale price for each housing type). N = 30,815 single family home sale samples in 2005. N = 12,885 single family home sale samples in 2008. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1. Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2). C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. Cumulative Max. % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})). Cumulative Max. N is counted until marginal coefficient per additional unit is zero. R1: 500 foot ring, R2: 501-1000 foot ring, R3: 1001-1500 foot ring.

Table 6.16. Estimates of Nonlinear and Clustered Impacts by Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices.

For GMM_2SLS_HAC_Quadratic Model (Model 8)								
Nearby FC Type	**DV: LN_ Condo Sale Prices in 2005**				**DV: LN_ Condo Sale Prices in 2008**			
	Independent Variable	**Marginal**	**Independent Variable**	**Quadratic**	**Independent Variable**	**Marginal**	**Independent Variable**	**Quadratic**
SFH Foreclosure # In Three Rings	SFH_FC_1R_C [500 ft]	5.96E-03 (0.573)	SFH_FC_1R_C2	-1.09E-03 (-0.406)	SFH_FC_1R_C [500 ft]	-2.21E-02* (-1.999)	SFH_FC_1R_C2	1.78E-03 (1.015)
	% change on one FC unit(1R)	+0.60%	% change per additional unit	-0.11%	% change on one FC unit(1R)	-2.22%	% change per additional unit	+0.18%
	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-	Cumulative Max. FC# in1R	-	Cumulative Max. % in1R	-
	SFH_FC_2R_C [501-1000 ft]	-2.10E-02*** (-4.635)	SFH_FC_2R_C2	6.16E-04 (1.560)	SFH_FC_2R_C [501-1000 ft]	-8.44E-04 (-0.158)	SFH_FC_2R_C2	-3.26E-04 (-1.192)
	% change on one FC unit(2R)	-2.10%	% change per additional unit	+0.06%	% change on one FC unit(2R)	-0.08%	% change per additional unit	-0.03%
	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-
	SFH_FC_3R_C [1001-1500 ft]	-3.87E-02*** (-10.620)	SFH_FC_3R_C2	1.59E-03*** (6.347)	SFH_FC_3R_C [1001-1500 ft]	-2.20E-02*** (-7.978)	SFH_FC_3R_C2	2.47E-04*** (4.363)
	% change on one FC unit(3R)	**-3.87%**	% change per additional unit	**+0.02%**	% change on one FC unit(3R)	**-2.20%**	% change per additional unit	**+0.02%**
	Cumulative Max. FC# in 3R	**12**	Cumulative Max. % in 3R	**-23.56% (-$36,000)**	Cumulative Max. FC# in 3R	**44**	Cumulative Max. % in 3R	**-48.36% (-$80,000)**
Condo Foreclosure # in Three Rings	CON_FC_1R_C [500 ft]	-3.82E-02*** (-9.777)	CON_FC_1R_C2	1.34E-03*** (4.025)	CON_FC_1R_C [500 ft]	-1.94E-02*** (-6.501)	CON_FC_1R_C2	2.65E-04*** (3.716)
	% change on one FC unit(1R)	**-3.83%**	% change(1R)	**+0.13%**	% change on one FC unit(1R)	**-1.94%**	% change(1R)	**+0.03%**
	Cumulative Max. FC# in1R	**14**	Cumulative Max. % in1R	**-27.26% (-$42,000)**	Cumulative Max. FC# in1R	**37**	Cumulative Max. % in1R	**-36.30% (-$60,000)**
	CON_FC_2R_C [501-1000 ft]	-1.51E-02*** (-4.332)	CON_FC_2R_C2	1.27E-04 (0.545)	CON_FC_2R_C [501-1000 ft]	1.11E-02 (1.565)	CON_FC_2R_C2	-7.17E-04* (-2.074)
	% change on one FC unit(2R)	-1.51%	% change(2R)	+0.01%	% change on one FC unit(2R)	+1.11%	% change(2R)	-0.07%
	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-	Cumulative Max. FC# in 2R	-	Cumulative Max. % in 2R	-
	CON_FC_3R_C [1001-1500 ft]	-2.64E-02*** (-6.370)	CON_FC_3R_C2	2.68E-04 (0.855)	CON_FC_3R_C [1001-1500 ft]	-1.36E-02*** (-3.431)	CON_FC_3R_C2	2.91E-04· (1.893)
	% change on one FC unit(3R)	-2.64%	% change(3R)	+0.03%	% change on one FC unit(3R)	**-1.36%**	% change(3R)	**+0.03%**
	Cumulative Max. FC# in 3R	-	Cumulative Max. % in 3R	-	Cumulative Max. FC# in 3R	**23**	Cumulative Max. % in 3R	**-15.94% (-$26,000)**

Notes. Dependent variable: log (sale price for each housing type). N = 6,205 condo sale samples in 2005. N = 2,003 condo sale samples in 2008. Significant levels: '***' 0.001 '**' 0.01 '*' 0.05 '·' 0.1.
Estimated incremental impact for clustered nearby foreclosures is R_C_Coefficient + R_C2_Coefficient × (C_i^2 - C_{i-1}^2).
C denotes the count of neighboring foreclosures within rings. C2 denotes the square of neighboring foreclosure counts within rings. Cumulative Max. % = $\sum_{i=0}^{n} ai$, ai =((Coefficient of marginal impact×{N_i: # of foreclosures}^{2}+Coefficient of quadratic term ×{N_i: # of foreclosures}^{2})-(Coefficient of marginal impact ×{N_{i-1}: # of foreclosures}+ Coefficient of quadratic term ×{N_{i-1}: # of foreclosures}^{2})). Cumulative Max. N is counted until marginal coefficient per additional unit is zero. R1: 500 foot ring, R2: 501-1000 foot ring, R3: 1001-1500 foot ring.

In Table 6.15 and Table 6.16 (see the column labeled "Marginal" and the row of "SFH or CON_FC_R_C": # of foreclosures), the estimates presented in rows of each SFH or CON_FC_R_C revealed that the marginal effect of a neighboring foreclosure within each ring had negative coefficient for the increase of foreclosures on a per unit basis. In comparison (see the column labeled "Quadratic" and the row of "SFH or CON_FC_R_C2": # of squared-foreclosures), rows of SFH or CON_FC_R_C2 revealed that the marginal effect of the square of foreclosure had a positive coefficient for the increase of the square of foreclosures on a per unit basis. The quadratic coefficients in Table 6.15 and Table 6.16 implied a diminishing marginal impact of foreclosures. Results indicated an expected decline of the neighboring sale prices with an increase of foreclosures, but the quadratic coefficients provided empirical evidence that the marginal effect of an additional neighboring foreclosure decreased as neighboring foreclosures increased.

It should be noted that not all coefficients are statistically significant at the 5% level; 3 pairs of the 6 pairs were significant for 2005 and 2008 single family home samples respectively (see Table 6.15).[25] In Table 6.15 (upper left), the upper 3 pairs denote the impact of single family foreclosures on single family home prices. It seems to be associated with the characteristic that the same types of housing properties tend to cluster closely in residential zoning areas, as previously discussed.

For 2005 single family home samples (see Table 6.15; upper left, figure on page 280 [Figure 6.2] upper section), the incremental (cumulative) impact of single family

[25] One pair denotes the coefficient for neighboring foreclosures (SFH_FC_R_C or CON_FC_R_C) and the coefficient for the square of neighboring foreclosures in each ring (SFH_FC_R_C or CON_FC_R_C2).

foreclosures on existing sale prices of single family homes was limited to no more than 4 foreclosures in the first ring (500 feet), 6 foreclosures in the second ring (501-1000 feet), and 8 foreclosures in third rings (1001-1500 feet) respectively. The maximum cumulative impact of neighboring single family home foreclosures reached -4.1% for 4 foreclosures in the first ring (500 feet), -6.0% for 6 foreclosures in the second ring (501-1000 feet), and -7.8% for the 8 foreclosures in the third ring (1001-1500 feet) on existing single family home prices in 2005. Considering that Phoenix's average sale price for single family homes in 2005 was about $256,000, the incremental price-depressing impact of neighboring single family home foreclosures reached a maximum of -$10,000 (-4.1%) within the 500 foot ring, -$15,000 (-6.0%) within the 501-1000 foot ring, and -$20,000 (-7.8%) within the 1001-1500 foot ring.

For 2008 single family home samples (see table on page 274 [Table 6.15] upper right, figure on page 280 [Figure 6.2] lower section), the cumulative (incremental) impact of single family home foreclosures on existing sale prices of single family home was limited to no more than 19 foreclosures in the first ring (500 feet), 30 foreclosures in the second ring (501 -1000 feet), and 45 foreclosures in third rings (1001-1500 feet). The maximum cumulative impact of neighboring single family home foreclosures reached a maximum of -13.95% for 19 foreclosures, -10.90% for 30 foreclosures, and -10.1% for 45 foreclosures on existing single family home prices in 2008. Considering that Phoenix's average sale price for single family homes in 2008 was about $200,000, the incremental price-depressing impact of neighboring single family home foreclosures reached a maximum of -$28,000 (-13.95%) within the 500 foot ring, -$22,000 (-10.9%)

within the 501-1000 foot ring, and -$20,000 (-10.1%) within the 1001-1500 foot ring, respectively.

On the other hand, only 2 pairs of 6 pairs were significant for 2005 condo samples and 3 pairs of 6 pairs were significant for the 2008 condo samples as shown in table on page 275 (Table 6.16).

For the 2005 condo samples (see table on page 275 [Table 6.16]; left section, figure on page 281 [Figure 6.3]; upper section), the cumulative (incremental) impact of neighboring condo foreclosures on existing condo prices in 2005 was limited to no more than 14 foreclosures in the first ring (500 feet). The maximum cumulative impact of neighboring condo foreclosures reached a maximum of -27.26% for 14 foreclosures in the first ring (500 feet). Another significant pair is the cumulative impact of neighboring single family home foreclosures on existing condo sale prices in the third ring (1001-1500 feet) for the 2005 sample. It was an interesting result that the cumulative impact of neighboring single family foreclosures on existing condo sale prices was limited to no more than 12 single family home foreclosures in the third ring (1001-1500 feet) for the 2005 sample. The maximum cumulative impact size of neighboring single family foreclosures on existing condo sale prices in 2005 reached a maximum of -23.56% for 12 single family foreclosures in the third ring (1001-1500 feet). Considering that Phoenix's average sale price for condos in 2005 was about $153,000, the incremental price-depressing impact of neighboring single family home foreclosures on existing condo prices in 2005 reached a maximum of -$36,000 (-23.56%) within the 1001-1500 foot ring. And the incremental price-depressing impact of neighboring condo foreclosures on existing condo prices in 2005 reached a maximum of -$42,000 (-27.26%) within the 500 foot ring.

For 2008 condo samples (see table on page 275 [Table 6.16]; right section, figure on page 281 [Figure 6.3] lower section), the cumulative impact of neighboring condo foreclosures on existing condo prices was limited to no more than 37 foreclosures in the first ring (500 feet) and the maximum cumulative impact size reached -36.30%. Another significant pair was the cumulative impact of neighboring single family foreclosures on existing condo sale prices in third ring (1001-1500 feet) for 2008 samples. The cumulative impact of single family foreclosures on existing condo sale prices in 2008 was limited to no more than 44 single family foreclosures in the third ring (1001-1500 feet). The cumulative impact size was a maximum of -48.36% in the third ring (1001-1500 feet) on existing condo prices in 2008. This result indicated that different housing type foreclosures and housing sales had a negative impact beyond the specific boundary (beyond 1000 feet in this case). Again, it seems to be associated with the characteristic that same types of housing properties tend to cluster in residential areas. Considering that Phoenix's average sale price for condos in 2005 was about $153,000, the incremental price-depressing impact of neighboring single family home foreclosures on existing condo prices in 2008 reached a maximum of -$80,000 (-48.36%) within the 1500 foot ring. And the incremental price-depressing impact of neighboring condo foreclosures on existing condo prices in 2008 reached a maximum of -$60,000 (-36.30%) within the 500 foot ring and -$26,000 (-15.94%) within the 1001-1500 foot ring.

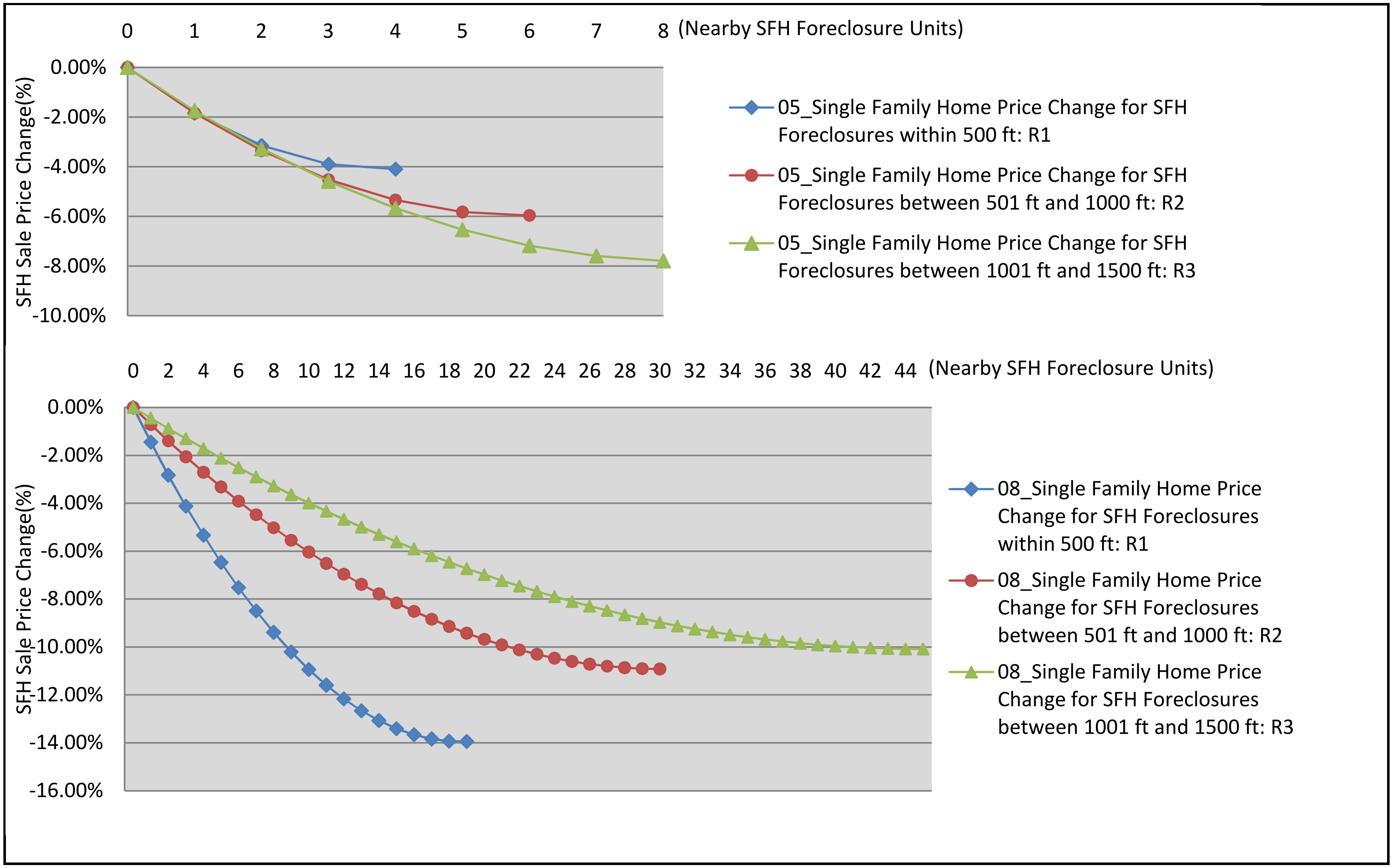

Figure 6.2. Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home Foreclosures on Existing Single Family Home Prices in a 2005 Housing Boom Year and a 2008 Housing Bust Year.

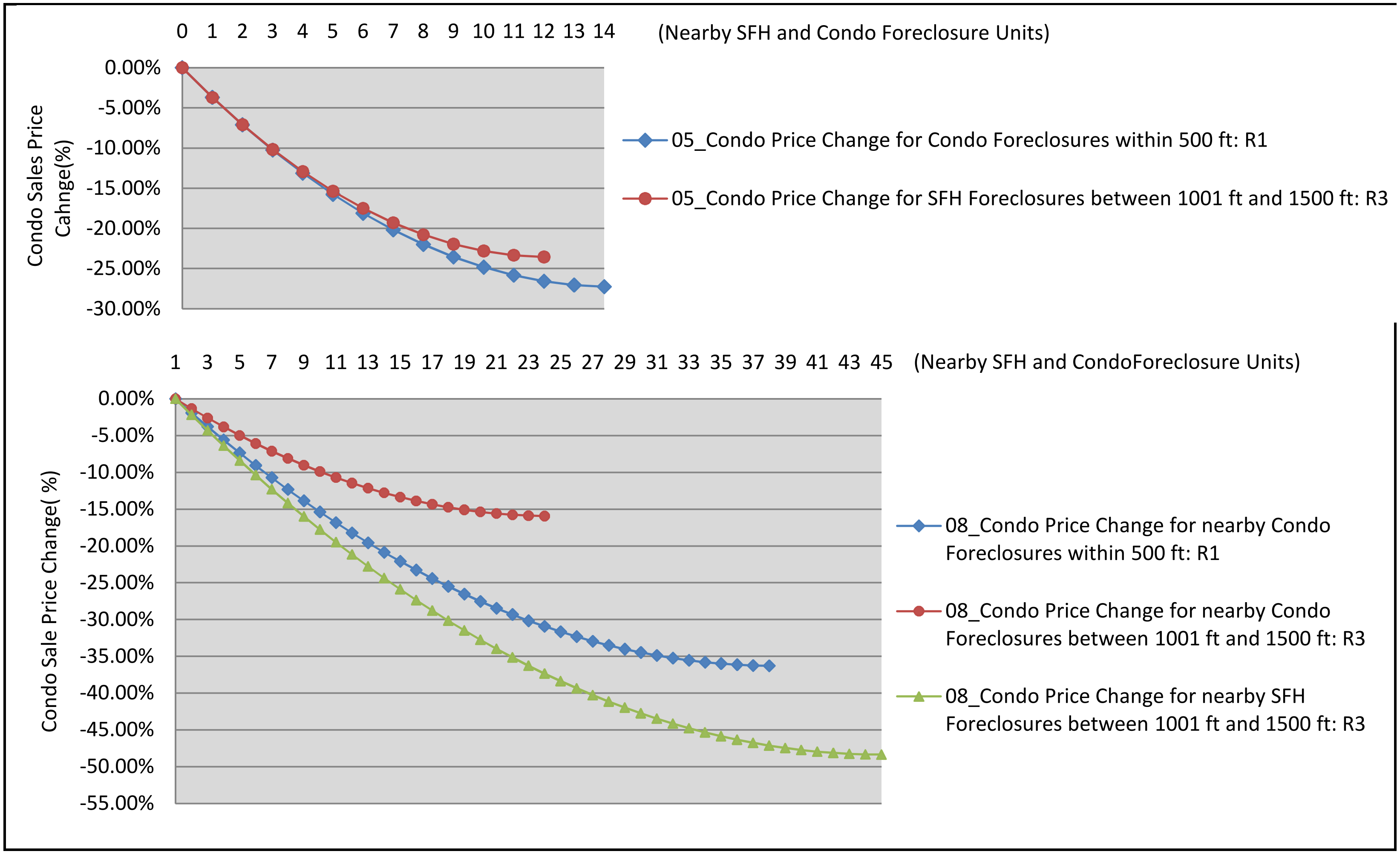

Figure 6.3. Nonlinear and Incremental Impacts by Clustered Neighboring Single Family Home and Condo Foreclosures on Existing Condo Prices in a 2005 Housing Boom Year and a 2008 Housing Bust Year.

The quadratic terms of neighboring foreclosures in each ring allow the marginal foreclosure impact to change, based on foreclosure density; the quadratic terms of neighboring foreclosures differentiate the price impact of the high-foreclosure density level in some neighborhoods from the low-foreclosure density level in other neighborhoods. These would reflect the nonlinear effects of neighboring foreclosures. That is, a rise in foreclosures when neighboring foreclosure frequencies (density) were low had a larger effect on nearby property sale prices than a rise in foreclosures when neighboring foreclosure frequencies were high (see Figure 6.2 and Figure 6.3). This supports the importance of early intervention for the negative effects of foreclosures on nearby home prices. Moreover, these results implied that the marginal impact of neighboring foreclosure in each ring was relatively larger in the housing boom year (2005) than in the housing bust year (2008) but the cumulative impact of foreclosure in 2008 was much larger than 2005 since foreclosure frequencies (density) in 2008 were more prevalent in the neighborhoods (compare figure on page 280 [Figure 6.2] and Figure 6.3).

Thus, this evidence shows that the high density of neighboring foreclosures can lead to neighborhood destabilization, causing neighboring house prices to further fall in a declining housing market.

As Rogers and Winter (2009) pointed out in their study of the St. Louis housing market, it is also hard to find out the tipping points of nearby foreclosure impacts in the Phoenix housing market, and this study reflects the diminishing marginal impact similar to the findings in the Saint Louis housing market. Furthermore, a high density of foreclosures in the declining housing market can lead to dramatic property depreciation in the neighborhood. This result indicated that the largest cumulative impact was that of neighboring single family home foreclosures in the third ring (1001-1500 feet) for 2008 condo samples and reached a maximum of -48.36% on existing condo prices.

6.2 Conclusions

The objective of this research is to quantify the price-depressing foreclosure effects on existing home sale prices as one of the social costs for communities. This study was estimated with traditional hedonic and spatial hedonic models specified during two different housing cycles, a strong housing market when prices were up (2005) and a weak housing market with falling prices (2008) in Phoenix, Arizona. It has been shown that foreclosures had negative effects on existing housing prices in the neighborhood, depending on housing types and cycles. Measuring price-depressing impact of foreclosures on housing prices with more accuracy is a key point of this study to recommend effective interventions for the current foreclosure crisis. Thus, the first methodological goal is to quantify simultaneously the magnitude of the direct and the spillover effects of foreclosures on existing home prices. The second is to provide usefulness concerning spatial econometric models in measuring the impact of foreclosures on housing prices.

This study conducted a series of specification tests in order to choose the best model among a variety of hedonic models to measure the impact of foreclosure on existing housing prices. All results of the three ordinary lease squares (OLS) models (model 1-3), two maximum likelihood (ML) spatial models (model 4&5), and three general method of moments (GMM) models (model 6-8) suggest a negative marginal foreclosure impact, but the marginal impact is smaller in a housing bust year (2008) than in a housing boom year (2005). However, the OLS models statistically do not correct spatial autocorrelation problems and endogeneity that exist in a cross section of housing prices. They tend to overestimate the absolute values of the coefficients. As alternatives, the maximum likelihood (ML) spatial lag or error model corrects spatial autocorrelation, but it still causes computation obstacles for large data sets and heteroskedasticity in error terms. Thus, the preferred specification is a generalized method of moments (GMM or GM) approach which requires weaker assumptions than the maximum likelihood application, and has a flexible form for large datasets.

As another main issue for this study, endogeneity violates the assumption of ordinary least squares (OLS) regression due to given characteristics for cross-sectional housing data. Thus, two-stage least-squares (GS2SLS) regression, using instrumental variables, is the most common suggested alternative. The general spatial two-stage least-squares (2SLS) method corrects for the endogeneity using spatially lagged explanatory variables as instruments. Moreover, in order to account for spatial heteroskedasticity and remaining spatial error autocorrelation, the most appropriate specification is the general spatial two-stage least-squares estimates (GMM_2SLS) with HAC (the spatial heteroskedasticity and autocorrelation consistent) variance estimators.

Relative to the OLS estimates in this study, most coefficients of focus variables in GMM_2SLS_HAC models (model 7&8) were smaller in absolute values. In terms of direct foreclosure effects, the main quantitative changes were obtained for the coefficients of DISTRESSED SALE, which were substantially or slightly smaller in magnitude and slightly less significant at a 5% or better level of confidence in the GMM_GS2SLS_HAC models (model 7&8) than in other analytical models. Moreover, the magnitude for the coefficients of indirect foreclosure effects (spillovers) in GMM_GS2SLS_HAC models (model 7&8) dropped to about half of the OLS results of previous study models. This suggests that the presence of spatial autocorrelation and endogeneity in OLS models would overestimate the absolute values of the coefficients. Relative to OLS estimates that don't control for the spatial effects such as spatial dependence, spatial heteroskedasticity, and endogeneity of neighboring house characteristics, GMM_2SLS_HAC models tend to deflate the absolute values of the coefficients.

For the direct effect of foreclosure on existing housing prices (see Table 6.17), the coefficient on a distressed sale associated with foreclosure indicates that, all else constant, a distressed single family home which previously faced foreclosure was approximately -0.22% (-$560) less than estimated average market price during a housing boom year (2005) but it was not statistically significant. On the other hand, it was about -3.42% (-$6,800) less during a housing bust year (2008). The direct foreclosure effect for a single family home was substantially smaller than previous study findings (see Table on page 36 [Table 2.1]) when controlling for the spatial effects.

Table 6.17. Summary of Findings for the Existence of Spatial Dependence and Foreclosure Direct Effect on Existing Home Prices.

The Existence of Spatial Dependence (Neighborhood Level)				
Hypotheses to be Tested	**Results of GMM_2SLS_HAC_Quadratic Models**			
These hypotheses are based on conceptual model that foreclosure has direct price-depressing effect on existing home prices	**Housing Type**		**Housing Boom (2005)**	**Housing Bust (2008)**
Hypo 1: Spatial Dependence of Housing Sale Prices H_{10}: $\beta_{\lvert \text{Spatial Dependence} \rvert} = 0$ H_{1A}: $\beta_{\lvert \text{Spatial Dependence} \rvert} > 0$	**Single Family Home Sale**	Moran's *I* _knn10	Reject*** 1.49E-01	Reject*** 9.43E-02
		Spatial Parameter _Rho	Reject*** 2.73E-01 (W1%↑→0.27%↑)	Reject*** 1.38E-01 (W1%↑→0.14%↑)
	Condo Sale	Moran's *I* _knn10	Reject*** 2.92E-01	Reject*** 3.77E-02
		Spatial Parameter _Rho	Reject*** 1.97E-01 (W1%↑→0.20%↑)	Reject*** 1.63E-01 (W1%↑→0.16%↑)
Direct Foreclosure Effects on Existing Home Prices (Property Level)				
Hypo 2: Discount of Distressed Sale Associated with Foreclosure H_{20}: $\beta_{\text{Distressed Sale associated with Foreclosure}} = \beta_{\text{Typical Sale}}$ H_{2A}: $\beta_{\text{Distressed Sale associated with Foreclosure}} < \beta_{\text{Typical Sale}}$	**Single Family Home Sale**		Not Reject	Reject*** (-3.42%) (-$6,800)
	Condo Sale		Reject* (-3.69%) (-$5,600)	Reject*** (-19.59%) (-$32,000)
Hypo 3: Discount of Renter Occupancy in Full Sale Samples for Each Housing Type H_{30}: $\beta_{\text{Renter Occupied Home}} = \beta_{\text{Owner Occupied Home}}$ H_{3A}: $\beta_{\text{Renter Occupied Home}} < \beta_{\text{Owner Occupied Home}}$	**Single Family Home Sale**		Reject*** (-2.12%) (-$5,400)	Reject*** (-5.78%) (-$12,000)
	Condo Sale		Reject*** (-5.49%) (-$8,400)	Not Reject
Hypo 4: Discount of Renter Occupancy in Distressed Sale Samples associated with Foreclosure H_{40}: $\beta_{\text{Foreclosure*Renter Occupied Home}} = \beta_{\text{Foreclosure*Owner Occupied Home}}$ H_{4A}: $\beta_{\text{Foreclosure*Renter Occupied Home}} < \beta_{\text{Foreclosure*Owner Occupied Home}}$	**Single Family Home Sale**		Reject* (-3.20%) (-$8,200)	Reject• (-4.62%) (-$9,200)
	Condo Sale		Not Reject	Reject* (-9.98%) (-$14,000)
Hypo 5: Discount of Cash Transactions in Full Sale Samples for Each Housing Type H_{50}: $\beta_{\text{Cash Sale}} = \beta_{\text{Mortgage Financing}}$ H_{5A}: $\beta_{\text{Cash Sale}} < \beta_{\text{Mortgage Financing}}$	**Single Family Home Sale**		Reject*** (-1.52%) (-$3,900)	Reject*** (-7.51%) (-$15,000)
	Condo Sale		Reject*** (-4.06%) (-$6,200)	Reject** (-5.92%) (-$9,700)
Hypo 6: Discount of Cash Transactions in Distressed Sale Samples Associated with Foreclosure H_{60}: $\beta_{\text{Foreclosure*Cash Sale}} = \beta_{\text{Foreclosure*Mortgage Financing}}$ H_{6A}: $\beta_{\text{Foreclosure*Cash Sale}} < \beta_{\text{Foreclosure*Mortgage Financing}}$	**Single Family Home Sale**		Not Reject	Reject*** (-12.25%) (-$24,500)
	Condo Sale		Not Reject	Reject*** (-20.73%) (-$34,000)

A distressed condo sale which previously faced foreclosure was approximately -3.69% (-$5,600) less than the estimated average market price during a housing boom year (2005). On the other hand, it was -19.59% (-$32,000) less than the estimated average market price during a housing bust year (2008). The result of the condo sample during a housing bust year had a still smaller price impact than in previous studies which have estimated around 20 % with both proportional and absolute terms.

Good instruments for the cause of foreclosure were unable to be developed in this study due to data limitation (e.g., loan performance data, household information). However, this study used neighboring housing characteristics as instruments to control endogeneity. The smaller estimated discounts are consistent with the expectation of this study, using an instrument variable (IV) approach. Thus, these findings provide further evidence that coefficients of OLS estimates on a foreclosure indicator tend to overstate the foreclosure discount, ignoring spatial effects such as spatial dependence, spatial heteroskedasticity, and endogeneity of neighboring housing characteristics.

With regard to the magnitude of this discount, Phoenix, the study area, has been in the midst of an extremely weak housing market with record foreclosures since beginning of 2007. A relatively large discount estimate for foreclosure on the property sale price was captured for condos which were smaller in size and had lower sale prices during a housing bust year (2008) compared to single family homes. Furthermore, one of the important results for this study is exploring the relationship between the distressed properties associated with the foreclosure and sale prices. In order to capture the selling characteristics of properties that may affect sale price, this study controls for such associated characteristics as renter occupancy status and a cash transaction on the sale price of each property type. This study found that renter occupancy status and a cash transaction had a negative impact on the single family home or the condo sale price, which was consistent with previous findings. This study provided interesting findings in that when the negative effect of previous foreclosure status interacts with these selling characteristics, the negative impact (price discount) was larger on a distressed sale related to foreclosure by a cash transaction or under renter occupancy status.

With regard to the neighboring spillover effect on home prices, one of the main factors is the distance of home samples from surrounding foreclosures and the prevalence of foreclosure in the neighborhood. Utilizing the distance-based measurement by three rings, both foreclosures of single family homes and condos were statistically significant and negatively impact on each type of property sale price. Neighboring single family home foreclosures closer to single family home samples as well as condo samples had a larger negative price impact than neighboring single family home foreclosures further away. Neighboring condo foreclosures closer to single family home samples as well as condo samples had a larger negative price impact than neighboring condo foreclosures further away (see Table 6.18).

More importantly, the marginal price impact of a neighboring foreclosure depends on the neighboring foreclosure types and foreclosure frequencies (density) as well as different housing cycles. One of the findings for the distance effect of foreclosures in this study demonstrates that the decline of home sale prices on per neighboring foreclosure unit basis would be smaller with a high density of foreclosure in the neighborhood during a housing bust year (2008) than a housing boom year (2005). To illustrate, the result showed a -1% price-depressing impact of a neighboring single family home foreclosure on existing single family home prices within 500 feet during a housing boom year (2005) or a -2.5% price-depressing impact of a neighboring condo foreclosure on existing condo prices within 500 feet during a housing boom year (2005) in GMM_2SLS_HAC linear model.

However, when moving from a housing boom cycle to a housing bust cycle, the result showed a -0.6% price-depressing impact of a neighboring single family home foreclosure on existing single family home prices within 500 feet during a housing bust year (2008) or a -1.2% price-depressing impact of a neighboring condo foreclosure on existing condo prices within 500 feet during a housing bust year (2008) for GMM_2SLS_HAC linear model. Thus, the marginal price impact of neighborhood foreclosures was lesser in the housing bust year (2008) than in the housing boom year (2005). This corresponds very well with previous findings (Rogers and Winter, 2009) even if the size of the marginal impact is different, but it shows new findings for condo foreclosures. Moreover, the notion of distance decay for marginal foreclosure impact is consistent with the findings of previous research (compare Table 6.18 to tables on pages 46-47 [Table 2.2]). However, it should be noted that the cumulative price-depressing effects of neighborhood foreclosures in a housing bust year (2008) were much larger than in a housing boom year (2005). This study provided the first estimation of cumulative impacts of neighboring foreclosures with exact foreclosure frequencies (density) measuring nonlinear effect for a GMM_2SLS_HAC Quadratic model.

Table 6.18. Summary of Findings for Spillover Effects of Neighboring Foreclosures on Existing Home Prices.

Spillover(Indirect) Effects of Foreclosures on Nearby Existing Home Prices (Neighborhood Level)				
Hypotheses to be Tested	**Results of GMM_2SLS_HAC_Linear Models & Quadratic Models**			
	Sample Housing Type	**Nearby Foreclosure Type**	**Housing Boom (2005)**	**Housing Bust (2008)**
[GMM_2SLS_HAC_Linear Models] ***Hypo 7: Marginal Impacts of Neighboring Foreclosures on Existing Single Family Home Prices by Distance*** H_{7}: $\beta_{\text{Neighboring Foreclosure in Each Ring}} < 0$, H_{70}: $\lvert \beta_{\text{Neighboring Foreclosure in Ring1}} \rvert = \lvert \beta_{\text{Neighboring Foreclosure in Ring2}} \rvert = \lvert \beta_{\text{Neighboring Foreclosure in Ring3}} \rvert$ H_{7A}: $\lvert \beta_{\text{Neighboring Foreclosure in Ring1}} \rvert > \lvert \beta_{\text{Neighboring Foreclosure in Ring2}} \rvert > \lvert \beta_{\text{Neighboring Foreclosure in Ring3}} \rvert$	**Single Family Home Sale**	Nearby SFH Foreclosure	R1: -0.96%***(-$2,500) R2: -0.79%***(-$2,000) R3: -0.81%***(-$2,100)	R1: -0.60%***(-$1,200) R2: -0.23%***(-$460) R3: -0.20%***(-$400)
		Nearby Condo Foreclosure	R1: Not Sig. R2: -0.33%***(-$850) R3: -0.41%***(-$1,000)	R1: Not Sig. R2: -0.17%%•(-$340) R3: Not Sig.
Hypo 8: Marginal Impacts of Neighboring Foreclosures on Existing Condo Prices by Distance H_{8}: $\beta_{\text{Neighboring Foreclosure in Each Ring}} < 0$, H_{80}: $\lvert \beta_{\text{Neighboring Foreclosure in Ring1}} \rvert = \lvert \beta_{\text{Neighboring Foreclosure in Ring2}} \rvert = \lvert \beta_{\text{Neighboring Foreclosure in Ring3}} \rvert$ H_{8A}: $\lvert \beta_{\text{Neighboring Foreclosure in Ring1}} \rvert > \lvert \beta_{\text{Neighboring Foreclosure in Ring2}} \rvert > \lvert \beta_{\text{Neighboring Foreclosure in Ring3}} \rvert$	**Condo Sale**	Nearby SFH Foreclosure	R1: Not Sig. R2: -1.66%***(-$2,500) R3: -1.86%***(-$2,800)	R1: -1.3%•(-$2,100) R2: -0.56%•(-$900) R3: -1.38%***(-$2,200)
		Nearby Condo Foreclosure	R1: -2.58%***(-$4,000) R2: -1.04%***(-$1,600) R3: -2.48%***(-$3,800)	R1: -1.21%***(-$2,000) R2: Not Sig. R3: -0.80%**(-$1,300)
[GMM_2SLS_HAC_Quadratic Models] ***Hypo 9: Nonlinear and Incremental Impacts of Clustered Neighboring Foreclosures on Existing Single Family Home Prices*** H_{90}: $\beta_{\text{Neighboring Foreclosure in Each Ring}} = 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Ring}} = 0$ H_{9A}: $\beta_{\text{Neighboring Foreclosure in Each Ring}} < 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Ring}} > 0$	**Single Family Home Sale**	Nearby SFH Foreclosure	R1: Max. -4.1%*** (-$10,000 / 4 SFH FCs) R2: Max. -6.0%*** (-$15,000/ 6 SFH FCs) R3: Max. -7.8%*** (-$20,000 /8 SFH FCs)	R1: Max. -13.95%*** (-$28,000/ 19 SFH FCs) R2: Max. -10.9%*** (-$22,000/ 30 SFH FCs) R3 Max. -10.1%*** (-$20,000/ 45 SFH FCs)
		Nearby Condo Foreclosure	R1: Not sig. R2: Not sig. R3: Not sig.	R1: Not sig. R2: Not sig. R3: Not sig.
Hypo 10: Nonlinear and Incremental Impacts of Clustered Neighboring Foreclosures on Existing Condo Prices H_{90}: $\beta_{\text{Neighboring Foreclosure in Each Ring}} = 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Ring}} = 0$ H_{9A}: $\beta_{\text{Neighboring Foreclosure in Each Ring}} < 0$ & $\beta_{\text{The Square of Neighboring Foreclosure in Each Ring}} > 0$	**Condo Sale**	Nearby SFH Foreclosure	R1: Not sig. R2: Not sig. R3: Max. -23.56%*** (-$36,000/ 12 SFH FCs)	R1: Not sig. R2: Not sig. R3 Max. -48.36%*** (-$80,000/ 44 SFH FCs)
		Nearby Condo Foreclosure	R1: Max. -27.26%*** (-$42,000/ 14 Condo FCs) R2: Not sig. R3: Not sig.	R1: Max. -36.30%*** (-$60,000/ 37 Condo FCs) R2: Not sig. R3 Max. -15.94%*** (-$26,000/ 23 Condo FCs)

To illustrate, the cumulative impacts of neighboring foreclosures with nonlinearity can reach a maximum of 4% price depression in no more than 4 neighboring single family home foreclosure frequencies (density) within a 500 foot ring in a housing boom year (2005). On the other hand, it reached a maximum of 14% price depression in no more than 20 neighboring single family home foreclosure frequencies (density) within a 500 foot ring in a housing bust year (2008). Thus, the cumulative effects of neighborhood foreclosures were much greater in a housing bust year (2008) since foreclosures were more widely spread throughout the neighborhood than during a housing boom year (2005).

Furthermore, this study emphasizes the price-depressing effects of pre-foreclosures and the importance of early intervention at the beginning of the foreclosure process. This would lead to policy recommendations for targeted early interventions during a foreclosure crisis.

6.3 Policy Recommendations

With respect to current foreclosure issues, one of the important roles of local planners and policy makers seeking to diminish the costs associated with foreclosures is preventing the effects of foreclosures and preserving the existing property values in the area. This study can be used as a framework to monitor or evaluate the housing market conditions of areas affected by foreclosures. The implication is monitoring not only when the foreclosure discount is the deepest regarding the housing cycle but also when community foreclosures are heavily concentrated and the risk of foreclosure is greatest, and therefore more damaging. From this perspective, this study's findings also suggest some type of government interventions regarding the current foreclosure crisis.

First, this study proved that direct and the spillover effects of foreclosures on existing home prices are dependent on housing types and housing cycles. Thus, local planners or policy makers should consider effective target intervention for the housing types of the greatest need due to limited local or federal funds. However, current policies tend to focus on supporting distressed single family homes which are under foreclosure action since there are a tremendous number of them in many areas, and the expected asset values are larger than other types of housing such as townhome and condo. The primary implication of these findings is that small condos or townhomes merit additional policy attention for greater price discounts than single family homes due to the foreclosure problem. Moreover, these affordable condos or townhomes are a critical component of the housing stock in Phoenix, especially for financially and socially vulnerable households. Thus, policymakers should primarily target interventions for property types that are expected to have larger discounts after foreclosure. This study also proves that condo or townhome prices are more impacted by nearby condo and/or townhome foreclosures within 500 feet since these two types of housing tend to be clustered closely together as complex of multi-floor semi-detached homes, and the effects of foreclosures are apt to be contagious. Thus, local policy makers primarily need to use limited government funds for the housing type of the greatest need (condos in this study) to mitigate foreclosure problems during housing bust periods rather than focusing on single family homes that did not face such price-depressing effects during foreclosures in either housing booms or busts.

Second, this study proved that even though foreclosure filings for properties are even at the first stage of the foreclosure process, they have a seriously negative impact on nearby home values, and neighboring foreclosure density affect the level of devaluation of existing home prices. This study supports evidence that a higher density of foreclosures would substantially lead to decreased prices in a weak neighborhood housing market where the price trend is dramatically falling or where property values were down already. Depending on local or neighborhood context, a continuation of the foreclosure crisis can lead to substantial abandonment and vacant homes with losses in neighborhood population. Thus, government or local policy makers need to correct the problem as soon as possible before foreclosure impact is much more serious and harder to remedy. Such early targeted intervention programs for properties during the foreclosure process would be more effective since foreclosure auctions and bank owned properties, or vacant properties have more negative effects on nearby property values (see table on page 36 [Table 2.1] and tables on pages 46-47 [Table 2.2]). Thus, this suggests more aggressive policies for current foreclosure crisis, such as mandatory mediation program or a well-structured counseling service at least between mortgage lender and home owner, in order to reach new loan terms that make the monthly payment more affordable for the borrower. Other options are converting the property from owned to rental or exploring a lease-purchase under good property conditions during the first stage of the foreclosure process before physical deterioration or vacancies occur.

Third, government and policy makers announced many policies and plans which have unique characteristics and alternatives in response to the housing crisis in the past three years. However, most government efforts which are aimed at stabilizing existing households during the housing and foreclosure crisis have largely focused on counseling services and loan modification programs to help home-owners maintain ownership. While many households have been helped by these programs, it is unclear if this homeowner-focused policy approaches the best loss mitigation tool without evidence of an effective policy. Many distressed homeowners no longer may be able to pay their mortgages due to economic difficulties such as income loss, tight lending market for refinancing, and declining property values if the foreclosure crisis continues to depress the housing market and the overall economy. Thus, policy makers or local planners must find other ways and shift to other types of foreclosure-prevention programs to help the millions of homeowners that have already experienced foreclosure as well as to halt the continuing foreclosures crisis.

One possible approach is to keep as many current residents in their communities as possible instead of home owners strategically walking away or being kicked out by legal action, they should stay in their own homes or move to a rental property in the same community. The own-to-rent policy would provide all distressed owners due to foreclosure the option of converting their title to becoming market-rate renters with a long-term lease. Currently, Fannie Mae has several different programs for renters or distressed home owners. The goal is to deter the displacement of families and the deterioration caused by vandalism and crime to vacant homes. This would prevent the upheaval of families, keep their children in the same school and social network in the neighborhood, minimize the disruption to communities, and keep home-price stabilization. If many households already have left the community due to the foreclosure problem, another possible policy is needed to stabilize a community with strategies that involve encouraging new households to move into properties which have already become REOs and vacant homes in the community. As similar tool is a form of the lease-purchase program in which homes can be converted to lease-purchase units and residents, either new home buyers or distressed homeowners, can lease for a number of years until they become eligible to purchase the home.

To date, local and federal programs have mainly tended to focus on attracting new or first-time homebuyers to the community through down payment incentives or a series of first-time homebuyer tax credits. However, it is too early to evaluate the success of these policies since more distressed homeowners are still working through the foreclosure process and double hits such as unemployment and economic depression continue to pressure the housing market. Moreover, a number of potential homebuyers in many areas may have the constraint of tight lending conditions under the weak housing market and feel anxiety for value loss due to the prevalence of the foreclosure problem in many communities. Currently, one recommended approach in response to the declining numbers of eligible buyers is a shared equity homeownership program. Rather than use high-cost loans, homebuyers share loans that are underwritten with standards that allow for sustainable homeownership over time.[26]

As a final comment, mortgage lenders or private parties in the foreclosure decision so far seem to ignore additional social costs which can be imposed on neighboring properties. If social costs due to distressed neighborhood homes extend to our cost as tax payers, the government needs to become more involved in the mortgage industry even though mortgage companies and bankers or private parties in foreclosure decisions are strongly against such involvements. Moreover, tax payers might rationally support such aggressive government intervention to reduce foreclosures for our future generations.

6.4 Study Limitations and Further Studies

Due to limited resources to cover the costs of data collection and analysis, the estimates from this analysis for the Phoenix housing market could be applied to other cyclical housing markets where many Sun Belt communities such as Las Vegas, Phoenix, and many California cities have experienced a significantly large housing boom and bust. Thus, this study cannot be applied to such housing markets as Detroit or Cleveland, where market failure because of economic downturn is pervasive and the supply of housing far exceeds the demand even before recent foreclosures expanded the number of

[26] Recently, Davis (2010) and Temkin (2010) analyzed several shared equity programs. Davis provides a detailed description of the principal shared equity homeownership models. Temkin proves that shared equity programs are successful in promoting sustainable homeownership opportunities for lower income families: only a very small number of shared equity homeowners lose their home because of foreclosure; and a very high percentage of low income, first-time homeowners remain homeowners five years after purchasing a shared equity home. For a particular approach to shared equity homeownership, Immergluck (2008a) asserts that local policy makers need to develop community land trusts or limited-equity cooperatives that provide for increased affordability and reduced long-term risk to future occupants.

vacant properties. Thus, the interpretation of these findings should be cautious. However, a replication of the study showing similar variations for the foreclosure discount in strong and weak real estate markets would increase the extent of the validity of the foreclosure study for cyclical housing markets. Thus, future studies could compare foreclosure impacts for Sun Belt cities and Rust Belt cities to get more general findings.

It is also important to point out that the methods used in this analysis have certain limitations. First, while a wide variety of structural characteristics and selling factors related to foreclosure have been included, this analysis left out important determinants that are found in the literature on property values such as economic, social, and characteristics of neighborhoods including neighborhood crime rates, vacancy status, physical conditions, and neighborhood income levels. Future studies will need to incorporate a considerable amount of contextual neighborhood data related to foreclosure impacts.

An additional drawback in this study is that it does not explore the timing of the foreclosure impacts due to data limitations. This model analysis includes the effect of any stage foreclosures in two years prior to the sale date. The foreclosure impacts will vary with foreclosure timelines between foreclosure filings and foreclosed properties or REOs. While fully separating these different mechanisms is quite challenging, some inferences may be drawn by observing differences in the timing of foreclosure impacts. Thus, this study preserves the empirical analysis that suggests a mechanism through foreclosure stages (the pre-foreclosure state, foreclosure at auction, and REOs) on home prices.

Finally, future study needs to examine the recursive relationships between foreclosure and neighborhood change. For example, to what extent do foreclosures lead to neighborhood change such as crime and vacancy, which in turn leads to more foreclosures? A general regression model may not be sufficient to explain the relationships among these neighborhood indicators and foreclosures because many variables are highly correlated with each other. The structural equation modeling (SEM) takes into account interactions including multiple latent independents, each measured by multiple indicators, with many additional instrument variables. This research will add to the understanding of the complex relationships between neighborhood change and foreclosure.

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