FROM CRISIS TO RECOVERY:

A STUDY OF WALKABILITY IMPACTS ON FORECLOSURE

IN LOS ANGELES, CALIFORNIA

A Dissertation

by

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ABSTRACT

Over the past decade, the literature has demonstrated negative price impacts for foreclosures; socioeconomically uneven foreclosure rates; and inconsistent durations in foreclosure status. However, while the evidence for sustainable benefits of walkable environments has been widely documented, the influence of built environments on such foreclosure-related activities has been largely neglected in the previous research. Using detailed data on foreclosed properties and transactions in the single-family housing market between 2008 and 2013 in Los Angeles, California, this dissertation examined if and how built environmental attributes (especially those supportive of neighborhood walkability) can moderate 1) price spillovers of foreclosures; 2) the density of real estate owned (REO) properties; and 3) the duration of REO status.

This dissertation consists of three stand-alone but interrelated studies. The first study objective provides an examination of current knowledge to assess price spillovers of foreclosures through a comprehensive literature review, and includes suggestions for future work and improvements. This review identified the various associations between neighborhood foreclosures and property values based on methodological differences across the literature in elaborating the foreclosure measurement while also managing control variables to deal with endogeneity problems. Additionally, the review illustrated different associations based on the heterogeneity of neighborhoods and housing markets.

To address the second study objective, the researcher utilized the Cliff-Ord spatial model to estimate the mitigation effects of neighborhood walkability (measured

as Walk Score) on price spillovers of foreclosures. The negative spillover effects on property values were mitigated for those properties located in walkable neighborhoods, but only for middle-to high-income communities. Compared to the housing market crash period of 2010, the results showed greater advantages of neighborhood walkability during the recovery period of 2013 in terms of resiliency against negative price impacts.

The third study objective analyzes how walkable environments (as represented by residential density, land-use mix, and street connectivity measures) help reduce REO density, using the spatial regression model, and REO duration, using the Cox hazard model. With regard to REO density, safer neighborhoods and more accessible and diverse built environments appeared to be important for reducing the REO density measured at the census-tract level. With reference to REO duration, high-value REO properties in denser and more accessible neighborhoods were more likely to be sold, whereas low-value REO properties – particularly concentrated among low-income and minority communities – were less likely to be sold.

In conclusion, it is necessary to encourage walkability-related development strategies as one important policy measure to achieve neighborhood stability and livability. Further enforcement efforts tailored to enhancing environmental quality are also needed. More importantly, resolving disparities in environmental support for resiliency from foreclosure impacts is critical.

DEDICATION

To my family

And

"*now, I bring the first-fruits of the soil that you have given me*"

(Deuteronomy 26: 10)

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CHAPTER I

INTRODUCTION

1.1 Background and Significance

The failure of mortgage markets in the U.S. caused a massive increase in foreclosures, and led to the foreclosure crisis that began in 2007. The number of foreclosures increased from 1.5 million in 2007 to 2.8 million in 2009, and the rate of delinquent mortgage loans was 5.2 percent in 2008 (Mayer, Pence, & Sherlund, 2009). According to a report from the Center for Responsible Lending (Bocian, Smith, & Li, 2012), 10.9 million homes were listed as foreclosures between 2007 and 2011, and home values declined 7.2 percent on average. A peak in foreclosure activity was recorded in 2010, with 2.9 million foreclosed properties in the U.S. (RealtyTrac., 2011). States have not fully recovered from this crisis. The foreclosure crisis was a result of greed and looting within the financial sector, as well as irresponsible policies that promoted high rates of homeownership. Rapidly increasing foreclosures led to irreparable harm to neighborhoods and communities, including a wide range of social, environmental, and economic problems (Kingsley, Smith, & Price, 2009).

Foreclosures can be viewed as a source of stressors that threaten the stability of communities in multiple ways. For example, a foreclosed property is often poorly maintained by the homeowner, who is experiencing financial challenges (Pennington-Cross, 2006) and losing the motivation to put financial resources into home maintenance (e.g., mowing the lawn) (Gerardi, Rosenblatt, Willen, & Yao, 2015; Lambie-Hanson, 2015). In addition, a foreclosed property has a tendency to become vacant and abandoned (Apgar, Duda, & Gorey, 2005). Furthermore, as a result of deferred maintenance, physical deterioration of abandoned buildings often promotes social problems (e.g., crimes) that threaten neighborhood safety (Ellen, Lacoe, & Sharygin, 2013; Hipp & Chamberlain, 2015; Katz, Wallace, & Hedberg, 2013). Such sources of danger have a negative impact on mental health due to increased psychological stress (Cagney, Browning, Iveniuk, & English, 2014; Hill, Ross, & Angel, 2005; Houle, 2014; Lindblad & Riley, 2015). Moreover, a lack of neighborhood safety can discourage outdoor physical activities in the neighborhood (Foster & Giles-Corti, 2008; Lorenc et al., 2012; Loukaitou-Sideris & Eck, 2007). Finally, social segregation can increase as a result of racial transition (Baxter & Lauria, 2000; Hall, Crowder, & Spring, 2015), which decreases diversity, social interaction, and the quality of life of residents (Batson & Monnat, 2015).

These types of negative externalities that erode neighborhood quality can in turn negatively affect market values of homes in the neighborhood. Due to negative externalities that arise when external costs are not paid by the mortgage holder (Wassmer, 2011), clusters of foreclosures can be negatively capitalized into nearby home values and, in turn, damage the overall housing market in the area. In addition, the distressed sale loses its bargaining power, due to the stigma associated with the foreclosure, which brings the overall housing market down (Frame, 2010), prompting lenders to sell the foreclosures at a discount (Campbell, Giglio, & Pathak, 2011). Increased inventories of homes also affect the housing market (K.-y. Lee, 2008).

The threat to the stability of the housing market and the quality of the neighborhood can also put a heavy burden on local government by increasing social costs, such as policing, legal expenses, and city service programs, and by decreasing tax revenue (Apgar et al., 2005; Frame, 2010). According to the report from the Community Research Partners (Garber, Kim, Sullivan, & Dowell, 2008), the service cost for 25,000 abandoned buildings in eight Ohio cities was nearly $15 million, and the loss of tax revenue was over $49 million. The costs that local governments levied to process one foreclosure was estimated to range from $5,000 to $35,000 (Apgar et al., 2005; Moreno, 1995).

The consequences have encouraged policy makers to continue their efforts to find adequate responses to the foreclosure crisis, and the federal government launched numerous programs for the housing market recovery and neighborhood revitalization.[1] The main forms of policy interventions include modifying financial lending options; reducing the likelihood of falling into foreclosure; and increasing the likelihood of foreclosures to be sold. Due to the necessity of establishing effective policies, previous research has explored the significant impacts of foreclosures on reduced property values,

[1] One examples is the Neighborhood Stabilization Program (NSP) launched in 2009. The NSP funds – amounting to nearly $7 billion across all three rounds (NSP1, NSP2, and NSP3) – have been granted to state and local governments and local nonprofits based on local market conditions. A total of $6.82 billion in NSP funds was granted through a series of appropriations (Joice, 2011): 1) $3.9 billion for NSP1 through the Housing and Economic Recovery Act of 2008; 2) $2 billion for NSP2 through the American Recovery and Reinvestment Act of 2009; and 3) $1 billion for NSP3 through the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. The main policy strategies of the NSP includes rehabilitation, demolition, and redevelopment of foreclosed and vacant properties. Many other government programs such as the Home Affordability Modification Program and the homebuyer tax credits were also implemented for the recovery. While other policy programs focus on providing loan modifications to homeowners, the NSP focuses on place-based policy efforts aimed at reducing foreclosed and vacant buildings, and revitalizing visual blight (Joice, 2011).

as well as the socioeconomically unequal distribution of foreclosures and the inconsistent duration of foreclosure status.

However, researchers have not thoroughly investigated how and why the foreclosure impacts are distributed unevenly across built environments. Further attention needs to be paid beyond foreclosure itself to include foreclosure spillovers, with the need for a comprehensive understanding of our neighborhood environments, especially the physical aspects of built environments. A review of the literature indicates that little is known about the role of neighborhood environments in foreclosure spillover effects.

The built environment provides the setting in which economic activities occur, and it consists of physical, social, behavioral, and natural components designed by human efforts and for human activities (Dannenberg, Frumkin, & Jackson, 2011). Places that have a high-quality built environment attract people (Gehl, 1987), which in turn, can spark positive social activity that can improve the quality of life (Rogerson, 1999). Walking-friendly urban environments can contribute to the sustainability of our communities because of their well-documented benefits to health (e.g., physical activity), environment (e.g., clean travel modes), and socio-economic factors (e.g., sense of belonging, property values) (Dannenberg et al., 2011; Litman, 2003). For example, walkable areas can make it easier for residents to engage in daily exercise (Frumkin, Frank, & Jackson, 2004). In addition, an increase in walking may also lead to a decrease in motor vehicle use and traffic, which in turn, reduces gasoline consumption and air pollution (Frank, Stone Jr, & Bachman, 2000; Zahabi, Miranda-Moreno, Patterson, & Barla, 2013). Furthermore, walkable neighborhoods can foster greater interaction among neighbors, promoting a sense of community attachment and belonging (Leyden, 2003; Stedman, 2003). Prior research (Eppli & Tu, 1999) found that property values increased from 4% to 25% for single-family homes located in neighborhoods with features of pedestrian-oriented design.

Such positive externalities may serve as environmental supports for achieving resiliency from the negative impact of foreclosures by improving the marketability of properties located in walkable neighborhoods. While studies suggest the sustainable benefits of the walkable built environment, more studies are needed to better understand the potential role of the built environment in exacerbating or alleviating the impacts of foreclosure.

In this dissertation, I explore the potential of environmental supports for reducing price spillovers of foreclosures, foreclosure rates, and foreclosure duration. This dissertation provides new evidence on the relationship between the built environment and foreclosure-related activities, and deals with an important planning policy agenda that has not been sufficiently addressed in previous studies. By focusing on the built environmental factors, this dissertation aims to initiate discussions on possible policy interventions as a larger strategy to mitigate the negative foreclosure spillover effects on communities and stimulate the stabilization of neighborhoods.

1.2 Structure of the Dissertation

This dissertation consists of six chapters. Chapter I provides the background and significance of the dissertation and states its overall objectives. Chapter II details the research framework, including the theoretical and analytical backgrounds, with the underlying theories and statistical models used. In addition, Chapter II provides conceptual models for each study, and the research aims and hypotheses to be tested in each study. Chapter III provides a critical assessment of the literature investigating the relationship between foreclosure spillovers and property values. It highlights knowledge gaps, so as to inspire future research. Chapter IV examines how the price spillovers of foreclosures can be mitigated in neighborhoods that achieve walkability. It also explores how the mitigation effects of neighborhood walkability can be different for different income groups and housing market conditions. Chapter V examines how walkability-related built environments influence the density of real estate owned (REO) properties and the likelihood of selling REO properties. Chapters III, IV, and V are independent studies, each including an introduction, literature review, method, results, discussions, and conclusion. The final chapter, Chapter VI, provides summaries of the findings from each previous chapter, and addresses their policy implications.

CHAPTER II

RESEARCH FRAMEWORK

2.1 Conceptual and Theoretical Framework

2.1.1 Foreclosure Process and Type

Foreclosure is the process of terminating legal rights of ownership by a lender. The legal procedures differ across states, but three stages are usually considered as possible outcomes given the foreclosure process (Harding, Rosenblatt, & Yao, 2009): pre-foreclosure, auction, and real estate owned (REO) or also called bank owned. Some states, such as Michigan, New Hampshire, Tennessee, West Virginia and District of Columbia, do not require judicial involvement in the foreclosure process, but many other states allow both judicial and non-judicial foreclosures. When the borrower fails to pay the loan in a timely manner, a mortgage default begins. If the mortgage in a delinquent condition for more than a certain period (e.g. 90 days in California), the lenders then file a public notice that initiate the foreclosure process, which is called a "Notice of Default" in non-judicial foreclosure and a "*Lis Pendens*" in judicial foreclosure (Ling & Archer, 2010). When filing a *lis pendens*, the lender should prove the mortgage default of a borrower and pursue court action. The pre-foreclosure phase begins with the notice of default, and during this phase, the borrower may redeem the mortgage default by selling the property, known as a "short sale," or reforming the financing structure (Clauretie & Sirmans, 2010). If the borrower does not solve the default problem, then the property moves to a public auction and is sold to a third party. If a property is auctioned under the authority of a sheriff's office or county, the property sale is known as a "sheriff sale." If the property is not sold in the auction, then the mortgage lender (or bank) has the right to take a possession of the property (Ling & Archer, 2010). In the REO phase, the lenders attempt to resell it to recover their unpaid loan from the borrower (Schuetz, Been, & Ellen, 2008). Figure 1 illustrates the foreclosure process in the case of non-judicial foreclosures.

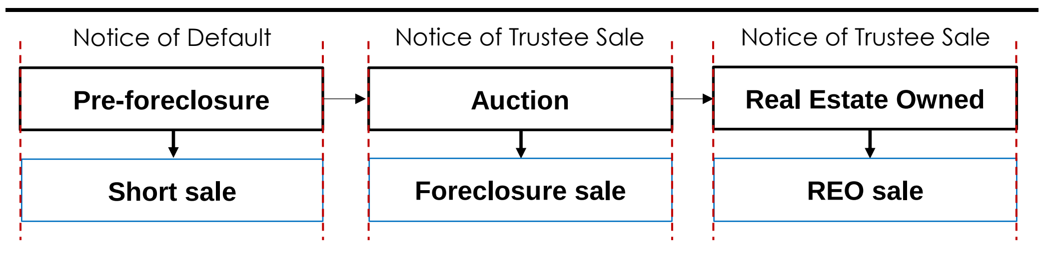

Figure 1. Foreclosure Process

The process is costly and time consuming for both the borrower and the lender. In addition, foreclosed properties are susceptible to physical deterioration, vandalism, and crimes during the process. REO activity is one possible outcome, particularly in the last phase of the foreclosure process, but a study found that 79% of properties having defaulted loans (in the case of subprime mortgage loan) eventually became REO properties (Capozza & Thomson, 2006). REO properties may have created a larger external impact on a neighborhood than any other foreclosure types; it might be reasonable to focus on REO properties when considering the foreclosure impact on a neighborhood.

2.1.2 Default Theory

There are two theoretical backgrounds for mortgage default behavior, which explain subsequent foreclosure occurrence (Clauretie & Sirmans, 2010): equity theory and ability-to-pay theory. The equity theory focuses on the financial costs and returns from the property (Jackson & Kaserman, 1980). This theory describes that default risks increase when property value drops below the outstanding mortgage balance. If homeowners have positive (or negative) equity, meaning that the equity on the property is much higher (or lower) than the current or expected market price of the property, the homeowners are more (or less) likely to keep up their mortgage payments. Under this theory, the measures of home equity such as loan-to-value ratio were examined as important factors for determining default (Quercia & Stegman, 1992). Research found that economic factors, such as interest rates and overall housing markets, also influenced the home equity that determined the mortgage default risks (Mayer et al., 2009; Quercia & Stegman, 1992).

On the other hand, the ability-to-pay theory, also known as the cash flow approach, focuses on the borrowers' ability to pay the mortgage. Certain unexpected events, which cannot allow a borrower to pay the mortgage any longer, can explain the default risks under this theory. Research showed that "trigger events" characterized by employment status and family structure shocks (e.g. divorce, death, illness) were significant reasons a borrower fell into delinquency (Morton, 1975; Quercia & Stegman, 1992).

These default theories were employed to deal with the determinants of mortgage defaults, concentrating on the characteristics of loans or borrowers (Avery, 1996; Bocian, Ernst, & Li, 2008; Ghent & Kudlyak, 2011). A borrower may generally experience both the decrease in housing price and the loss of ability to pay the mortgage. Foote, Gerardi, and Willen (2008) noted that "double-trigger"–negative home equity and negative life events–resulted in more foreclosures.

2.1.3 Valuation Theory

Economic valuation methods have provided a guide for governments to establish or change their policy intervention strategies. Methods for assessing environmental amenities are based on an understanding of how an individual's preferences are evaluated. Methods to value environmental amenities and disamenities have been broadly classified into an indirect approach, also known as revealed preferences, and a direct approach, also known as stated preferences (Turner, Pearce, & Bateman, 1993).

The indirect approach examines the purchases of goods, both market and non-market, by addressing the revealed preferences of consumers (Adamowicz, Louviere, & Williams, 1994). Underlying preferences for goods can be calculated through the relationship between prices and goods, such as the demand curve, empirically estimated by true economic transactions (Mendelsohn & Olmstead, 2009). By observing the shift in the demand curve, the value of environmental amenities and disamenities can be measured to assess environmental interventions for policy changes or strategies (Whitehead, Pattanayak, Van Houtven, & Gelso, 2008).

Alternatively, the direct approach measures the demand for environmental goods by asking consumers if they would be willing to pay for the goods (Adamowicz et al., 1994). This approach employs surveys that are designed to evaluate consumers' behaviors in a hypothetical market (Mendelsohn & Olmstead, 2009). The survey generally constitutes a set of (1) descriptions for amenities and disamenities to be valued, (2) hypothetical choices or situations for respondents to value amenities and disamenities, and (3) questions about the socio-economic characteristics of the respondents (Young, 2005).

Both methods have their own strengths and weaknesses. One common weakness of the indirect method is its limitation in testing demands for environmental goods based only on a current set of experiences (Adamowicz et al., 1994; Bartholomew & Ewing, 2011). The indirect method may provide unreliable estimates for the forecast of demand on new policy-driven suggestions such as new subway lines because such projects are non-existent (Bartholomew & Ewing, 2011). Whereas the indirect method quantifies the estimation based on actual consumers' behavior, the consumers are not perfectly randomized, and this methodological limitation can be another weakness of the indirect method (Mendelsohn & Olmstead, 2009). In addition, a collinearity problem among goods often threatens the exogeneity of factors that influence behavior (Adamowicz et al., 1994). Nonetheless, by using empirical data based on actual demands, the indirect method can draw statistical inferences to demonstrate on which environmental amenities people place their values (K. J. Boyle, 2003).

On the other hand, the direct method can overcome the limitations of the indirect method. Because the direct method uses surveys to directly question consumers' preferences, researchers can test their interests, allowing them to include questions for goods that do not exist. A frequently used direct method is called the contingent valuation method (CVM). The CVM is a survey-based valuation method to evaluate the value of environmental goods by asking questions about willingness-to-pay or willingness-to-accept (Garrod & Willis, 1999). Compared to the revealed preference approach, this stated preference approach can be useful in that it can capture all kinds of environmental goods through estimating consumers' actions contingent on a hypothetical situation (Garrod & Willis, 1999). However, like survey methodology, the direct method also cannot avoid various problems derived from the survey, such as sample selection bias, incomplete information, low response rates, etc. (Nestor, 1998; Shadish, Cook, & Campbell, 2002; Whitehead et al., 2008).

In the real estate literature, the hedonic price model (HPM), which is an indirect approach, is the most commonly used method for economic valuation. This dissertation uses the hedonic price model to assess neighborhood externalities. The framework for the HPM, developed by Lancaster (1966) and Rosen (1974), is derived from the price function having a joint envelope of the equilibrium between bid and offer functions (Rosen, 1974; Taylor, 2008). The HPM takes the following basic functional form, which represents a relationship between the price of a property and its characteristics (Sirmans, Macpherson, & Zietz, 2005):

$$\text{Price} = \text{f}\,(\text{property characteristics}, \text{other factors}),$$

The HPM evaluates implicit prices of observed quantities (or qualities) of a set of characteristics, including structural characteristics (e.g. square feet of a building, number of bedrooms, etc.), market and financial characteristics (e.g. time-on-the market, mortgage type, etc.), and neighborhood characteristics (e.g. socio-economic status of neighborhoods, accessibility to amenities, crimes, etc.) (Nicholls & Crompton, 2005; Sirmans et al., 2005).

The hedonic function has several forms, linear, quadratic, semi-log, log-log, and Box-Cox, for addressing the appropriate functional relationships between housing products and price. Each form has its advantages and limitations, and each form does not have a strong theoretical basis (Halvorsen & Pollakowski, 1981). An appropriate functional form can be chosen according to the data characteristics and interpretation of the model.[2] By using various econometric techniques, a hedonic function can be estimated.

[2] Malpezzi (2003) suggested five advantages of the semi-log form: 1) the semi-log form allows nonlinear relationships between housing attributes and prices, 2) the coefficients are easily interpreted as the elasticity of a unit change in housing attributes, 3) the semi-log form often mitigates heteroscedasticity of error terms, 4) the functional form is easily computed, and 5) a flexible model specification and estimation are allowed.

2.2 Analytic Framework

2.2.1 Spatial Hedonic Model

2.2.1.1 Spatial Autocorrelation and Model Specification

The basic assumption[3] of the error term for the ordinary least square (OLS) is often violated due to the spatial dependence or heterogeneity (Anselin & Lozano-Gracia, 2008). It is now widely accepted that research related to the estimation of property values necessarily incorporates spatial adjustments into the regression model. Spatial patterns can be illustrated by spatially aggregated objects that are related through their locations and are characterized by certain features of the aggregations (Dubin, 1988; Fotheringham & Rogerson, 2009). In real estate, spatial effects can be addressed when certain similar patterns of property values are systematically associated across locations. Several reasons (e.g., unobserved neighborhood effects and covariance effects of built environments) can explain the spatial effects accepted by the dependency of housing prices (Basu & Thibodeau; Militino, Ugarte, & García-Reinaldos, 2004). By incorporating spatial dependency into a covariance matrix of errors in the spatial regression model, spatial effects such as unobserved neighborhood effects and market heterogeneity would be controlled (Anselin & Lozano-Gracia, 2008; Lipscomb, 2006; Pace, Barry, & Sirmans, 1998). Several foreclosure studies (Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009) corrected spatial dependency by adding variables to capture spatial effects and/or specifying the covariance structure of errors. This

[3] Generally, a random sampling assumption is adopted: sample is independent and identically distributed (i.i.d.).

dissertation attempts to capture the spatial dependency of property values and unobserved neighborhood effects.

There are two ways to deal with a spatial autocorrelation problem [4] (Pace et al., 1998): 1) modeling $\mu(X)$ and 2) modeling ε. Spatial dependency may be removed by considering factors that can capture spatial effects. For example, an adequate specification of $\mu(X)$ can be dealt with by adding important factors such as distance to amenities or locational indicators such as zip codes and location coordinates (Pace et al., 1998). This is one of the most common ways to handle observed spatial effects underlying real property markets in the hedonic study. However, incorporating all locational variables into the model may not be enough to capture spatial effects. The power of the degree of freedom can be decreased by adding too many variables (Valente, Wu, Gelfand, & Sirmans, 2005). Pace et al. (1998) also noted that spatial patterns usually remain even in the model with locational indicators. In terms of basic specification form and estimation, modeling $\mu(X)$ will not make any difference from the conventional hedonic model.

The specification and estimation of the modeling $\boldsymbol{\varepsilon}$ approach is different from the conventional hedonic model in that spatial dependence is specified in the form of an error matrix, $\boldsymbol{K}$, especially for the treatment of unobserved spatial effects. This is

[4] There are several different approaches to address spatial autocorrelation, and different ways to group them. For example, Dormann et al. (2007) classified six different methods into three groups: 1) autocovariate and spatial eigenvector mapping approaches, 2) generalized least squares, autoregressive, and spatial generalized linear mixed approaches, and 3) a generalized estimating equations approach. See Dormann et al. (2007) for details.

generally called the spatial hedonic model. The generalized least square (GLS) or autoregressive model approaches (e.g., simultaneous autoregressive model (SAR), conditional autoregressive model (CAR)) can be used to address spatial autocorrelation (Dormann et al., 2007). The variance-covariance matrix, $\boldsymbol{K}(s_i, s_j)$ that represents the spatial correlation between observations i and j is used to estimate the coefficients, β in the model:

$$\beta = (\mathbf{X}'\mathbf{K}^{-1}\mathbf{X})^{-1}(\mathbf{X}'\mathbf{K}^{-1}\mathbf{Y})$$

Depending on the ways of specifying a spatial relationship, the proper covariance function is determined. Examples are exponential, spherical, Gaussian, and Matern covariance functions (Schabenberger & Gotway, 2005).[5] These covariance functions postulate that the spatial dependency is based on a function of the distance between locations. If each observation of a random variable identified in a stochastic process has a constant mean and variance, the covariance structure can take the stationarity assumption of the residual (Anselin, 1988; Dubin, 2003). If the covariance structure is specified as a function of the absolute distance regardless of direction, the function is referred to as isotropy; otherwise, the function is anisotropy (Schabenberger & Gotway, 2005).

[5] For example, the exponential covariance function is $K = a\, exp(-d/b)$, where a and b are the estimated parameters, d is the distance between observations, s_i and s_j, and K =1 if i = j. Further details about other covariance functions can be found in Pace et al. (1998) and Schabenberger and Gotway (2005).

2.2.1.2 Spatial Weight Matrix

The spatial relations among neighbors can be defined by identifying the spatial structure between the observed locations. The spatial weights are generally specified in an n × n matrix, in which **W** quantifies the measures of spatial interactions between observations i and j. The spatial weight matrix is expressed as (Anselin & Rey, 2014):

$$\mathbf{W} = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix},$$

where w_{ij} is the spatial weights between observations i and j. If i is defined as a neighbor of j, w_{ij} is a non-zero; otherwise w_{ij} is zero. By convention, the diagonal elements of the matrix, which represent the self-neighbor relation, are zero ($w_{ij} = 0\ if i = j$). The spatial weights are often transformed as a row-standardized form such that each weight in a row is divided by the sum of its row. The weights in a matrix are given values between 0 and 1.

In the specification of the spatial weights, contiguous geographic units are generally regarded as neighbors. There are several approaches to specify spatial weights, such as contiguity, distance, or k-nearest neighbors (LeSage & Pace, 2009). This contiguity approach is most properly used when spatial units are polygons (or areal data); for example, the spatial weights are non-zero when the spatial units share borders, and zero otherwise. Several types, such as rook, bishop, and queen, are used to operationalize the contiguity-based spatial weights (Anselin, 1988). For example, rook-type contiguity defines spatial units as neighbors when they share any borders. Bishop-type contiguity defines spatial units as neighbors when they share vertices. If neighbors are defined as geographic areas sharing borders or vertices of polygons, the spatial weights have a queen-type contiguity.

For the point reference data, either the distance or k-nearest approach can be properly used. The distance approach is based on the distance between each pair of spatial units (Anselin & Rey, 2014). A pair of spatial units are simply defined as neighbors when they are within a given distance; for example, w_{ij}=1 when the distance between observations i and j is less than a certain distance band ($d_{ij} \leq \delta$), and w_{ij}=0 otherwise. Spatial weights are also measured as the inverse of the distance between neighbors; for example, $w_{ij} = 1/d_{ij}^{p}$. The k-nearest approach structures spatial weights by defining a number of the nearest neighbors, which are assigned a one or zero otherwise (Kelejian & Prucha, 1999). While the distance-based weight approach constrains neighbors within a critical distance, each spatial weight in the k-nearest approach has the same number of neighbors. There is no theoretical-based agreement on the selection of an accurate weight matrix (Anselin & Rey, 2014), but an appropriate spatial weight matrix for this dissertation will be identified based on the previous literature and selected with alternative weights, comparing the model fit statistics.

2.2.1.3 Diagnostics for Spatial Dependence

To detect the presence of spatial dependency, the two most commonly used statistics are Moran's *I* and the Lagrange Multiplier (LM). Moran's *I* tests the spatial autocorrelation by checking the similarity of the value at one location with the values at other locations. The specific form is defined as (Cliff & Ord, 1972):

$$I = \frac{\mathbf{e}'\mathbf{W}\mathbf{e}\ /S}{\mathbf{e}'\mathbf{e}\ /\mathrm{n}}$$

where **e** is a vector of OLS residuals, n is the sample size, **W** is the spatial weight matrix, and $\mathrm{S} = \sum_i \sum_j w_{ij}$ as the sum of the weights. From the mean and variance of Moran's I under the null hypothesis of no spatial dependence, the distribution has an asymptotic standard normal and the Moran's *I* statistic can be tested.[6] This statistic is useful to apply to various contexts of analysis; however, it may not be reliable when misspecifications such as heteroscedasticity exist (Anselin & Rey, 1991).

With the evidence from simulation experiments, the LM tests for the spatial error dependence (LM-Error) and the lag dependence (LM-Lag) provides an indication to determine the better model between the spatial error model and the spatial lag model (Anselin & Rey, 1991, 2014). The LM test is defined as Anselin (1988):

$$LM = \left(\frac{1}{T}\right)(d)^2 \sim\chi^2$$

where d is replaced with $\mathbf{e}'\mathbf{W}\mathbf{y}/\hat{\sigma}^2$ for the LM-Lag test and with $\mathbf{e}'\mathbf{W}\mathbf{e}/\hat{\sigma}^2$ for the LM-Error test, **e** is a vector of OLS residuals, **Wy** and **We** are the spatial lag and error terms respectively, $\hat{\sigma}^2$is $\mathbf{e}'\mathbf{e}/\mathrm{n}$, and T is $\mathrm{tr}(\mathbf{W}\mathbf{W} + \mathbf{W}'\mathbf{W})$ with tr as a trace expression. The LM statistics follow an χ^2 distribution, and null hypotheses of no spatial dependence are tested.

[6] The standardized value is obtained as $I = \frac{I-E[I]}{\sqrt{Var[I]}} \sim N(0,1)$, where $E[I] = \frac{tr(MW)}{n-k}$ with $M = I - X(X'X)^{-1}X'$, and $Var[I] = \frac{tr(MWMW\prime)+tr(MWMW)+[tr(MW)]^2}{(n-k)(n-k+2)} - (E[I])^2$. For more information, see the Cliff and Ord (1972) and Cliff and Ord (1981)

2.2.1.4 Spatial Lag and Error Models

In relation to the hedonic model, the weight matrix approaches such as the SAR lag model and the SAR error model are commonly used. Spatial relationships among neighbors are captured in a transformed matrix, commonly referred to as a spatial weight matrix.

The spatial error model examines the existence of spatial dependence in random error terms. Unobserved error effects such as neighborhood effects influence units of observations in the area (Anselin, 2003; Anselin & Lozano-Gracia, 2008). This can be incorporated into the covariance structure using the weight matrix in the error term (Schabenberger & Gotway, 2005):

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u}$$

$$\mathbf{u} = \rho\mathbf{W}\mathbf{u} + \upsilon$$

$$\mathbf{B} = \rho\mathbf{W}$$

where $\mathbf{W}$ is the n × n spatial weight matrix with $w_{ii} = 0$, and υ, the residuals that partial out spatial autocorrelation are assumed to have a mean of zero and a diagonal variance matrix, Σ_{υ} . Based on the Gaussian application in the data, the error terms in $\mathbf{u}$ follow mean zero and a covariance-variance matrix, Σ_{SAR} . The parameter, ρ addresses the magnitude of the spatial dependence. The error specification can be transformed as a reduced form, $\mathbf{u} = (\mathbf{I} - \mathbf{B})^{-1}\upsilon$. The variance-covariance matrix can be obtained by $\mathbf{\Sigma}_{SAR} = (\mathbf{I} - \mathbf{B})^{-1}\mathbf{\Sigma}_{\upsilon} (\mathbf{I} - \mathbf{B}')^{-1}$. The SAR model can be expressed as Schabenberger and Gotway (2005):

$$\mathbf{y} = \mathbf{X}\beta + (\mathbf{I} - \mathbf{B})^{-1}\upsilon, \qquad \text{where } y \sim N(\mu, \mathbf{\Sigma}_{SAR})$$

The spatial lag model uses an additional variable for capturing the spatial interactions from neighboring units (Anselin & Lozano-Gracia, 2008). This model can explain a part of the mechanisms that determine a property value; for example, a housing value might depend on nearby housing values. For this reason, the spatial lag model is widely adopted to control for a spatial spillover. A weighted average of values in nearby units is added in the form of repressors as a spatial interaction effect (Anselin, 1988):

$$\mathbf{y} = \lambda\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \mathbf{u},$$

$$\mathbf{u} \sim N(0,\ \sigma^2\mathbf{I}),$$

where $\mathbf{W}_{\boldsymbol{l}}$ is the spatial weight matrix and λ is a magnitude of spatial dependence between housing prices. The reduced form can be obtained for the estimation:

$$\mathbf{y} = (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{u}$$

These spatial regression models are widely used in foreclosure studies. For example, in the studies (Leonard & Murdoch, 2009), it is important to consider the housing cycle or market trends to correctly estimate spillover effects. Because lower local market trends in housing prices may influence the depression of housing values, this may result in a reverse causation problem. The studies (Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009) found that actual foreclosure spillover effects were diminished after spatial weighted average values of nearby houses in a neighborhood. In addition, the studies commonly dealt with unobserved neighborhood effects including endogeneity problems and spatial effects. Using the spatial hedonic model, unobserved neighborhood effects were considered to identify any potential bias that resulted from possible correlations with both foreclosures and sales prices across the studies (Biswas, 2012).

Although the details for the model specification to estimate spillover effects varied across the studies, the uses of sophisticated spatial models are being proven. This dissertation will also measure spillover effects using the spatial hedonic models to control for unobserved neighborhood effects and covariance between observations.

Both spatial lag and error models can be incorporated (Anselin, 1988; Kelejian & Prucha, 1998):

$$\mathbf{y} = \lambda\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \mathbf{u},$$

$$\mathbf{u} = \rho\mathbf{M}\mathbf{u} + \upsilon,$$

where $\mathbf{W}$ and $\mathbf{M}$ are n × n spatial weight matrices, and υ is idiosyncratic errors. Using the reduced forms, the specifications above can be substituted as (Kelejian & Prucha, 1998):

$$\mathbf{y} = (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{u},$$

$$\mathbf{u} = (\boldsymbol{I} - \rho\mathbf{M})^{-1}\upsilon.$$

The variance-covariance matrix of $\mathbf{u}$ is $\boldsymbol{\Omega} = E(\mathbf{u}\mathbf{u}) = \sigma^2(\boldsymbol{I} - \rho\mathbf{M})^{-1}(\boldsymbol{I} - \rho\mathbf{M}')^{-1}$. The error terms, u are spatially correlated and may also be heteroscedastic. More importantly, the specification above generally yields that $E[(\mathbf{W}\mathbf{y})\mathbf{u}'] = \mathbf{W}(\mathbf{I} - \lambda\mathbf{W})^{-1}\boldsymbol{\Omega} \neq 0$, and therefore, it implies an endogenous problem (Kelejian & Prucha, 1998). To produce unbiased estimates, the generalized spatial two-stage least squares (GS2SLS) method is suggested, which consists of three steps (Kelejian & Prucha, 1998, 1999, 2010a). In the first step, the model specification above is estimated by a two-stage least square (2SLS) using the instruments for the endogeneous spatial lagged variable, $\mathbf{W}\mathbf{y}$. A set of spatially lagged explanatory variables are demonstrated as the proper instruments $\mathbf{H} =$

[$\mathbf{X}, \mathbf{WX}, \mathbf{W^2X}, \mathbf{MX}$, ...] (Kelejian & Prucha, 1998). In the second step, the 2SLS residuals from the first step and the generalized method of moments (GMM) are used to estimate the parameter of the spatial lagged error variable, ρ. The model in the first step is re-estimated incorporating the parameters estimated in steps one and two.

2.2.2 Survival Model

Researchers have developed a different type of statistical model, known as "survival analysis," to time-to-event data. Also called "duration analysis" among economists, time-to-event data is measured as the length of time in which a certain event of interest occurs. Survival analysis is used for a range of different research areas including health, economics, finance, and social science. Time to sales in the housing markets is one example of the time-to-event data.

The statistical model for predicting the duration of foreclosed property sales needs to consider both how long a foreclosed property remains in the process and when the property is sold. The time-to-event (or duration) data is characterized as censored, indicating that the occurrence of the event is only observable within a time window given the data (Wooldridge, 2010). Although the measure of duration is positive, because of censoring, the normality of error terms is often violated and the predicted value could be negative (Greene, 2012). Therefore, a typical type of regression such as ordinary least square (OLS) is not appropriate for the duration data (Guo, 2010). The subjects for an OLS regression should be observed and non-censored (Greene, 2012). A logistic regression can be used for predicting the proportion of exiting foreclosures or the likelihood of a property remaining in foreclosure. However, this does not predict the duration clearly, and it ignores the question about "how long" (Guo, 2010). Instead, survival analysis has been employed when researchers are interested in questions about how long a real property stays on the real estate market, when the property is sold, and what other covariates (e.g., property attributes) affect the time-to-event (Benefield & Hardin, 2013; Haurin, 1988).

A survival model primarily uses the hazard function, which is the probability of the event occurring subsequently within a time interval given that the event has not yet happened at time, *t* (Cleves, Gould, Gutierrez, & Marchenko, 2008; Guo, 2010; Wooldridge, 2010). The hazard function is written as (Wooldridge, 2010):

$$h(t) = \lim_{s \to 0} \frac{\Pr(t \leq T < t + s \mid T \geq t)}{s},$$

where *T* is the length of time until the event occurs, *t* is a particular time, and *s* is the time interval.

T has the probability distribution, $f(t)$, and the cumulative distribution function is $\mathrm{F}(t) = \Pr(T \leq t) = \int_0^t f(u)du$ where *t* is a particular value of *T*. The survivor function is represented as $\mathrm{S}(t) = \Pr(T > t) = 1 - F(t)$, which is the probability of surviving (no occurrence of event) until time *t*. The probability of the event occurring in the time interval can be expressed as (Wooldridge, 2010):

$$\Pr(t \leq T < t + s \mid T \geq t) = \frac{\Pr(t \leq T < t + s)}{\Pr(T \geq t)} = \frac{F(t + s) - F(t)}{1 - F(t)}.$$

Therefore, the hazard function can be expressed as (Wooldridge, 2010):

$$h(t) = \lim_{s \to 0} \frac{F(t+s) - F(t)}{s} \cdot \frac{1}{1 - F(t)} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}.$$

Since the associations between duration and explanatory variables are of primary interest in this dissertation, the hazard function is considered conditional on a set of explanatory variables, **x**. The hazard function is written as (Guo, 2010):

$$h(t,x) = \frac{f(t|\mathbf{x})}{1 - F(t|\mathbf{x})} = \frac{f(t|\mathbf{x})}{S(t|\mathbf{x})}.$$

The probability of the hazard can differ by the characteristics of the covariates. One popular model for specifying the hazard function is a proportional hazard model; it is written as (Wooldridge, 2010):

$$h(t,x) = h_0(t) \cdot k(\mathbf{x}),$$

where $k(\mathbf{x})$ is a function of the explanatory variables, **x**, and $h_0(t)$ is the baseline hazard function in the absence of explanatory variables. The baseline hazard function can be specified according to the distribution of the survival time, *T*. Commonly used parametric distributions are based on the exponential, the Weibull, and the log-logistic hazard functions (Cleves et al., 2008). In the case of the exponential distribution, the hazard function is constant; if the Weibull or log-logistic distribution is chosen, the hazard function increases or decreases nonlinearly according to the values of the defined parameters (Cleves et al., 2008; Greene, 2012).

The Cox proportional hazards model is a popular type of regression in survival analysis. It does not require any assumptions or information regarding the shape of the hazard distribution being studied. The Cox model for the hazard risk at time t is specified as follows (Cox, 1972):

$$h(t, x) = h_0(t) \cdot \exp(\mathbf{X\beta}),$$

where $k(\mathbf{x})$ is defined as $\exp(\mathbf{X\beta})$, and $\boldsymbol{\beta}$ is the estimated coefficient. The baseline hazard, $h_0(t)$, is cancelled out in the likelihood estimation. This suggests an advantage in that there is no need to make an assumption for the shape of the hazard function and it offers computation feasibility (Hosmer, Lemeshow, & May, 2008). Given the proportional form, the Cox hazard model can estimate the coefficients of explanatory variables without knowing the baseline hazard. It is a useful method for estimating the hazard ratio of interest after adjusting for other covariates (Guo, 2010). Therefore, the Cox proportional hazard model can be adequately considered for the analysis on which the built environmental characteristics in a neighborhood influence the likelihood of an REO being sold.

The assumption for the Cox proportional hazard model is that an explanatory variable has the same effects across all points in time. This proportional-hazard assumption can be checked by plotting hazard curves and/or testing the correlation between time and "Schoenfeld residuals" (Cleves et al., 2008).[7] However, the assumption is likely to be violated for some variables in many applications. In such cases, the coefficient can be interpreted as "average effect" of the variable over the time period (Allison, 2010). In some applications, the violation could be critical and it should be taken into consideration (Hosmer et al., 2008).

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[7] Comprehensive information about Schoenfeld residuals can be found in Grambsch and Therneau (1994)

2.3 Research Aims and Hypotheses

The focus of this dissertation centers on 1) how the built environment can affect the spillover effects of foreclosures on property values and 2) how the built environment can help reduce the density of REO properties and the duration of REO status. This dissertation consists of three stand-alone but interrelated studies. Based on the proposed conceptual models (Figure 2 and 3), the following primary aims and hypotheses are proposed for Study 1, 2, and 3 (Chapter III, IV, and V) in this dissertation.

Study 1 assesses the current state of knowledge on the methodological approaches for examining the impact of foreclosure spillovers on nearby property values by conducting a literature review.

- **Aim 1**: To provide a critical assessment of the status of knowledge on the methods used to assess the spillover effects, and recommendations for future work and improvements.

Study 2 investigates how neighborhood walkability influences the negative spillover effects of foreclosures on nearby property values (Figure 2).

- **Aim 2-1**: To examine how the walkability premium can interact with price spillovers of foreclosures. This study examines whether neighborhood walkability can mitigate the negative spillover effects of foreclosures on nearby property values.

- **Aim 2-2**: To investigate how the mitigation effects differ by housing market periods (housing market crash period of 2010 versus housing market recovery period of 2013). The mitigation effects are expected to be more significant during the recovery period. This study proposes that neighborhood walkability can provide an advantage for a neighborhood setting during housing market recovery.
- **Aim 2-3**: To analyze how the mitigation effects of neighborhood walkability on price spillovers of foreclosures differ by income groups (low versus high-income groups). The mitigation effects are expected to be significant and greater in high-income neighborhoods. This study explores the potential income disparities in the mitigating role of neighborhood walkability.

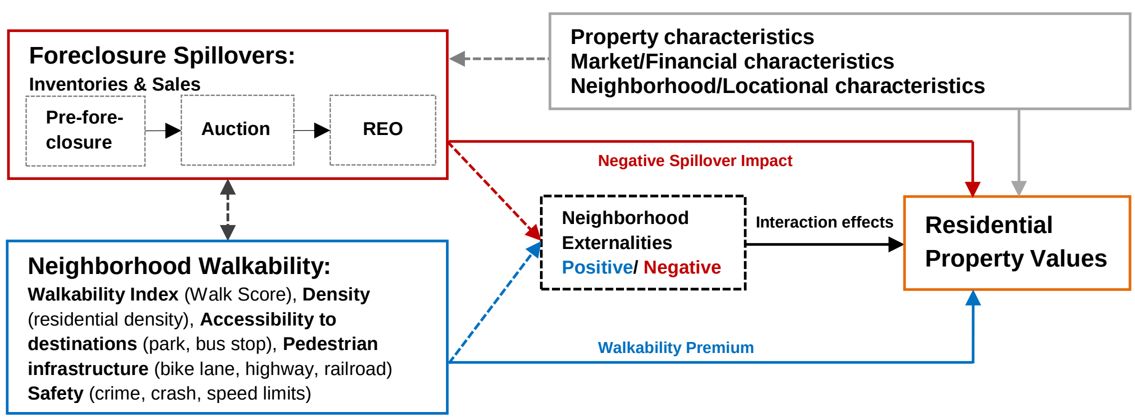

Figure 2. Conceptual Model for Study 2
Note: The sold lines represent the associations between the explanatory variables and dependent variables. The red, blue, and black solid lines are the main effects to be estimated in Study 2.

Hypotheses for Aims 2-1, 2-2 and 2-3 of Study 2:

- *H2-1*: Neighboring foreclosure stock (inventories and sales) is negatively associated with single-family home values; neighborhood walkability is positively associated with single-family home values; and the interaction terms (referred to as the mitigation effects) between neighborhood walkability and neighboring foreclosure stock are significant and positive.

- *H2-2*: The mitigation effects of neighborhood walkability were more significant and greater in the housing market recovery period of 2013 than in the housing market crash period of 2010.
- *H2-3*: The mitigation effects of neighborhood walkability are more significant and greater in high-income neighborhoods than in low-income neighborhoods.

Study 3 examines how the built environments influence the REO density and REO duration (Figure 3)

- **Aim 3-1**: To examine how walkable built environments are associated with REO density. This study examines whether or not the walkable built environment plays a role in the density of REO properties.
- **Aim 3-2**: To determine the environmental predictors of turnover of REO properties. This study analyzes how walkable built environments influence the duration in REO.
- **Aim 3-3**: To investigate how the predicted effects of built environments on REO duration vary across the market values of REO properties, especially for low-value REO properties. This study explores the different impacts of built environments on REO duration in low-value REO properties.

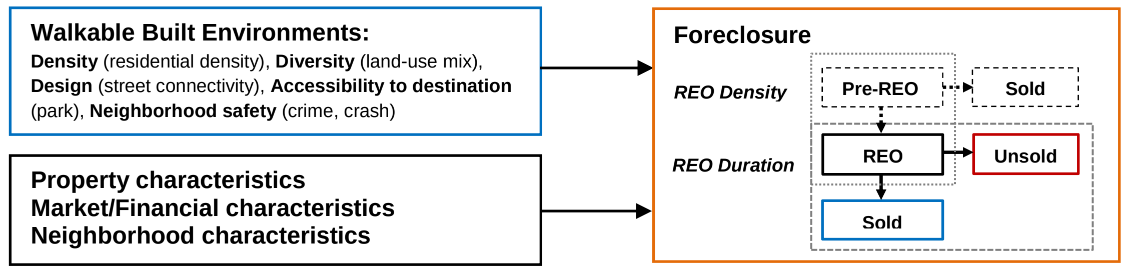

Figure 3. Conceptual Model for Study 3

Hypotheses for Aims 3-1, 3-2, and 3-3 of Study 3:

- *H3-1*: The built environmental correlates of walking are associated with REO density. This study hypothesizes that REO density decreases in more dense, mixed, and street connected areas.
- *H3-2*: The built environmental attributes are correlated with the likelihood of REO properties being sold. This study hypothesizes that REO duration decreases in more dense, mixed, and street connected areas.
- *H3-3*: The lower-value REO properties are more likely to be sold. However, in the highly dense residential areas, low-value REO properties are less likely to be sold, and high-value REO properties are more likely to be sold.

CHAPTER III

AN ASSESSMENT OF THE LITERATURE ON THE SPILLOVER EFFECTS OF FORECLOSURE ON NEARBY PROPERTY VALUES

3.1 Introduction

Since the mortgage market crashed in 2007, numerous studies have explored the impact of foreclosure on neighborhoods. The negative influences of foreclosures are not limited to the individuals who are suffering from the loss of home equity and lowered credit scores. The main concern of communities and policy makers is that a rapidly increasing number of foreclosures is threatening the stability of our communities by distorting overall housing markets and increase social disorders.

It has been widely believed that foreclosures bring price-depressing effects not only to the property itself but also to nearby properties. However, methodological challenges still exist in effectively quantifying the spillover effects of foreclosure. Based on the review of previous literature, this study examines how previous studies a) employed study designs, b) modified measurement approaches, and c) specified statistical models including proper handling of control variables, in order to deal with endogeneity problems. In addition, existing studies have identified different spillover effects by spatial and temporal dimensions, but it is still unclear how to delineate an adequate spatial boundary to determine the spatial extent of foreclosure spillover effects.

In addition to methodological issues, a knowledge gap exists in the understanding of how the spillover effects vary with a) study locations and settings (e.g., urban and suburban), b) neighborhood contexts (e.g., socio-economic status), c) housing market periods (e.g., boom-and-bust housing markets), and d) heterogeneous housing markets (e.g., single- and multi-family homes and condominiums), which can help local planners or policy makers to develop tailored strategies to better handle the spillover effects that occur in response to the specific characteristics of their local communities.

This review provides a critical assessment of the methods available for evaluating spillover effects of foreclosures on nearby property values and suggests substantive research gaps to better understand the extent and magnitude of the spillover effects. This review aims to stimulate discussion on the policy implications of the broad range of topics related to foreclosure spillover effects.

3.2 Methods

3.2.1 Conceptual Framework for Assessing the Spillover Effects of Foreclosures

An analysis of the literature review is based on the hedonic price (HP) framework developed by Rosen (1974), which has been commonly used for evaluating implicit prices of integrated housing products. Various characteristics that determine a price have been examined in the body of hedonic price literature. Based on the studies that provide an extensive discussion of variable characteristics in the HP model (Nicholls & Crompton, 2005; Sirmans et al., 2005), the set of variables have been reclassified into six categories:

(1) Structural characteristics: lot size, square footage, age, number of bathrooms, etc.;

(2) Market characteristics: time-on-the market (TOM), time when sales occur, etc.

(3) Financial characteristics: mortgage type, whether or not a property is in foreclosure status, etc.

(4) Socioeconomic neighborhood characteristics: median household income, race/ethnicity, educational attainment, owner occupancy, etc.

(5) Locational neighborhood characteristics: geographical locations, school attendance zones, central business districts, etc.

(6) Contextual neighborhood characteristics: views from the property, air quality, accessibility to amenities, land use patterns, crimes, crashes, etc.

To determine the economic impact of foreclosure spillovers, the six categories above can be presented as three control groups: structural controls, market/financial controls, and neighborhood controls (socioeconomic, locational, and contextual characteristics). The conceptual framework adopted in this review is illustrated in Figure 4. According to the constructs, this research evaluates diverse control variables and their influence on the relationships between neighboring foreclosures and property values.

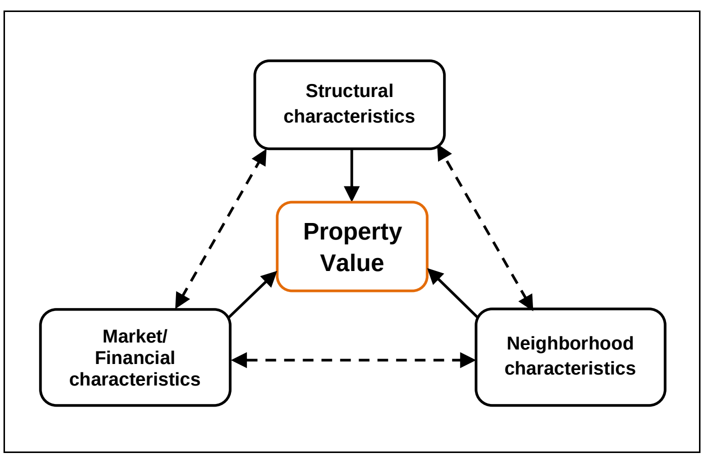

Figure 4. Conceptual Framework

3.2.2 Article Selection and Data Extraction

This review was conducted between 2015 and 2016. Relevant articles were searched using four electronic databases: Business Source Complete (January 2000-December 2015), EconLit (January 2000-December 2015), ABI/INFORM Complete (January 2000-December 2015), and Social Science Citation Index (January 2000-December 2015). Combinations of the following search terms were used to obtain relevant articles: foreclosure, real estate owned, spillover, contagion, neighborhood decline, negative externality, property value, sales price, depressed prices, and housing market. The search strategy for the database selection and the combinations of search terms were based on the librarian's expertise in the database search.

A total of 642 unique records were obtained from the search. Duplicates were excluded, leaving 349 records. Of those 349, studies were deemed irrelevant and excluded if they: (a) did not examine the associations between foreclosure spillovers as the main independent variables and property values as the dependent variable, (b) did not use parcel-level foreclosure measures, (c) were not empirical studies (e.g., no review articles or case studies), or (d) were not published in peer-review journals (e.g., working papers). Ultimately, 24 of the 349 studies were identified for a full-text review. The references of the retrieved studies were also reviewed to find additional studies that could be included. From each identified study, the information was entered into Table 1, which includes references, data sources, study settings, study designs, statistical analyses, dependent variable, independent variable, control variables, and main results.

3.3 Results

3.3.1 Study Characteristics

Table 1 presents the study characteristics of the 24 articles. Because of its unique mortgage system, all studies were conducted in the United States. Of the 24, 8 studies were conducted in so-called “sand state” such as California, Florida, and Nevada, and two were undertaken in a Rust Belt state such as Ohio. Other study areas included Illinois, New York, Texas, Missouri, Wisconsin, and Massachusetts. Samples ranged from 3,855 to 1,831,393 properties. Three studies used a longitudinal approach, and the remainder were cross-sectional. The twenty-one cross-sectional studies presented various control variables in order to yield unbiased estimates of the foreclosure spillover effects.

Table 1. Summary of the Reviewed Studies

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Immergluck and Smith (2006); Chicago, Illinois	N=9,600; County Assessor's Office	1: Logged sales price 2: Single-family 3: not specified 4: Random sampling from transactions in 1999	M: Count D: 0-1/8, 1/8-1/4 mile B: Circular buffer T: 0-2 years before the subject property sale F: Inventory (foreclosure filings based on conventional loan, government loan) - *Inventory* P: single-family, multi-family, commercial property Y: 1997 – 1998	St: land area, building area, age, bedrooms, story, masonry construction, finished basement, central air conditioning, fireplace, one- or two-car garage, located within a block or so of a railroad track Ma: Quarterly dummies Fi: N/A So: 2000 Census tract data: population density, income, race (Black, Hispanic), violent crime, percentages of residents on public assistance Lo: Locational indicators Co: Distance from an elevated train or subway stop increases	Cross-sectional; Hedonic price model; Regression (OLS)	<Before controlling for tract median property values> 0-1/8 mile: -0.01136*** 1/8-1/4 mile:-0.00325*** <After controlling for tract median property value> 0-1/8 mile: -0.00907*** 1/8-1/4 mile:-0.00189
Schuetz et al. (2008); New York, New York	N=89,814; City's Department of Finance, Public Data Corporation	1: Logged sales price 2: Single-family, Two-family 3: not specified 4: All transactions during 2002-2005	M: Count, Dummy, Logged D: 0-250, 250-500, 500-1000 feet B: Circular buffer T: 0-18 months before the subject property sale, 18+ months after the sale F: *Lis Pendens* (LP) filings from mortgage default - *Inventory* P: Single-family, Multi-family Y: 2000 – 2005	St: square footage of the lot/building/unit, number of building on lot, age of unit, detached or attached, stories Ma: Boro×Quarter×year Fi: N/A So: Census tract 2000: log (population), housing density, % of owner-occupancy, % of subprime Lo: ZIP codes Co: distance to the nearest subway stop	Cross-sectional; Hedonic price model; Regression (OLS)	<Count of LP> 0-18 months, 0-250 ft: 0.00228* 18+ months, 0-250 ft: -0.00478** Post-sale, 0-250 ft: -0.00434*** 0-18 months, 250-500ft: -0.000834 18+ months, 250-500ft: 0.00235*
Lin, Rosenblatt, and Yao (2009); Chicago Primary MSAs (Cook, DuPage, Lake Counties), Illinois	N=14,427; Fannie Mae and Freddie Mac, Loan performance data	1: Logged sales price 2: Single-family 3: Non-distressed 4: Random sampling from transactions in 2003, 2006	M: Count D: 0-0.1, 0.1-0.2, 0.2-0.3, 0.3-0.4, 0.4-0.5, 0.5-0.6, 0.6-0.7, 0.7-0.8, 0.8-0.9, 0.9-1, 1-1.5, 1.5-2, 2-2.5, 2.5-3, 3-3.5, 3.5-4, 4-4.5, 4.5-5, 5-6, 6-7, 7-8, 8-9; 9-10; 10-15; 15-20 km B: Circular buffer T: 0-2, 3-5, 6-10 years before the subject property sale F: Foreclosure sales P: Single-family Y: 1990 – 2006	St: log square footage, log lot size, # of baths, age, square of age Ma: Quarterly dummies Fi: N/A So: N/A Lo: Counties and zip codes Co: N/A	Cross-sectional; Hedonic price model; Regression (OLS)	< Within 2 years > All significant results 0-0.1 km: -9.8% 0.1-0.2 km: -5.8% 0.2-0.3 km: -4.3% 0.3-0.4 km: -4.3% 0.4-0.5 km: -4.3% 0.5-0.6 km: -2.2% 0.6-0.7 km: -2.8% 0.7-0.8 km: -2.4% 0.8-0.9 km: -1.9%

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Harding et al. (2009); 7 MSAs (Atlanta, Charlotte, Columbus, Las Vegas, Los Angeles, Memphis, St. Louis)	N=24,334 (Atlanta), N=8,711 (Charlotte), N=11,858 (Columbus), N=3,303 (Las Vegas), N=2,887 (LA) N=6,087 (Memphis), N=3,528 (St. Louis);	1: Logged sales price 2: Single-family 3: Non-distressed 4: All transactions during 1989-2007	M: Count, Quadratic D: 0-300, 300-500, 500-1000, 1000-2000 feet B: Circular T: 13 different phases during the period from 12 months before the foreclosure sale (F) and through 12 months after the REO sale (R) F: From 13 phases of the foreclosure process, the foreclosure types included inventory (pre-foreclosure or auction, REO) and sale (foreclosure sale, REO sale) P: Single-family Y: 1989-2007	St: N/A Ma: Sales dates Fi: N/A So: N/A Lo: N/A Co: N/A	Longitudinal; Repeated sales model; Regression (GLS)	<Within 0-300feet buffer> F-12 to F-9: -0.15% F-9 to F-6: -0.19% F-6 to F-3: -0.43% F-3 to F:-1.08% F to F+3: -0.83% F+3 to F+6:-0.96% F+6 to F+9:-0.69% F+9 to F+12: -0.81% S to S+3: -0.97% S+3 to S+6: -0.97% S+6 to S+9: -0.83% S+9 to S+12: -1.05%
Leonard and Murdoch (2009); Dallas County, TX	N=23,218; Dallas Central Appraisal District, RealtyTrac	1: Logged sales price 2: Single-family 3: All included 4: All transactions in 2006	M: Count D: 0-250, 251-500, 501-1000, 1001 - 1500 feet B: Circular buffer T: A quarter before the subject property sale F: Foreclosures in the process; the foreclosure was measured as any stage of foreclosure in the process (pre-foreclosure, auction, or REO) P: Single-family Y: 2005 – Second quarter of 2007	St: square footage of living area, square footage of the lot, # of bathrooms, age of house, # of stories (1.5 stories dummy, two or more stories dummy), # of fireplaces (one fire place dummy, two or more fireplaces dummy), condition of the property as coded by DCAD appraisers (very poor, poor, average, good, very good, excellent), pier and beam dummy, the type of foundation (slab foundation dummy), type of fence (chain fence, iron fence, wood fence dummies), the existence of a pool, attached or detached garage, attached or detached carport, central air conditioning, central heat Ma: monthly dummies, trends in housing price as spatial average Fi: Indicator of foreclosure status So: Census block group: percentage of population (African American, Hispanic), percentage of the population (65+ years old), the average household size, owner occupancy rate. Lo: School districts Co: N/A	Cross-sectional; Hedonic price model; Spatial regression model (OLS, ML, GMM)	<OLS> 0-250ft: -0.011*** 251-500ft: -0.006*** 501-1000ft: -0.003*** 1001-1500ft: -0.003*** <OLS+controls for pricing trends > 0-250ft: -0.012*** 251-500ft: -0.006*** 501-1000ft: -0.004*** 1001-1500ft: -0.004*** <GMM-Spatial lag & error model> 0-250ft: -0.005 *** 251-500ft:-0.002 501-1000ft:-0.001** 1001-1500ft:-0.001*

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
W. H. Rogers and Winter (2009); St. Louis County, Missouri	N=98,828; St. Louis County Assessor, Recorder of Deeds	1:Logged sales price 2:Single-family 3:Non-distressed 4:All transactions during 2000-2007	M: Count, Count squared D: 0-200, 200-400, 400-600 yard B: Circular buffer T: 0-6, 7-12, 13-18, 19-24 months before the subject property sale F: Foreclosures based on the deed information; the foreclosures can be measured as inventory or sale, but they were not separated. P: Single family Y: 1998 – 2007	St: age, area (acres), living area (sqft), stories, bedrooms, bathrooms, halfbath, air conditioning (dummy), chimney (discrete), private pools (discrete), private tennis courts (discrete) Ma: yearly dummies, spatially lagged dependent variable Fi: N/A So: N/A Lo: flood zone Co: distance to nearest arterial road, distance to nearest interstate onramp, distance to nearest light-rail station	Cross-sectional; Hedonic price model; Spatial lag and error model (GMM)	*=statistically significant at the 5% level <OLS> y200m06: frcl:-0.0335**/frcl_sq:0.0051** y200m12: frcl:-0.0294**/frcl_sq:0.0063** <GMM> y200m06: frcl:-0.0139*/frcl_sq:0.0023* y200m12: frcl:-0.0172**/frcl_sq:0.0043**
W. H. Rogers (2010); St. Louis County, Missouri	N=103,827; St. Louis County Assessor, Recorder of Deeds	1:Logged sales price 2:Single-family 3:All included 4:All transactions during 2000-2007	M: Count D: 0-200, 200-500 yard B: Circular buffer T: 0-1, 1-2, 2-3, 3-4 year before the subject property F: Foreclosure sale P: Single-family Y: 1996 – 2007	St: age, area (acres), living area (sqft), stories, bedrooms, bathrooms, half bath, air conditioning (dummy), chimney (discrete), private pools (discrete), private tennis courts (discrete) Ma: yearly dummies, spatially lagged dependent variable Fi: Foreclosure sale indicator So: N/A Lo: Flood zone Co: distance to nearest arterial road, distance to nearest interstate onramp, distance to nearest light-rail station	Pooled cross-sectional; Hedonic price model; Spatial error model (ML)	*=statistically significant at the 5% level Two dummy variables–the housing boom period (2003-2005) and the bust period (2006-2007)–were included as interaction terms with neighboring foreclosures. <Full sample> 0-200 yard, 0-1 yr: -0.0089*, 0.0035* (Boom), 0.0078* (Bust) 0-200 yard, 1-2 yr: -0.0038*, 0.002 (Boom), 0.0026 (Bust) <Subsample –lower income area > 0-200 yard, 0-1 yr: -0.007**, 0.0004 (Boom), 0.0041* (Bust) 0-200 yard, 1-2 yr: -0.0038*, 0.002 (Boom), 0.0026* (Bust)

Table 1. Continued

Reference; Study area	Data Set (N=sample size; Data Source)	Dependent Variable (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	Foreclosure Measurement (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	Control variables (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	Theoretical framework; Study design; and Statistical analysis	Main results
Kashian and Carroll (2011); City of Milwaukee, Wisconsin	N=3683; City of Milwaukee Assessor's Office	1: Logged sales price 2: Condominium 3: All included 4: All transactions during Jan. 2005-Dec. 2009	M: Count / Dummy D: 0-50, 50-625,625-1250,1250-2640, 2640-5680 feet B: Circular buffer T: 0-1, 1-2, 1-3, 4-6, 7-12 months before the subject property sale F: Sheriff sale P: Condominium Y: 2005 – 2009	St: bedroom, full bath, half bath, age, sqft Ma: yearly dummies Fi: sheriff's sale indicator So: N/A Lo: aldermanic district Co: N/A	Cross-sectional; Hedonic price model; Regression (robust standard error least square)	0-50ft, 0-1 mo:-0.224*** 0-50ft, 1-3 mo:-0.018 0-50ft, 3-6 mo:-0.002 0-50ft, 6-12 mo:-0.040 50-625ft, 0-1 mo:-0.118*** 50-625ft, 1-3 mo:-0.053*** 50-625ft, 3-6 mo: -0.045*** 50-625ft, 6-12 mo:-0.031*
Wassmer (2011); 6 counties (El Dorado, Nevada, Placer, Sacramento, Yolo, Yuba), California	N=35,822; Multiple Listing Service	1: Logged sales price 2: Single-family 3: All included 4: All transactions in Jan. 2008 – Jun 2009	M: Count; This study also included a rate of REO sale for a quarterly period in zip codes D: 0-1/10, 1/10-1/4, 1/4-1 mile (only for count measure) B: Circular buffer (only for count measure) T: Quarter before the subject property sale F: REO sale P: Single-family Y: Jan 2008 – Jun 2009	St: age, squared age, years since remodeled, home area, lot area, stories, bedrooms, bathrooms, half bath, fireplace, garage, wood exterior, brick exterior, lap exterior, vinyl exterior, tile roof, metal roof, slate roof, shake roof, contemporary , Mediterranean, Victorian Ma: days on market 100s, quarter dummies Fi: whether or not it is sold as REO sale Lo: horse Property, Community Service District, Covenant Restriction, Neighborhood Association, Neighborhood Association Dues, 60 Zip code So: N/A; Co: N/A	Cross-sectional; Hedonic price model; Spatial error model	<OLS> 0-1/10 mile:-0.0059*** 1/10-1/4 mile:-0.0018*** 1/4-1 mile:-0.0003*** Rate of REO sale in zip code:-0.0556*** <Spatial Error model> 0-1/10 mile: -0.0061*** 1/10-1/4 mile:-0.0019*** 1/4-1 mile:-0.0003*** Rate of REO sale in zip code:-0.0431**
Daneshvary, Clauretie, and Kader (2011); Las Vegas MSA, Nevada	N=22,532; Greater Las Vegas Association of Realtors	1: Logged sales price 2: Single-family 3: All included 4: All transactions in Dec 2007 – Dec 2008	M: Count, Count squared D: 0-0.1, 0.1-0.25, 0.25-0.5 mile B: Circular buffer T: 0-3 months before the subject property sale; 0-6 months before the subject property sale; two different time dimensions were used in separate models F: Short-sale, REO sale/Sale in the foreclosure process P: Single-family Y: Dec.2007 – Dec. 2008	St: property physical condition (assessed by the listing agent-excellent, good, fair, and poor), occupancy status (vacant, owner occupied, and tenant occupied), age, building sqft, lot sqft, bedrooms, bathrooms, garages, fireplace, pool, spa, two-story building, golf course view, mountain view, strip view, park view, city view, lake view Ma: Monthly dummies, Time-on-the market Fi: foreclosure sale So: percentage age 25-35, percentage age 55 or older, education (percentage of highschool, college degree deploma), percentage with a child at home Lo: Locational indicators (Summerlin, Anthem, Lake Las Vegas, Seven Hills, and The Lakes) Co: N/A	Cross-sectional; Hedonic price model; Regression (OLS, 3SLS)	<6month spillover effect> *Short sale* 0-0.1 mile: 0.0063, 0.0011 (squared) 0.1-0.25 mile:0.0034, 0.0005 (squared) 0.25-0.5 mile: 0.0063***, -0.0002 (squared) *Foreclosure sale/REO sale* 0-0.1 mile:-0.0086***, 0.0004** (squared) 0.1-0.25 mile: -0.007***, 0.0002*** (squared)

Table 1. Continued

Reference; Study area	Data Set (N=sample size; Data Source)	Dependent Variable (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	Foreclosure Measurement (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	Control variables (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	Theoretical framework; Study design; and Statistical analysis	Main results
Campbell et al. (2011); Massachusetts	N=1,831,393; Warrant Group	1: Logged sales price 2: Single-and multi-family, condominium 3: All included 4: All transactions during 1987-2009	M: Count D: 0-0.1, 0.1-0.25 mile B: Circular buffer T: 1 year before / after the subject property sales F: Foreclosure sale P: Single-and multi-family, condominium Y: 1987-2009	St: interior area, lot area, number of rooms, bedrooms, and bathrooms, the age of the house, square; dummies for recent renovation, condominiums and winsorization of characteristics Ma: Month dummies to control for seasonality in the housing market Fi: whether or not a transaction is forced sale Lo: Census tract-year effects Co: N/A	Cross-sectional; Hedonic price model; Regression (used Piecewise linear function)	<Using only foreclosures before transaction> 0-0.1 mile: -0.011*** 0.1-0.25 mile: -0.072*** <Estimated difference in coefficients: Before and After> 0-0.1 mile: -0.003*** 0.1-0.25 mile: -0.017***
Kobie and Lee (2010); Cuyahoga County, Ohio	N=23,130 (Cuyahoga model); N=5,879 (Cleveland model); N=17,251 (suburban model) Cuyahoga County clerk of courts, Cuyahoga County auditor	1: Logged sales price 2: Single-family 3: Not specified 4: All transactions during 2006-2007	M: Count D: Face block B: Block boundary T: 1-90, 91-180, 181-270, 271-360, longer than 360 days after filing foreclosures; The time dimensions were not used for Sheriff's sale foreclosures. F: Inventory (foreclosure filing), Sale (Sheriff's sale) P: Single-family Y: 2005-2007	St: Age, Home area, Lot area, Stories, Bedrooms, Bathrooms, HalfBath, Fireplace, Crawlspace basement, Slab basement, Finished basement, partially finished/unfinished, Bungalow Ranch, Colonial Ranch, Other style Ranch, Asbestos shingles/reference Brick, aluminum, vinyl, composite siding/reference brick, wood siding/reference brick, attached garage, Central air conditioning, Porch Ma: Dummy sale in 2006/reference sale in 2007, Seasonal dummies Fi: NA So: Census block group: Income (block group in 1000s of dollars), Impacted property density, Housing unit density, Percentage African-American, Percentage Hispanic, Percentage of persons living in poverty Lo: Cleveland's east side, west side, Inner ring surburbs, Distance to the CBD (miles), Waterfront property Co: N/A	Cross-sectional; Hedonic price model; Spatial lag or error model	<Cuyahoga County model> Sheriff sale: -0.029** 1-90 days: -0.008 91-180 days:0.004 181-270 days:-0.007 271-360 days:-0.001 > 360 days:-0.017*** <Cleveland Central city model> sheriff sales:-0.024*** 1-90 days:-0.009 91-180 days:0.016 181-270 days:-0.004 271-360 days:-0.002 > 360 days:-0.007 <Suburban model> sheriff sales:-0.044*** 1-90 days:-0.004 91-180 days:0.018*** 181-270 days:-0.014** 271-360 days:-0.006 > 360 days:-0.031***

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Groves and Rogers (2011); St. Louis County, Missouri	N=87,734; Integrated Assessment Systems (IAS) Database	1: Logged sales price (adjusted in 2007 dollars) 2: Single-family 3: All included 4: All transactions during 2000 – Jun. 2007	M: Count D: 0-200, 200-400, 400-600 yard B: Circular buffer T: 1-12, 13-24 months before the subject property sales F: Foreclosure sale based on the deed records P: Single-family Y: 2000 – Jun. 2007	St: (logged) land area of the lot, (logged) total square footage of living space, # of bedrooms, # of bathrooms, # of fireplaces, the presence of central air, # of stories, age of the home at the time of the sale, age squared, style of the home Ma: quarter and year Fi: foreclosure sale indicator So: N/A Lo: 137 tax zones Co: distance to Metro station, distance to Interstate on-ramp, distance to arterial road	Cross-sectional; Hedonic price model; Spatial lag and error model (2SLS)	Interactions between the RCA dummy and neighboring foreclosures were included to test how foreclosure impacts were different for homes engaged in RCA <Spatial lag and error model> 200-400yard,12mo: 0.0012 (RCA), -0.0038*** (no RCA) 400-600yard,12mo: 0.0014* (RCA), -0.0013*** (no RCA)\
Daneshvary and Clauretie (2012); Las Vegas, Nevada	N=22,532; Greater Las Vegas Association of Realtors (GLVAR)	1: Logged sales price 2: Single-family 3: Non-distressed 4: All transactions during Apr. 2008-Jun. 2009	M: Count, Count squared D: 0-0.1, 0.1-0.25, 0.25-0.5 mile B: Circular buffer T: 0-3 months before the subject property sales; 0-6 months before the subject property sales; two different time dimensions were used in separate models F: Short sale, REO sale P: Single family Y: Jan. 2008 – Jun. 2009	St: property physical condition (assessed by the listing agent)-excellent, good, fair, and poor, vacant, occupancy status (vacant, owner occupied, and tenant occupied), age, building sqft, lot sqft, # of bedrooms, # of bathrooms, # of garages, fireplace (dummy), pool (dummy), spa (dummy), two-story building Ma: Monthly Time trend Fi: N/A So: percentage age 25-35, percentage age 55 or older, education (percentage of highschool, college degree deploma), percentage with a child at home Lo: Summerlin, Anthem, Lake Las Vegas, Seven Hills, The Lakes Co: View (golf course view, mountain view, strip view, park view, city view, lake view)	Cross-sectional; Hedonic price model; Spatial lag and error model (GS2SLS)	<6month spillover effect> *Short-sale* 0-0.1 mile: -0.007 0.1-0.25mile:-0.006 0.25-0.5mile:-0.004 *REO sale* 0-0.1 mile: -0.01*** 0.1-0.25mile:-0.008*** 0.25-0.5mile:-0.003***

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Rutherford and Chen (2012); Tarrant County, Texas	N=62,415; Multiple Listing Service	1: Logged sales price 2: Single-family 3: All included 4: All transactions during 2001-2005	M: Count D: 0-1/8, 1/8-1/4, 1/4-3/8, 3/8-1/2, 1/2-1 mile B: Circular buffer T: 0-2, 2-4, 4-5 1/2 years before the subject property sales F: Foreclosure sale in a MLS setting P: Single-family Y: 2001-2005	St: bedroom, bathroom, age of the property in unit of 10 years, sqft of the property in unit of 100, pool (dummy), fireplace(dummy), stories (number), vacant (1:yes,0:no) property class (1- 8 dummy variables) Ma: Year and quarter dummies, Time on market in days, List price change Fi: distressed sale indicator So: N/A Lo: location dummies Co: N/A	Cross-sectional; Hedonic price model; Regression (OLS)	Three different submarkets based on the quartiles of property size were separately examined. <Full sample> 0-1/8 mile, 2yr:-1.17%*** 1/8-1/4 mile, 2yr:-0.71%*** <Low quartile> 0-1/8 mile, 2yr: -0.13% 1/8-1/4 mile, 2yr:-0.15%* <Middle quartile> 0-1/8 mile, 2yr: -1.00%*** 1/8-1/4 mile, 2yr:-0.56*** <Upper quartile> 0-1/8 mile, 2yr:-1.95%*** 1/8-1/4 mile, 2yr:-1.54%***
Biswas (2012); the City of Worcester, Massachusetts	N=18,270; Warren Group	1: Logged sales price 2: Single-family 3: Non-distressed 4: All transactions during 1993 - 2008	M: Count D: 0-660, 660-1320 feet B: Circular buffer T: 1 year before, 1 year after, 1-2 year before, and 1-2 year after the subject property sales F: Foreclosure sale based on the deed information P: Single-family, Multi-family Y: 1991 – 2008	St: Bathrooms, Lot size(x1000), Interior sqft(x1000), Rooms, Fireplaces, Age (x10), Distance to Railroad(x100 ft) Ma: Quarterly dummies Fi: N/A So: N/A Lo: Police Statistical Area (PSA) x year fixed effect Co: distance from the railroad, crime rate	Cross-sectional; Hedonic price model; Spatial lag model	+p<0.1, *p<0.05, **p<0.01, <1 year window> *Single-family foreclosures* 0-660ft, 1yr before: -0.018* 661-1320ft, 1yr before: 0.002 *Multi-family foreclosures* 0-660ft, 1yr before: -0.030+ 661-1320ft, 1yr before: -0.030**

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Whitaker and Fitzpatrick IV (2013); Cuyahoga County, Ohio	N=13,991; Cuyahoga County Fiscal Officer	1: Logged sales price 2: Single-family 3: All included 4: All transactions during Apr. 2010-Dec. 2011	M: Count D: 0-500 feet B: Circular buffer T: 1 year before F: Sheriff's sale with information about vacancy and tax delinquency P: Single-family, Multi-family, Condominium Y: Mar. 2009 - Nov. 2011	St: Bedrooms, Bathrooms, Vintage (decade in which the home was built), Style (Cape Cod, colonial, etc.), Lot size, Condition, Construction quality, Exterior material, Heating and cooling systems, Garages, Attics, Porches, and Fireplaces Ma: monthly time trend, census tract median home sale price Fi: vacancy, tax delinquency, and foreclosure status of the sold property itself So: poverty rate, college attainment rate for each census tract (using 2005-2009 ACS) Lo: census-tract fixed effects Co: N/A	Cross-sectional; Hedonic price model; Spatial lag and error model (GMM)	<Full sample> Vacant:-0.018*** Tax delinquent:-0.015*** Foreclosed: -0.047*** Vacant-tax delinquent-foreclosed: 0.102 <High-poverty subsample> Foreclosed: -0.01 Tax delinquent: -0.008* Vacant-tax delinquent-foreclosed: 0.252* <Low-poverty subsample> Vacant: -0.029*** Tax delinquent:-0.025*** Foreclosed: -0.074*** Vacant-foreclosed: -0.043* Vacant-tax delinquent-foreclosed:-0.024 Occupied-tax delinquent-nonforeclosed: -0.020***
Cheung, Cunningham, and Meltzer (2014); Florida	N=316,267; CoreLogic, Loan Performance	1: Logged sales price 2: Single-family 3: All included 4: All transactions during Jan. 2000 – Dec. 2008	M: Rate in zip codes D: zip code B: zip code T: N/A F: delinquency, foreclosure filing P: Single-family, Multi-family, Condominium Y: 2000-2009	St: Lot size, assessor-determined level of the construction quality of the housing unit, ranging from 'minimum' to 'superior', Year built, Total living area, Number of housing units in property, indicator for vcant, indicator for single-family Ma: N/A Fi: N/A So: N/A Lo: Geographica fixed effect: county-year fixed effects (also used zipcode-year fixed, and municipality-year fixed in different models) ; share of homes in zip code within an HOA Co: Dummy variable indicating Home Ownership Association for interaction effects	Cross-sectional; Hedonic price model; Regression	Interaction terms between HOAs and delinquency were estimated. Delinquency: -0.149*** HOA: 0.0228*** HOA× Delinquency:0.0153* Foreclosure:-0.139*** HOA: 0.0218** HOA× Foreclosure:0.00348

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Han (2014); the City of Baltimore, Maryland	N=101,497; Baltimore City Department of Housing and Community Development, Circuit Court of Baltimore City	1: Logged sales price 2: Single-family 3: 4: All transaction but only sales pairs are included during Jan. 1991 – Dec. 2010	M: Count D: 0-250, 251-500, 501-1000, 1001-1500 feet B: Circular buffer T: N/A F: foreclosure filing (included as a control variable); the main independent variable was abandoned buildings P: Single-family Y: 1991-2010	St: N/A Ma: market price trends Fi: N/A So: N/A Lo: N/A Co: N/A	Longitudinal; Weighted repeat sales model	<Foreclosure filings> 0-250ft: -1.374*** 251-500ft: -0.213* 501-1000ft:-0.303*** 1001-1500ft:-0.118***
Ihlanfeldt and Mayock (2014); 10 Counties in Florida (Alachua, Broward, Dade, Duval, Palm Beach, Hillsborough, Lee, Leon, Pinellas, and Volusia)	N=1,307,949; DataQuick	1: Logged sales price 2: Single-family 3: All included 4: All transactions during 1996 - 2011	M: Count / Density D: 0-300, 300-500, 500-1000, 1000-2000, 2000-3000 feet B: Circular buffer T: 0-1, 1-2, 2-3 year before sale F: Inventory and Sale - Current REO, Ex-REO (owner-occupied), Ex-REO (investor-owned), No-REO-rental units P: Single-family Y: 1996-2011	St: interior square footage, lot size, presence of pool, bedrooms, bathrooms, age Ma: Monthly dummies Fi: foreclosure sale indicator So: N/A Lo: neighborhood-year fixed effect Co: N/A	Cross-sectional; Hedonic price model; Regression	<Results from the Alachua County case> 0-300ft REO: -0.0347*** Non-REO: -0.00494*** Exited REO Status 0-1 Years Before Sale: -0.0333** (Non-Homesteaded) Exited REO Status 1-2 Years Before Sale: 0.0246* (Homesteaded) Exited REO Status 2-3 Years Before Sale: -0.0376** (Non-Homesteaded)

Table 1. Continued

Reference; Study area	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Zhang and Leonard (2014); Dallas County, Texas	N=12,465; RealtyTrac, University of Texas at Dallas Real Estate	1: Logged sales price 2: Single-family 3: Non-distress 4: All transactions in 2008	M: Count D: 0-250, 250-500, 500-1000, 1000-1500 feet B: Circular buffer T: Four quarterly periods in 12 months before the foreclosure auction and four quarterly periods in 12 months after the foreclosure auction F: Pre-foreclosure, foreclosure sale P: Single-family S: Inventory and sale Y: 2007-2009	St: Living area, Lot area, Baths, Effective age (number of years (in 10 years) since house has significant refurbishing), Pool, Story 1, Story 1.5, Slab Central heat, One fire, Two fires, Attached garage, Attached carport, Detached carport Ma: Monthly dummies Fi: N/A Lo: dummies for institutional (e.g. school districts) So: N/A Co: N/A	Cross-sectional; Hedonic price model; Spatial quantile regression (2-stage quantile regression)	Three different quantiles of home price distribution were analyzed. The distance effects were only reported in the study. <0.25 quantile> 0-250ft:-0.0349*** 250-500ft:-0.001 500-1000ft:-0.0017*** 1000-1500ft:-0.002*** <0.50 quantile> 0-250ft: -0.0218*** 250-500ft:-0.0021* 500-1000ft:-0.0021*** 1000-1500ft:-0.016*** <0.75 quantile> 0-250ft: -0.0147*** 250-500ft:-0.0011 500-1000ft:-0.0029*** 1000-1500ft:-0.0017***
Anenberg and Kung (2014); MSAs (Chicago, Phoenix, San Francisco, and DC)	N= ; listing data from AltosResearch, home sales from DataQuick	1: Logged sales price 2: Single-family 3: Non-distress 4: All transactions during 1988-2009	M: Log of count D: 0-0.1, 0.1-0.33 mile B: Circular buffer T: 90-day intervals within 1 year before foreclosure, after foreclosure but before listing, and REO listing (pre-listing, during listing, soon after listing, and after listing); F: foreclosure, REO Y:1988-2009	St: Square footage, age, bathrooms, bedrooms, dummies for whether it is single-family Ma: time on the market Fi: dummies for whether the property is an REO Lo: quarter-by-census tract fixed effects So: N/A Co: N/A	Cross-sectional; Regression	<Difference in difference estimates of During REO Listing relative to Before Listing> During REO listing/0-0.1 mile:-0.006** During REO listing/0.1-0.33 mile:-0.008**

Table 1. Continued

Reference; **Study area**	**Data Set** (N=sample size; Data Source)	**Dependent Variable** (1. Transformation, 2. Property type, 3. Non-distressed only or all included 4. Sampling)	**Foreclosure Measurement** (M: Measure, D: Distance dimension, B: Spatial boundary, T: Time lag dimension, F: Foreclosure type, P: Property type Y: Data period)	**Control variables** (St: structural characteristics Ma: market characteristics Fi: Financial characteristics So: Socio-economic neighborhood characteristics Lo: Locational neighborhood characteristics Co: Contextual neighborhood characteristics)	**Theoretical framework; Study design; and Statistical analysis**	**Main results**
Hartley (2014); the City of Chicago, Illinois	N=165,313; Record Information Services	1: Logged sales price 2: Single-family 3: Non-distress 4: All transactions during Jan. 2000 – May. 2011	M: Count D: 0.05, 0.05-0.10, 0.10-0.15, 0.15-0.20, 0.20-0.25 miles B: Circular buffer T: 1 year before / after the subject property sale F: Foreclosure filing P: Single-family, renter-occupied multi-family, owner-occupied multi-family, condominium S: Inventory Y: Jan. 1998-June. 2011	St: log of land square-footage, log of building square-footage, 14 decadal structure age indicators, indicator variables (2 bathrooms, 3 or more bathrooms, masonry exterior, frame and masonry exterior, basement, full basement, finished basement, attic, full attic, finished attic, garage, detached garage, 2 car or larger garage, air conditioning, fireplace) Ma: monthly dummies Fi: N/A So: Tract in 2000: median household income, median home value, median rent, proportion African American, proportion college grad, housing vacancy rate Lo: census block*year Co: N/A	Cross-sectional; Hedonic price model; Regression	<Spillover effects within a 0.05-mile buffer> Single-family type: -1.33%*** Multi-family/Renter occupied: -0.14% Multi-family/Owner occupied: -0.72% Condominium: 0.27%
Gerardi et al. (2015); MSAs (Atlanta, Boston, Chicago, Las Vegas, Los Angeles, Miami, New York, Orlando, Philadelphia, Phoenix, Riverside, Seattle, Tampa, DC)	N=950,234; Fannie Mae , Lender Processing Services	1: Logged sales price 2: Single-family 3: Non-distress 4: All transactions during 2001-2007	M: Count D: 0-0.1, 0.1-0.33 mile B: Circular buffer T: 1 year before sale, 1-2 year before sale F: delinquent mortgage, REO inventory, REO sale P: Single-family S: Inventory, sale Y: 2001-2007	St: physical condition of lender-owned properties (from REO property appraisals), property-level vacancy status (from US postal service) Ma/Lo: triple-interaction fixed effect: geographic fixed effect (census block group, census tract, MSA, or county) So: N/A Co: N/A	Longitudinal; Repeat sales model	<Spillover effects within 0.1-0.25mile buffer> Delinquent mortgage: -0.004*** REO inventory: -0.007*** REO sold in 1 year ago: -0.003*** REO sold in 1-2 year ago: 0.001 <REO inventory by physical condition (within 0.1 mile) > Below average: -0.026*** Above average: 0.020* <Delinquent mortgage by vacancy (within 0.1 mile)> Occupied: -0.009** Vacant: -0.010**

3.3.1.1 Dependent Variable

Studies in the review used the sales price as a dependent variable. Because the sales price is the observed market value from the true transaction based on the market equilibrium between sellers and buyers (Taylor, 2008), the sales price is the applicable dependent variable in the HP model. The sales data were acquired from various sources, including local government offices such as the County Assessor and city departments, private database vendors, and the Multiple Listing Service (MLS). In this review, most studies except two focused on single-family transactions. One study (Kashian & Carroll, 2011) focused on condominiums, and the other study (Campbell et al., 2011) included single- and multi-family homes and condominiums. While some studies (Biswas, 2012; Daneshvary & Clauretie, 2012; Lin et al., 2009; Rutherford & Chen, 2012) predicted the foreclosure effects on non-distressed property values, other studies included both non-distressed and distressed (or foreclosed property) sales as the dependent variable. In most studies, all transactions during the sample periods were estimated, but a few studies (Immergluck & Smith, 2006; Lin et al., 2009) used random draws from all transactions. Studies generally excluded non-arm's length transactions, such as gift and trust deed transfers. Some studies also excluded flipped properties, which were transacted within short time period such as six months (Gerardi et al., 2015; Han, 2014). As a dependent variable, sales transactions with an extremely high or low price were often excluded to avoid a statistical bias with the sample inflated by outliers. The log transformation of the selling price was commonly used across the studies.

3.3.1.2 Independent Variable: Foreclosure Spillovers

As the main independent variable to assess foreclosure spillover effects, studies in the review measured the number of foreclosures within certain distances around each subject property and certain time dimensions prior to the sales. The measurement of neighborhood foreclosures varies across the studies with differences in spatial and temporal dimensions and foreclosure and property types.

First, studies used different radii of buffer areas around a subject home location. The spatial boundary of a neighborhood was mostly operationalized as a circular buffer within the diverse Euclidean distances (e.g., 1/8 mile, 1/4 mile, etc.) of each home. The distance dimensions were generally decided by the empirical evidence in the previous literature and consideration of the characteristics of the study area, such as density (Daneshvary & Clauretie, 2012). To trace the spatial extent of foreclosure externalities, the distance intervals (e.g., 0-1/8 mile, 1/8-1/4 mile, and 1/4-1/2 mile) were exclusively used in most studies. However, a study by Kobie and Lee (2010) used the face block to account for the physical structure of neighborhoods and the visual impact of deterred maintenance on neighborhoods. Cheung et al. (2014) measured the share of foreclosures within a zip code boundary.

Second, most studies measured neighboring foreclosures within a certain time frame prior to the home sales, assuming that the critical spillover effects last for months. The foreclosures were measured at varying time lags in order to detect the temporal extent of foreclosure externalities. There is no clear-cut time frame, but studies often identified the time lags based on the time period that the foreclosure process lasted.

While most studies framed the time span within two years, several studies (Ihlanfeldt & Mayock, 2014; Lin et al., 2009; Rutherford & Chen, 2012) measured foreclosures occurring beyond a two-year time frame. Like exclusive distance intervals, most studies also used smaller time frames (e.g., 0-6 months, 7-12 months, and 13-18 months).

Third, the foreclosure types accounted for at each stage of the foreclosure process were not consistently measured across the studies. These foreclosure types usually included pre-foreclosure, auction, and real estate owned (REO). Some studies measured foreclosure filings after properties fell into mortgage delinquency or entered REO status. These on-going foreclosures are often termed “inventory.” The status of foreclosure changes when it is sold at a certain stage in the foreclosure process, and some studies focused on the foreclosure-related “sales” at certain stages, such as a short sale, sheriff’s sale, or REO sale. Most studies focused on one type of foreclosure such as REO, and a few studies included different types of foreclosures. The data used in one study (Leonard & Murdoch, 2009) included all three types of foreclosures, but they were not separately measured. Only a few studies (Daneshvary & Clauretie, 2012; Daneshvary et al., 2011) included foreclosure-related sales in two or three different stages of the process.

Fourth, most studies considered one property type of foreclosure: single-family homes. Only a few studies considered different property types (Biswas, 2012; Campbell et al., 2011; Hartley, 2014; Zhang & Leonard, 2014), which included single- and multi-family housing to distinguish disamenity effects of foreclosures, although they regressed the single-family home values on foreclosure spillovers. The studies pointed out that any property types of foreclosure may impact neighborhood house prices through dilapidated externalities.

3.3.1.3 Structural Characteristics

Structural characteristics are the most fundamental factors determining property value. The most common measures from the reviewed studies include age, square footage of the building, lot size, the number of bedrooms and bathrooms, and the number of stories. Some studies also included various external features such as garages, pools, and types of foundations. Apart from these characteristics, in some studies (Daneshvary & Clauretie, 2012; Daneshvary et al., 2011; Rutherford & Chen, 2012), the physical condition of a property assessed by appraisal or a real estate agency was included to determine housing value.

3.3.1.4 Market Characteristics

Market characteristics that appear most frequently in the studies are time trends and price trends. All of the studies in this review included various forms of market characteristics, taking into consideration price variation over time. Since it is not only nearby foreclosures but also the decline in nearby home values that are possibly correlated with depressed home values (Schuetz et al., 2008), the trends in the value of nearby homes needed to be controlled for. Studies used the median home value at the census tract level (Immergluck & Smith, 2006; Whitaker & Fitzpatrick IV, 2013) or spatially-weighted average values of nearby houses to control for endogenous correlations (Daneshvary & Clauretie, 2012; Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009). Time trends to capture seasonal effects were generally included in the form of monthly, quarterly, or yearly dummy variables. Time on the market (TOM) was also included in three studies (Daneshvary et al., 2011; Rutherford & Chen, 2012; Wassmer, 2011). Since TOM and sales price are often investigated as interactive variables, Daneshvary et al. (2011) utilized an instrumental estimation to isolate the endogeneity of the price and the TOM.

3.3.1.5 Financial Characteristics

In this review, an indicator of whether or not a property is sold as a distressed property was the most frequent use for financial characteristics. If the observed properties included foreclosed properties as well as market sales properties, financial characteristics were included to control for the distressed effect of its foreclosure status.

3.3.1.6 Socioeconomic Neighborhood Characteristics

Eight studies (Daneshvary & Clauretie, 2012; Daneshvary et al., 2011; Hartley, 2014; Immergluck & Smith, 2006; Kobie & Lee, 2010; Leonard & Murdoch, 2009; Schuetz et al., 2008; Whitaker & Fitzpatrick IV, 2013) included socio-economic characteristics of neighborhoods, such as population density, median income, demographic composition, poverty, education attainment, average household size, housing unit density, vacancy, or owner occupancy. These neighborhood characteristics were measured at the census tract or block group level by data from the Census. Socio-economic characteristics were also used to control for local effects.

3.3.1.7 Locational Neighborhood Characteristics

All reviewed studies included locational indicators to capture local fixed effects that were possibly associated with foreclosures. The most frequently used locational indicators were administratively defined locations (e.g., county, city, community district, postal unit, zip code, tax zone, etc.). Geographical locational indicators (such as latitude and longitude) were also used to account for heterogeneous markets across space (Immergluck & Smith, 2006). The interactions between locations and time trends were also often used across the studies to control for local effects as well as market trends (Anenberg & Kung, 2014; Cheung et al., 2014; Gerardi et al., 2015; Hartley, 2014; Ihlanfeldt & Mayock, 2014).

3.3.1.8 Contextual Neighborhood Characteristics

Six studies covered contextual neighborhood characteristics, which include proximity to arterial roads and subway stops or railroads (Biswas, 2012; Immergluck & Smith, 2006; W. H. Rogers, 2010), and views of golf courses, mountains, parks, or lakes (Daneshvary & Clauretie, 2012). In addition, crime rates that were included as variables of neighborhood safety showed up in only three studies (Biswas, 2012; Immergluck & Smith, 2006; Lin et al., 2009). No study in the review investigated built environmental attributes, which specify land-use patterns (such as density and mixed land-use) or urban form patterns (such as street connectivity).

3.3.2 Associations between Neighboring Foreclosures and Property Value

All studies in the review found a significant spillover effect of foreclosures on nearby property values. In terms of the significance and magnitude, the associations between foreclosure spillovers and property values vary depending on how the studies measured neighboring foreclosures, used control variables to solve endogeneity problems, and moderated the foreclosure spillover effects by neighborhood characteristics and housing markets.

3.3.2.1 Different Associations by Foreclosure Measurements

All of the studies generally showed a diminished effect of foreclosure spillovers with an increased distance from the subject property. The significant impacts of foreclosure were found mostly within a half-mile distance. Some studies (Lin et al., 2009; Rutherford & Chen, 2012) also found significant impacts within a one-mile distance.

Studies showed some variance in the estimated spillover effects at varying temporal lags, which may hinge upon which stage (pre-foreclosure, auction, or REO) the foreclosure was in and whether the foreclosure status was in process or sold (inventory or sale, respectively). Kobie and Lee (2010) found that while foreclosures that had been filed for more than a year were significantly related to the discount of nearby property values, foreclosures that had been filed for less than a year did not have any significance, and the coefficients had positive signs. Other studies (Harding et al., 2009; Ihlanfeldt & Mayock, 2014) found that properties remaining in foreclosure status over a longer period of time had a greater discount impact on property values, but as did the shorter the time after an REO sale (Harding et al., 2009; Ihlanfeldt & Mayock, 2014; Zhang & Leonard, 2014). Daneshvary et al. (2011) found that only short-sale counts in a 0.25-0.5 mile interval were significant, but they had positive signs. Daneshvary and Clauretie (2012) found significant spillover effects for short sales, but the size of the coefficients was smaller than that of REO sales. However, Kobie and Lee (2010) showed a negative impact of the sheriff's sale counts on nearby property values. They also found that the sheriff's sales had a larger size of estimated spillover effects than did foreclosure filings.

Some studies attempted to unravel foreclosure spillover effects on property value by specifying foreclosure conditions or property types. Whitaker and Fitzpatrick IV (2013) also measured foreclosures by integrating conditions such as vacancy or tax delinquency. The results did not clearly identify negative spillover effects of foreclosures when combining these two conditions, but vacant and delinquent homes that were non-foreclosed were negatively associated with nearby property values. Gerardi et al. (2015) found that the poor physical condition of foreclosures, which was assessed by appraisals, made negative spillover effects greater. Hartley (2014) specified the spillover effects with dis-amenity effects and supply effects by including single-family as well as multi-family and condominium types of foreclosures. However, the study did not find statistically distinguishable price effects for other types of foreclosures.

Within each time and distance interval, some studies tested the non-linear effects of foreclosure using either the dummy variables for the presence of foreclosures (Schuetz et al., 2008) or a quadratic form of the count of foreclosures (W. H. Rogers & Winter, 2009). The studies argued that the discount of the subject property value may not be equally affected by additional foreclosure. Schuetz et al. (2008) also noted that using a dummy variable may reduce the problems resulting from unevenly distributed foreclosures.

3.3.2.2 Different Associations by Control Variables Capturing Potential Endogenous Effects

A common concern addressed across the studies is about the endogenous problem raised from the possibility of reverse causality. For example, it is not clear whether lower market prices trigger foreclosures or neighborhood foreclosures worsen home values. To isolate potential endogenous effects from the causality and/or simultaneous bias issues, market characteristics, such as housing price trends or time trends between properties, was given significant consideration across the studies. Most studies in this review often found that the magnitude of spillover effects was attenuated after controlling for the overall market prices or trends. In a study by Daneshvary and Clauretie (2012), the price spillover of short sales became insignificant after controlling for market trends. Immergluck and Smith (2006) incorporated median household income to control for reverse causality and found reduced spillover effects.

Another potential endogeneity could be from unobserved neighborhood or spatial autocorrelation effects. To reduce the bias from potential correlation between foreclosures and unobserved neighborhoods, studies widely incorporated either locational controls or spatially correlated error terms. Studies often found that the spatial correction in error terms changed the size of the negative spillover effects (Daneshvary & Clauretie, 2012; Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009). Most studies found that the negative impact of foreclosure spillovers became smaller or insignificant, but a study by Wassmer (2011) found a larger impact for REO sales.

3.3.2.3 Different Associations by Neighborhood Characteristics and Housing Markets

Most studies were conducted in a generally homogeneous study setting (urban) and housing market (single-family). A few studies examined the different spillover effects with different study settings (e.g., urban versus suburban areas), neighborhood characteristics (e.g., low- versus high-income groups), housing market periods (e.g., bad versus good market periods), or housing submarkets (e.g., smaller versus bigger property sizes and lower versus higher property values). Two studies (Cheung et al., 2014; Groves & Rogers, 2011) examined the mitigating effects of negative price spillovers for properties that were part of homeowner associations (HOAs) or residential community associations (RCAs). The spillover effects were differentiated by these moderating factors.

Urban versus suburban areas

Kobie and Lee (2010) separately tested statistical models for the suburbs, the city, and all county area that included both suburbs and city. They found more negative spillover effects for foreclosure filings and sheriff's sales in the suburban areas than within the city of Cleveland. In addition, within the city of Cleveland, foreclosure filings in any time intervals did not have any significant association with nearby property values. This may be explained by diverse environmental externalities in the city. Incorporating built environmental factors may help to adjust this issue.

Low-income versus high-income groups

Immergluck and Smith (2006) estimated a separate model for the foreclosure spillovers in low- and moderate-income neighborhoods based on the census tracts. They found more vulnerable results of foreclosure spillovers on properties located in low- and moderate-income areas. Whitaker and Fitzpatrick IV (2013) also examined how the impact of foreclosures differs in high-poverty versus low-poverty neighborhoods. They found that a vacant foreclosure created negative impacts on property values in low-poverty neighborhoods, but a positive impact of vacant foreclosures was found in high-poverty neighborhoods. W. H. Rogers (2010) ran a separate regression of neighboring foreclosures on property values for a subsample located in a foreclosure-concentrated and low-income area but found similar results of negative foreclosure impacts with the full sample.

Bad market versus good market periods

Lin et al. (2009) separated the subsamples to investigate different foreclosure impacts by boom versus bust market periods. They identified two different market periods, a boom year in 2003 and a bust year in 2007. They found that the spillover effects during the housing bust year were much worse than those in the boom year. W. H. Rogers (2010) identified a smaller impact of foreclosures in the bust period of 2006-2007 than in the boom period of 2003-2005. W. H. Rogers and Winter (2009) used interaction terms between neighboring foreclosures and time dummies to examine different foreclosure impacts in the good housing market period, 2003-2005, and in the bad housing market period, 2006-2007. They found a smaller foreclosure impact in the bad housing market period.

Housing submarkets

Rutherford and Chen (2012) examined how the price spillovers of foreclosure are different across the submarkets defined by the size of single-family homes. The subsamples grouped by three quartiles were separately analyzed. A larger price spillover effect of foreclosure was found in the large size quartile, and no spillover effect was found in the small size quartile. Zhang and Leonard (2014) used a quantile regression approach to estimate different foreclosure impacts on nearby homes varying across the submarkets represented by four quantiles of housing price distribution. In their study, the most severe price spillover effect of foreclosure was found in lower-priced houses.

Mitigating role of the residential community associations

Groves and Rogers (2011) estimated the positive impact of residential community associations (RCAs) on price externalities of foreclosure by interacting neighboring foreclosures with RCA dummies that indicated whether or not properties were located in an RCA. A study by Cheung et al. (2014) also used interaction terms between the homeowner associations (HOAs) and the share of foreclosure filings in zip codes, and found a mitigating effect of HOAs on price spillovers of foreclosures. They found more significant and ameliorated impacts of HOAs on properties located in larger and younger HOAs.

3.4 Discussions

Studies exploring neighborhood foreclosures and property values have identified several methodological challenges. All cross-sectional studies in this review used the hedonic price model to assess the spillover effects and dealt with the concern of the hedonic regression model regarding endogeneity problems from reverse causation, unobserved neighborhood effects, or spatial effects.

Among various control variables, market-related characteristics were important in considering potential bias that could result from any possible correlations with both foreclosures and sales prices. Because local market trends in low housing prices may influence the depression of housing values which result in more foreclosures, this may result in a reverse causation problem. To minimize the endogeneity problem, the studies included market characteristics, such as housing cycles (Lin et al., 2009), overall market trends (Daneshvary et al., 2011), neighborhood median values (Immergluck & Smith, 2006), or spatial weighted average values of nearby houses in a neighborhood (Leonard & Murdoch, 2009). The property condition variable was also controlled for to mitigate the endogenous problem (Foote et al., 2008). The poor physical condition of a property may aggravate the depression of the value and push the property into foreclosure, but an above-average condition may not be affected by the housing market. The studies (Clauretie & Daneshvary, 2009; Gerardi et al., 2015) found that the property condition assessed by the listing agent was sensitive to the foreclosure correlates of the selling price even though validity problems existed with the assessed data. Groves and Rogers (2011) also demonstrated a significant physical difference between foreclosures and non-foreclosures through a t-test. In addition, studies attempted to eliminate unobserved neighborhood effects or local fixed effects by incorporating locational characteristics such as geographical locations, census tracts, and zip codes, and/or socioeconomic characteristics of neighborhoods at the block group or census tract level. Some studies (Anenberg & Kung, 2014; Gerardi et al., 2015; Hartley, 2014; Schuetz et al., 2008) included foreclosures occurring after the subject property sale in order to capture local effects.

A few studies (Gerardi et al., 2015; Han, 2014; Harding et al., 2009) in the review employed the repeated sales model to overcome the omitted variable bias. Contrary to the hedonic price model, the repeated sales model does not need a large set of variables for property and neighborhood characteristics (Frame, 2010). By taking the differences between observations across time, unobserved effects would be removed

(Case & Shiller, 1989; Harding et al., 2009). However, the repeat sales model needs a data set that consists of observations over time, and it is assumed that unobserved factors are constant over time. If the unobserved neighborhood effects covary with observed factors over time, the repeated sales model could be biased (Harding et al., 2009). Due to data availability and methodological limitations, the repeated sales model is not appropriate for the case of a dynamic housing market area where frequent neighborhood changes occur (Daneshvary & Clauretie, 2012).

As an alternative, the cross-sectional studies in the review employed a modified regression model that accepted spatial effects for capturing unobserved neighborhood effects. A simple way to handle observed spatial effects underlying real property markets is by adding variables to the statistical model, such as distance to amenities or locational indicators (Pace et al., 1998). However, it may be impossible to incorporate all variables into the model to capture spatial effects. Too many variables can also lessen the power of the degree of freedom (Valente et al., 2005). Pace et al. (1998) noted that spatial effects were not clearly controlled for even after incorporating various locational variables. Studies in the review captured spatial effects by specifying the error terms with spatially weighted covariance structures. With the advance of statistical tools, the application of sophisticated spatial modeling is growing. In the studies (Daneshvary & Clauretie, 2012; Groves & Rogers, 2011; Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009; Whitaker & Fitzpatrick IV, 2013), both spatially lagged error and dependent variables were incorporated to capture unobserved neighborhood effects and spatial interactions between neighboring housing prices.

In addition to the omitted variable bias, an endogeneity problem is often found in the estimation of the regression model due to a simultaneous bias or measurement error (Wooldridge, 2013). The simultaneous bias can arise from the explanatory variables which are jointly determined with the dependent variable (Taylor, 2008; Wooldridge, 2013). The TOM is often used to reduce the potential simultaneous bias problem (Taylor, 2008). For example, a higher price of a property may affect the length of time that a property is listed on the market (Sirmans et al., 2005). However, a study by Daneshvary et al. (2011) found that the results of foreclosure spillover effects controlling for the TOM variable was consistent with other existing studies that did not include the TOM variable. Further, the effect of TOM became insignificant when spatial correlations were accounted for in the model.

Although all of these efforts might help to produce the unbiased estimates of price spillovers of foreclosures, little has been examined about unobserved neighborhood effects with respect to built environmental attributes. The literature that explored the economic values of built environments identified determinants that set the price premiums. The built environmental correlates of property values include urban-form related elements such as accessibility to destinations (Leinberger & Alfonzo, 2012), street connectivity (M. Duncan, 2010), street layout (Matthews & Turnbull, 2007), sidewalk density (Sohn, Moudon, & Lee, 2012), average sidewalk width (Diao & Ferreira Jr, 2010), and steepness of the terrain (M. Duncan, 2010), and land-use related elements such as land-use mix (Koster & Rouwendal, 2012) and residential density (Song & Knaap, 2004). In the literature, environmental features have also been reported as significant correlates of foreclosures (Gilderbloom, Riggs, & Meares, 2015) or mortgage default risks (Pivo, 2014). Gilderbloom et al. (2015) found that an area with a higher walkability had a smaller number of foreclosure sales. Pivo (2014) found that a mortgaged property in a neighborhood having sustainable environmental features had lower default risk. Other social environmental measures such as crimes were found to be negatively associated with property values (Linden & Rockoff, 2008), and researchers also found significant relationships between foreclosures and crime activities (Ellen et al., 2013; Katz et al., 2013). In this review, while a few studies included contextual attributes of neighborhoods, such as proximity to railroads and view to park, no study included specific elements of built environments, such as density, land-use mix, street connectivity, or accessibility to amenities, which might have the potential to increase or decrease foreclosure activity. Therefore, for future research, foreclosure spillover effects need to be investigated in conjunction with built environmental attributes, which are underrepresented in the foreclosure literature.

Another key issue in examining the spillover effects is the measurement of foreclosures. Although little research mentioned measurement errors, the hedonic function may cause bias in the measurement error when the property information is not consistently recorded (Taylor, 2008). If the error is caused by randomly assigned factors and is not correlated with other explanatory variables, the estimation may not be biased (Wooldridge, 2013). To measure foreclosures, all studies in the review used counts of foreclosures at different distances from the sales property and at different time periods during the foreclosure process. The studies in the review demonstrated that the spillover effects abated with distance. However, the effects of foreclosure spillovers varied over time, and a definition of an adequate buffer size to consider the foreclosure spillovers still remains unclear.

Most studies in the review constructed a circular buffer around the centroid of each subject property. However, an equal neighborhood delimitation may not be applied to all targeted neighborhoods in study areas because the spatial extent of foreclosure externalities could vary across neighborhood settings. While the study by Kobie and Lee (2010) used the face block, which takes into consideration the spatial structure of neighborhoods, recent studies in urban planning and transportation often delineate a neighborhood by using a network buffer, which is based on a street-network distance. The network buffer may account for actual delimitation where people can move around their neighborhoods. The application of an adequate neighborhood definition to the foreclosure literature would be an area for future research.

Within a spatial boundary, early published studies measured foreclosures without indicating the foreclosure stage, which might be due to a lack of complete information in data sources and data availability. For example, while some studies (Immergluck & Smith, 2006; Schuetz et al., 2008) measured foreclosures based on loan performance or mortgage default data, others (W. H. Rogers & Winter, 2009) measured foreclosure filings based on deed information. Also, it was not clearly identified whether a foreclosure process was on-going or completed. Considering the dynamic nature of foreclosure, neighboring foreclosures should be measured by the most recent status of foreclosures in process with all relevant dates from which foreclosed properties enter a certain stage or are sold. Recent studies (Gerardi et al., 2015; Hartley, 2014; Ihlanfeldt & Mayock, 2014; Whitaker & Fitzpatrick IV, 2013; Zhang & Leonard, 2014) have disentangled negative externality effects (such as blight, valuation, and supply) through which nearby property values decreased. The studies measured foreclosures separately by foreclosure stage (pre-foreclosure, auction, and REO) and status (inventory and sale), property types (single-family, multi-family, and condominium), and/or property conditions (e.g., vacant and tax delinquent).

In addition to the methodological issues, several studies have identified differential foreclosure effects on property values for different neighborhood settings (urban versus suburban), housing market periods (bad versus good), and housing submarkets (lower versus higher property values and smaller versus bigger property sizes). Because the differential effects were inconsistent across the studies, no firm conclusions could be drawn. The variations in the study areas, time periods, foreclosure measurements, and statistical methodologies may have contributed to the mixed findings. Further research is encouraged to attain consistent findings. Two studies found that the negative price spillovers of foreclosures were ameliorated for properties located in RCAs (Groves & Rogers, 2011) and HOAs (Cheung et al., 2014). For future research to expand on the previous research, it might be important to examine the potential mitigating role of environmental intervention in curtailing spillover effects of foreclosures.

3.5 Conclusion

This review highlights methodological issues and illustrates that foreclosure measurement in particular. Specifying foreclosure measures over time is encouraged to account for causality channels through which foreclosures impact nearby property values. To date, sufficient evidence suggests that neighboring foreclosures influence property values. However, knowledge gaps still exist in addressing how foreclosure spillover effects are different based on neighborhood settings, housing submarkets, and market periods. Furthermore, important environmental interventions to reduce spillover effects are a suggested research area.

Neighborhood characteristics would also be important for examining foreclosure spillovers and property value relationships, as research related to contextual neighborhood environments may contribute to the further establishment of policy intervention programs such as the Neighborhood Stabilization Program, which has targeted the recovery of neighborhood quality from foreclosure impacts. With advances in data collection and foreclosure measurement, more sophisticated study designs, such as a longitudinal approach, would assist in drawing intervention-driven conclusions. More research to fill the knowledge gaps would strengthen the evidence base for coping with current foreclosure problems and provide insights for preventing a future foreclosure crisis.

CHAPTER IV

PRICE SPILLOVERS OF FORECLOSURES AND NEIGHBORHOOD WALKABILITY [*]

Since 2007, many studies have explored the price spillovers of foreclosures. However, the potential moderating effects of built-environment characteristics such as walkability have not been examined. By utilizing interactions between foreclosures and walkability, this study found that properties in walkable neighborhoods are more resilient to the foreclosure spillover effects on property values; however, the mitigating effects are only significant for middle-high-income communities. Walkable neighborhoods also provided more effective advantages in maintaining neighborhood stability during the recovery of 2013, compared to the market crash of 2010. This study supports walkability related development strategies and policies to achieve neighborhood stability and livability.

4.1 Introduction

The foreclosure surges after 2007 exacerbated negative externalities in neighborhoods by devastating neighborhood quality (e.g., increasing vacant or abandoned homes, contributing to growing crime rates) and disrupting the housing

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market (e.g., depressing the value of neighboring homes, increasing housing stocks in a supply market). These consequences have urged policy makers to find adequate responses to the foreclosure crisis. Studies have documented the price-depressing effects of foreclosure on nearby property values as evidence of its negative spillover (Harding et al., 2009; Hartley, 2014; W. H. Rogers & Winter, 2009). However, most previous studies have focused on the mechanism of price spillover of foreclosure and the estimation of its magnitude. Going beyond foreclosure itself, further attention is needed to understand the potential roles of built environmental characteristics such as walkability that can alleviate or aggravate the spillover effects.

Recent urban studies have focused on the positive externalities of walkable neighborhoods including public health (e.g., physical activities), environmental (e.g., clean travel modes), and socio-economic dimensions (e.g., sense of belonging, property value premium) that anchor the concepts of sustainable communities (Dannenberg et al., 2011). Emerging studies in the real estate field have demonstrated the pricing premiums of the walkable or pedestrian-oriented built environment, one of the key planning principles commonly advocated by New Urbanism, Compact City, and Traditional Neighborhood Development (TND). These studies have only attempted to identify neighborhood walkability that elicits economic benefits, and have not explored whether or not walkable neighborhoods can mitigate the impact of negative externalities, such as foreclosures, on property values.

This study aims to fill this gap by examining how walkability-related environments interact with the negative spillover effects of foreclosures on property values. Walkability is increasingly recognized as an important means to achieve neighborhood sustainability (Farr, 2008) which can help reduce vulnerability to adversity and risk (Callaghan & Colton, 2008). By analyzing the sales transactions of single-family properties in Los Angeles during 2008-2013 and utilizing the Walk Score as a measure of neighborhood walkability, this dissertation investigated whether higher neighborhood walkability can mitigate the negative impact of neighboring foreclosure on sales prices. This dissertation also examined if such a mitigation effect differs between the housing market crash period of 2010 and the housing market recovery period of 2013. I hypothesized that the mitigation effect is more significant during the recovery period, indicating that neighborhood walkability provides an effective advantage in the housing market recovery.

While foreclosures spread during the recession, they have been inequitably distributed according to the socio-economic status (SES) of communities. Research shows that low-income and minority communities experience a higher level of foreclosures. They carry greater social costs (Apgar et al., 2005), which may make it harder for communities to recover from the crisis. In addition to income disparities in foreclosures, research shows low SES communities have poor neighborhood design/maintenance and limited opportunities for walking especially for recreational purposes (Sugiyama, Neuhaus, Cole, Giles-Corti, & Owen, 2012). Although people of low SES sometimes have more utilitarian destinations, the quality of social and physical environments are less privileged than other groups (Sallis et al., 2011). This study therefore separately examines the impact of neighborhood walkability on foreclosure spillover effects among higher versus lower income neighborhoods. I hypothesized that the mitigating role of walkability is greater in higher income neighborhoods than in lower income neighborhoods. This approach will help draw additional insights related to the potential disparities in neighborhood residence and walkability.

4.2 Literature Review

4.2.1 Impact of Foreclosure Spillovers on Property Values

Since 2007, an increasing number of studies have explored the negative associations between subject property values and nearby foreclosed properties. While the size of the spillover effects varied across the studies depending on study locations and time periods, statistical model specifications, control variables, and foreclosure measurements, these studies generally found an approximately 1-2% decrease in property values for each neighboring foreclosure (Daneshvary & Clauretie, 2012; Immergluck & Smith, 2006; Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009).

A key methodological challenge in addressing the spillover effects of foreclosures is related to the generation of unbiased estimates. Among various control variables to reduce the threat of endogeneity such as omitted variable bias or reverse causation, the previous studies significantly considered market-related characteristics, such as neighborhood median values at the census tract level (Immergluck & Smith, 2006), housing market trends (Daneshvary et al., 2011; Lin et al., 2009), or spatially weighted average prices of nearby homes (Leonard & Murdoch, 2009). In addition to the market-related factors, some studies also included geographical boundary dummy variables such as census tracts and zip codes (Cheung et al., 2014; Schuetz et al., 2008) or socio-economic factors (Leonard & Murdoch, 2009). However, while previous studies have suggested various neighborhood controls to estimate the spillover effects, potential endogeneity with respect to unobserved built environmental effects has rarely been addressed. Incorporating various built environmental measures, our study aims to reduce the potential bias of foreclosure spillover effects.

Another challenge is the measurement of foreclosures, which includes delineating adequate neighborhood boundaries. With regard to the spatial boundary or extent of foreclosure externalities, an equal distance circular buffer around each subject property was commonly used in previous studies. Discrepancy might exist between the circular and actual delimitation of a neighborhood where people move around often along streets (Moudon et al., 2006). While recent studies in the urban planning and transportation fields often used a network buffer created by measuring a distance along the street network, no foreclosure-related studies have used a network buffer. The use of a network buffer in this paper will help capture neighborhood exposures and walkability with increased accuracy.

Within certain distance bands, most studies counted the number of foreclosures entering but not remaining at a certain stage during the process (pre-foreclosure, auction, real estate owned (REO), short-sale, or REO sale). However, because foreclosure involves a dynamic process, it may be more accurate to count a foreclosure by its status in the process (Ihlanfeldt & Mayock, 2014). For example, although a REO property that begins at some point is considered a spillover on a nearby property value, it is not clear if the REO status lasts for a certain time period before the sale of the subject property. The foreclosed property can be settled back to a normal property. Therefore, it is more reasonable to measure most recent status of foreclosures from all available transactions.

4.2.2 Impact of Walkability on Property Values

The positive externality of the walkable environment has been demonstrated in various fields of literature. Urban planning and transportation researchers have examined the effect of pedestrian-friendly environmental factors, such as mixed land-uses, street connectivity and sidewalk availability, on walking or travel mode choice (Ewing & Cervero, 2010; C. Lee & Moudon, 2004). Public health researchers have examined neighborhood walkability as a means to promote walking and other outdoor activities for health purposes (Saelens & Handy, 2008; Sallis et al., 2015). Studies have also used an interdisciplinary approach to consider transportation, health, and social (e.g. social capital, quality of life) benefits of walkable environments (Leyden, 2003; S. H. Rogers, Halstead, Gardner, & Carlson, 2011). Such positive effects of walkability may be translated into higher home values in a more walkable area.

Empirical evidence has shown a higher price increase ranging from 4% to 25% for single-family homes located in pedestrian-friendly neighborhoods (Eppli & Tu, 1999). The built environmental correlates of property values include urban-form related elements such as accessibility to destinations, street connectivity, street layout, sidewalk density, and steepness of the terrain (Diao & Ferreira Jr, 2010; Matthews & Turnbull, 2007); and land-use related elements such as land-use mix and residential density

(Koster & Rouwendal, 2012; Kupke, Rossini, & McGreal, 2012). Prior research also included other social and physical environmental measures associated with property value, such as crimes, crashes, and proximity to transit stations, highways, and railroads (W. Li et al., 2015).

In addition to these individual attributes, a composite measure of walkability has also been used. The use of a composite measure has the advantage of avoiding potential multicollinearity problems commonly found among environmental variables (Frank et al., 2010) and may reduce the complexity of the statistical model specifications. One popular composite measure is the Walk Score (WS) which is based on proximity to various walkable destinations (e.g., retails, shops, parks, educational, entertainment, etc.), population density and street connectivity (intersection and block length). The WS utilizes a nonlinear decay function to give full weights to destinations within 0.25-mile distances (approximately a 5-minute walk[8]) and lower weights up to 1.5 miles of an address. The WS, provided as a normalized score (from 0 to 100), is used to categorize the area into five levels of walkability (Carr, Dunsiger, & Marcus, 2010; D. T. Duncan, Aldstadt, Whalen, Melly, & Gortmaker, 2011): car-dependent, only available for driving (0-24), car-dependent with a few walking destinations (25-49), somewhat walkable (50-69), very walkable (70-89), and walker's paradise (90-100).

Although WS is not a complete or error-free measure of walkability (Manaugh & El-Geneidy, 2011), it has been proved to be a fairly valid and reliable walkability

[8] A three mile per hour walk speed is assumed.

measure (Carr et al., 2010; D. T. Duncan et al., 2011); it has been increasingly used in academic research, partly due to its simplicity and availability for individual addresses. Prior research showed the positive impact of WS-measured neighborhood walkability on residential property values (W. Li et al., 2014, 2015; Rauterkus, Thrall, & Hangen, 2010). Despite the growing literature on the role of walkability, a study by A. Boyle, Barrilleaux, and Scheller (2014) found that the significance of walkability (measured as WS) on housing prices disappeared when controlling for unobserved fixed effects. They pointed out that specified models in the previous literature had not been sufficiently controlled for unobserved neighborhood-level variations, and also noted the difficulty of capturing neighborhood characteristics using the same neighborhood delineation. Therefore, by holding sufficient neighborhood controls within the defined delimitation around each home, this dissertation improved the model specifications. The details are described later in the methods section.

4.2.3 Neighborhood Walkability and Foreclosure Spillovers

This study contributes to the line of research on the negative spillover effects of foreclosures, and links it with the literature on the economic benefits of neighborhood walkability. The mechanisms through which positive externalities of walkable environments are produced, as described earlier, could avert the price declines related to neighboring foreclosures. To our knowledge, this is the first study that investigates if and how walkable neighborhoods are more resilient to negative spillover effects of foreclosure on property values.[9] To demonstrate this, this study used the interaction term between neighborhood foreclosures and the WS as a walkability measure.

4.3 Methods

4.3.1 Study Design and Area

This study design is cross-sectional. The repeat-sales model, which is often employed for overcoming the limitations of the cross-sectional approach (Gerardi et al., 2015; Harding et al., 2009), may not be appropriate for this study which estimates the impact of time-invariant measured neighborhood characteristics. In addition, this study assessed and compared the spillover effects of foreclosure during two different time periods, the housing market crash period of 2010 and the housing market recovery of 2013; and therefore, the cross-sectional approach was employed for our analyses.

The city of Los Angeles was selected as the study area where a large number of foreclosures and diverse populations and neighborhoods are located. In 2010, approximately 546,000 foreclosure cases were recorded in California, the highest number among all U.S. states (RealtyTrac., 2011). The total population in Los Angeles was approximately 3.8 million in 2010 with a median household income of $49,497. The population consisted of 48.5% Hispanics or Latinos, 28.7% non-Hispanic Whites, 11.3% Asians, and 9.6% African Americans (US Census Bureau, 2010). Neighborhoods in Los

[9] A recent study by Cheung et al. (2014) showed conceptual similarity in terms of testing how negative spillover effect of foreclosure can be mitigated. They examined the effectiveness of the Home Ownership Association (HOA) in bearing the negative impact of foreclosures, using the interaction term between mortgage delinquency rate within the zip code boundary of the subject properties and the HOA indicator. They found that the property under HOA is less likely to be influenced by threats of properties under mortgage defaults.

Angeles represent large variation in socio-demographics, geography, urban development history, and urban/suburban/exurban settings. Figure 5 illustrates the trends of single-family foreclosures within the city of Los Angeles from 2007 to 2013 on an annual basis. The number of new foreclosure filings and sales rapidly increased from 2007 to 2009, exceeding 40,000 at its peak in 2009, and then decreased. The foreclosure trend in our dataset requires separate analyses of the spillover effects for the market crash period where foreclosures trended upward and for the post-crash housing market where foreclosures trended downward.

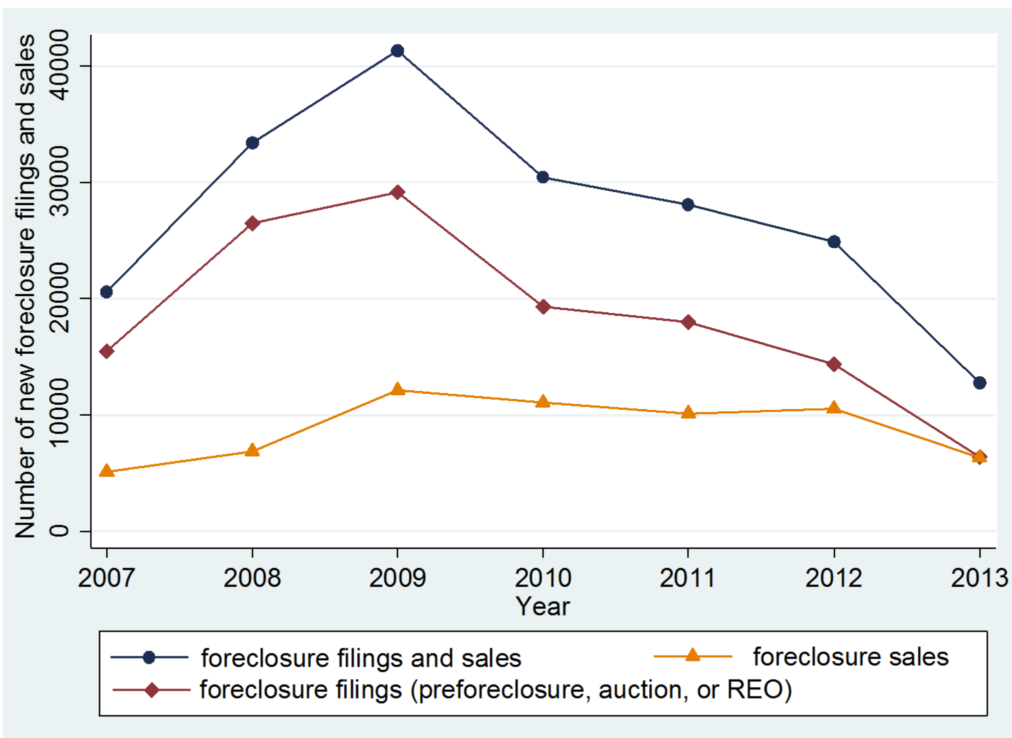

Figure 5. Foreclosure Trends in the City of Los Angeles

4.3.2 Data

The property sales and foreclosure data were obtained from a private database vendor, Property Radar. The sales data include sales information (sales price, transfer dates, and transfer types) and parcel-level details (property characteristics and location information). The transfer type indicates whether a transaction was a full-value market transfer, foreclosure short sale, or REO sale; the relevant information that Property Radar provided was based on records from the county assessor's and recorder's offices. The sales data for the city of Los Angeles included a total of 17,488 single-family sales transactions from January 2010 to December 2010 and 19,100 single-family homes transactions from January 2013 to December 2013. Two separate datasets for home sales in 2010 and 2013 were cleaned by removing transactions that had incomplete information (e.g. zero square footage of a building), duplicates, and non-market transactions. This study also excluded transactions recorded as the top and bottom 1 percentile of the total sales prices (3,300,000/86,000 for the 2010 sample and 3,452,500/109,500 for the 2013 sample), which can be regarded as outliers for the statistical analysis. After data cleaning, I finalized the datasets including 13,438 transactions for 2010 and 14,502 transactions for 2013. The final datasets were geocoded by linking the Assessor's Pin Number (APN) to the parcel data provided as a

Geographic Information System (GIS) shapefile format. The spatial distribution of single-family sales in the city of Los Angeles is depicted in Figure 6.[10]

The foreclosure data contained information on foreclosure stages (pre-foreclosure, auction, and bank owned), recording dates when properties entered a certain stage of the foreclosure process, and parcel-level details. The sales data was combined into the foreclosure data by matching the APN in order to obtain the information on whether a foreclosure was sold or not.

The Walk Score (walkscore.com) was used for the measure of neighborhood walkability. The geospatial data about neighborhood environments were collected from the websites published by the Los Angeles County Department of Regional Planning (land uses, streets, bike lanes, crashes), the Metropolitan Transportation Authority (bus stops, rail stations), the Sheriff's Department (crimes), and the U.S. Census Bureau (socio-economics). The data were either already digitized as GIS shapefiles by providers or contained geospatial information (such as X and Y coordinates). ArcGIS 10.2 was used to generate and analyze the geospatial data.

[10] Figure 6 illustrates the distribution of the density of single-family home sales per acre in each census tract for 2010 and 2013. The density change of single-family sales per acre in each census tract is also illustrated in Appendix A.

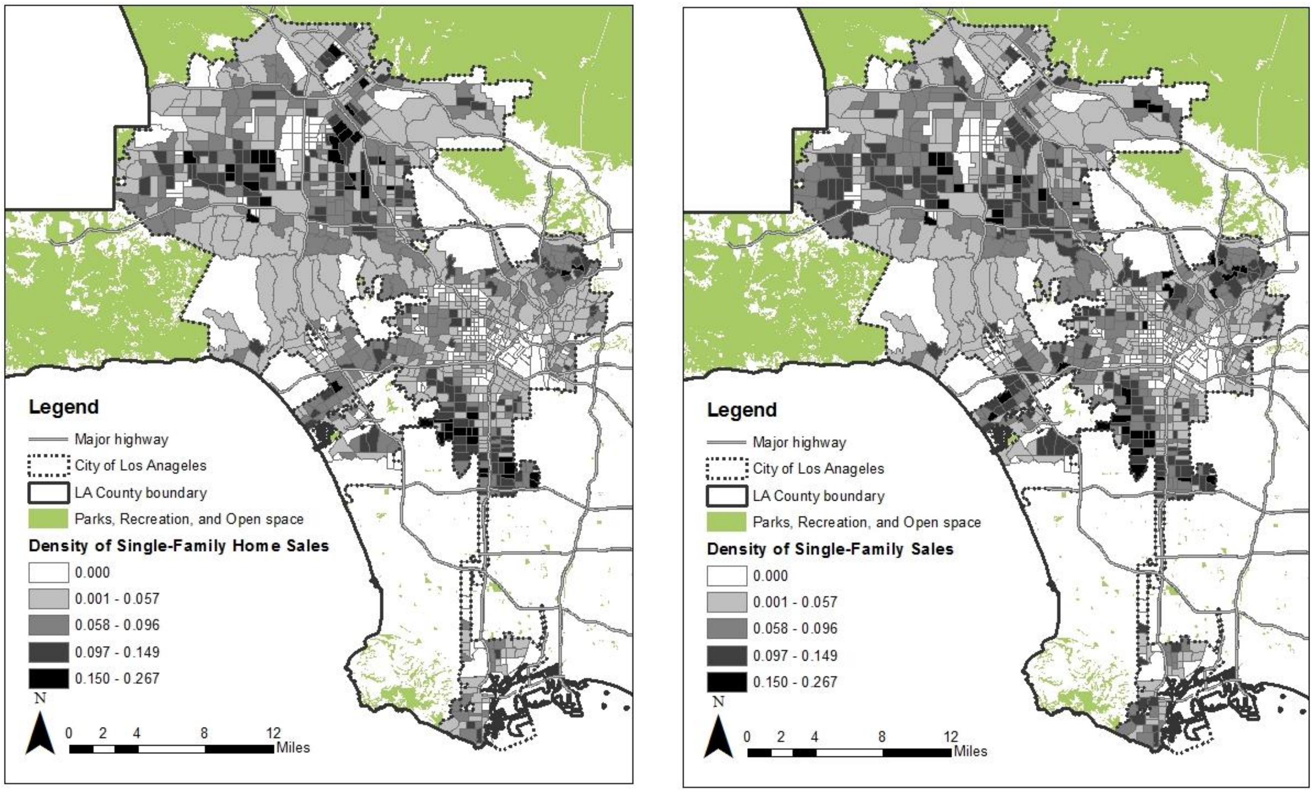

Figure 6. Distributions of the Density of Single-Family Sales in 2010 (left) and 2013 (right) per Census Tract

Note: The density was calculated by dividing a total count of single-family home sales by the acre of each census tract. The maps are based on our final datasets including 13,438 single-family transactions in 2010 and 14,502 single-family transactions in 2013.

4.3.3 Variables and Measurements

The log-transformation of the single-family home sales price was our dependent variable. The 1/4 mile network buffer was selected to generate the foreclosure and built environment variables for each property because the literature suggested 1/4 miles as an effective neighborhood boundary for detecting significant price spillovers of foreclosures (Daneshvary et al., 2011; Gerardi et al., 2015; Hartley, 2014; Immergluck & Smith, 2006). Such a distance, equivalent to approximately 5 minutes of walk time, has also been identified as a comfortable walking distance (Moudon et al., 2006).

The foreclosure variable was measured as the count of the most recent stage of foreclosure within 1/4 mile from a transacted property during a two-year time frame prior to the sales transaction.[11] A two-year window was used because foreclosed properties generally remain in foreclosure status for about one to two years (Harding et al., 2009; Schuetz et al., 2008); Lin et al. (2009) demonstrated that a two-year time frame for foreclosure filings had the most significant impact on nearby property values. Research showed that properties foreclosed for over a year were significantly related to the discount of the nearby property value (Gerardi et al., 2015).

In addition to using the continuous WS, the WS was converted into three levels of walkability to facilitate more straightforward interpretations and to assess non-linear marginal effects: car-dependent (WS: 0-50), walkable (WS: 50-69), and very walkable

[11] This study combined foreclosure inventory (pre-foreclosure, auction, REO) and sales (short-sale, REO-sale) into one foreclosure variable. If a short- or REO-sale was sold again in a normal market transaction during the two-year time window prior to sales transaction, it was not counted.

(WS: 70-100). Considering the multi-dimensional nature of the built environment, additional variables were included: residential density, average speed limits, and presence of bike lanes, highways, rail roads, bus stops and parks. These variables were measured as dummy variables (whether each was present or absent in the buffer) due to skewed and unbalanced distributions. To capture safety conditions of the neighborhood, which is an important determinant of walkability (Saelens & Handy, 2008), speed limits, crash density, and crime density were included.

The structural characteristics of properties include lot size, number of bedrooms and bathrooms, presence of a pool, presence of a garage, year built, and number of stories (single or multiple stories). A dummy variable indicating whether or not a sales transaction was a foreclosure sale was included to parcel out its own discount effect. The monthly and geographical dummies were included to control for the seasonality and locational fixed effects. The eight regions from the Service Planning Areas of LA, which are aggregated from census tracts, were used for our geographical dummies. Median household income, unemployment rate, and percentage of housing unit with mortgages were included to capture socio-economic status (SES), which came from the 2013 American Community Survey (ACS) 5-year (2008-2013) estimates. To measure SES within the 1/4 mile buffer area, this study calculated the weighted average of SES characteristics based on the proportion of block group areas overlapping within the buffer area.[12] A number of other SES variables, such as race and poverty level, were generated but determined inappropriate due to the multicollinearity problem.

4.3.4 Analytic Methods

This study uses the hedonic price model (HPM) developed by Rosen (1974) to assess neighborhood externalities. A log-linear functional form was used due to several advantages highlighted in the literature. According to Malpezzi (2003), the log-linear form offers several advantages in terms of an easy interpretation of the coefficients, an easy computation, and a flexible specification. The regressors are adequately transformed based on the assessment of each variable through scatterplots and histograms. This study incorporated the interaction terms between neighboring foreclosures and walkability in the hedonic specification as follows:

$$\mathbf{y} = \boldsymbol{\alpha} + \mathbf{Z} \cdot \boldsymbol{\beta} + \mathbf{X} \cdot \boldsymbol{\gamma} + \mathbf{u} \tag{4.1}$$

where $\boldsymbol{y}$ is an $n \times 1$ vector of the log-transformed selling prices; $\mathbf{Z}$ is an $n \times k$ matrix of control variables as described in Table 1; $\mathbf{X}$ is an $n \times k$ matrix of independent variables to be tested: neighborhood walkability ($\mathrm{H_i}$), neighboring foreclosure stocks ($\mathrm{F_i}$), and interaction term ($\mathrm{H_i} \cdot \mathrm{F_i}$ for $i = 1, 2, \ldots, n$); $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the parameters to be estimated; and $\mathbf{u}$ is the error term.

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[12] In order to obtain more precise measures of SES, this study calculated the weighted average of SES based on residential areas in block groups, not whole block group areas. For example, if 50% of the residential area of block group 1 and 30% of the residential area of block group 2 overlap within the 1/4 mile buffer of the subject property, the total number of unemployed population within the buffer is 0.5 × the total number of unemployed population in block group 1 + 0.3 × the total number of unemployed population in block group 2.

This study performed the Lagrange Multiplier (LM) test by Anselin and Rey (2014) and detected potential spatial dependency in both the dependent variable and the error term.[13] Therefore, the spatial hedonic model was employed to address the spatial interdependence between neighboring properties. A spatially lagged dependent variable could capture the influence of neighboring properties' values on a subject's property value. This can help resolve a reverse causality problem from any possible correlations with both foreclosures and sales prices. A spatially lagged error variable could help us mitigate the risk of potential unobserved neighborhood externalities and heterogeneities (Anselin & Lozano-Gracia, 2008). To consider both a spatially lagged dependent variable and error term, the Cliff-Ord spatial regression model was used as follows (Anselin & Rey, 2014; Cliff & Ord, 1981):

$$\begin{aligned} &\mathbf{y} = \boldsymbol{\alpha} + \mathbf{Z} \cdot \boldsymbol{\beta} + \mathbf{X} \cdot \boldsymbol{\gamma} + \boldsymbol{\lambda} \cdot \mathbf{W} \cdot \mathbf{y} + \mathbf{u} \\ &\mathbf{u} = \boldsymbol{\rho} \cdot \mathbf{W} \cdot \mathbf{u} + \boldsymbol{v} \qquad (4.2) \\ &\boldsymbol{v} \sim \mathbf{N}(\mathbf{0},\ \boldsymbol{\sigma}^{\mathbf{2}}\mathbf{I}) \end{aligned}$$

where $\mathbf{W}$ is the $n \times n$ spatial weight matrix; $\mathbf{W} \cdot \mathbf{y}$ is the spatially lagged dependent variable; $\mathbf{W} \cdot \mathbf{u}$ is the spatially lagged error term; λ and ρ represent the magnitude of spatial dependence between observations; and $\boldsymbol{v}$ is the iid error term. For the weight matrix, this study adopted the inverse distances among observations within 1/4 mile to be consistent with our measurement of the built environments within a 1/4 mile spatial

[13] The test values of Moran's I are 58.85 ($p<0.0001$) from the 2010 sample and 64.09 ($p<0.0001$) from the 2013 sample. The test values of LM-lag and LM-error are 465.6 ($p<0.0001$) and 3033.7 ($p<0.0001$) from the 2010 sample and 598.2 ($p<0.0001$) and 4071.8 ($p<0.0001$) from the 2013 sample, respectively.

boundary of each property. The different approaches of weight matrices, such as k-nearest and binary weighting matrix, were also tested for the robust check. The coefficient results were similar in terms of size, significance and direction. To estimate Equation (4.2), this study followed Kelejian and Prucha's suggestions by using the generalized spatial two-stage lease square (GS2SLS) for removing the possible endogeneity of $\mathbf{W} \cdot \mathbf{y}$ and the generalized method of moments (GMM) for producing more efficient estimates (Kelejian & Prucha, 2010b). Prior studies (Leonard & Murdoch, 2009; W. H. Rogers & Winter, 2009) found that actual foreclosure spillover effects were attenuated after spatial weighted average values of nearby houses in neighborhoods were accounted for. Therefore, in this model, a smaller size of coefficients were expected. The GeoDa Space Program developed by the GeoDa Center at Arizona State University was used to conduct the spatial regression analyses.

Based on the same modeling approach shown above, we also estimated the influence of walkability on the foreclosure spillover effects for subsamples of two income groups: the samples were divided into the low-moderate-income group, which is below 80 percent of the city of LA's household median income, and middle-high-income group, which is 80 percent and over. The median household income from the ACS estimates at the census block group level is used to determine income level at each subject property location. The relevant results enable us to describe the existence of income disparities in the resilient impact of neighborhood walkability.

4.4 Results and Discussions

4.4.1 Summary Statistics

The summary statistics of variables are displayed in Table 2. As expected, the statistics show the differences of the market conditions between the housing market crash in 2010 and the housing market recovery in 2013. In the dataset, compared to the 2010 sample, the 2013 sample shows more home sales transacted, higher sales prices on average, less depressed sales, and less neighboring foreclosures on average. Both samples also showed that around 62% of total home sales were located in an area with WS of over 50, indicating more homes were sold in walkable neighborhoods. The average crime density in the 2013 sample was higher than the crime density in the 2010 sample. It may be that crime activities increase in a change of economic conditions with a lag, following an economic recession, and a certain type of crime, such as property crime, responds more to economic recovery. Other variables have similar statistics in both the 2010 and 2013 samples.

Table 2. Variable Descriptions and Summary Statistics

Variables	Descriptions	2010 (N=13,438) Mean/Freq. (S.D./%) Min.-Max.	2013 (N=14,502) Mean/Freq. (S.D./%) Min.-Max.
Dependent variable			
Sale price ($)	Continuous: Single-family home sales price	519331 (441,772) 86000-3300000	631257 (485820) 110000-3450000
Log (Sale price)	Continuous: Log-transformed sale price	12.91 (0.67) 11.36-15.01	13.14 (0.63) 11.61-15.05
Property characteristics			
Log (lot size)	Continuous: Log-transformed square footage of lot size	8.88 (0.43) 7.05-12.03	8.88 (0.45) 6.84-11.74
Year built	Continuous: Year built	1952.52 (18.57) 1890-2010	1951.06 (18.12) 1887-2013
Beds	Continuous: Number of bedrooms	3.08 (0.92) 1-9	3.03 (0.94) 1-11
Baths	Continuous: Number of bathrooms	2.06 (0.96) 1-9	2.02 (0.94) 1-9
Story	Binary: 1=a property has 2 or more stories 0=otherwise	1577 (11.74%) 11861 (88.26%)	1912 (13.18%) 12590 (86.82%)
Pool	Binary: 1=a property has a pool 0=otherwise	2735 (20.35%) 10703 (79.65%)	3035 (20.93%) 11467 (79.07%)
Garage	Binary: 1=a property has a garage 0=otherwise	11607 (86.37%) 1831 (13.63%)	12799 (88.26%) 1703 (11.74%)
Financial characteristics			
Depressed sale	Binary: 1=a property is sold as a foreclosure 0=otherwise	5039 (37.50%) 8399 (62.70%)	1930 (13.31%) 12572 (86.69%)

Table 2. Continued

Variables	Descriptions	2010 (N=13,438) Mean/Freq. (S.D./%) Min.-Max.	2013 (N=14,502) Mean/Freq. (S.D./%) Min.-Max.
Socio-economic characteristics of neighborhood			
Income [a]	Three categories: Median household income		
	1=low/moderate income group	2152 (16.01%)	2035 (14.03%)
	2=middle income group	3459 (25.74%)	3463 (23.88%)
	3=high income group	7827 (58.25%)	9004 (62.09%)
Unemployment [b]	Continuous: Unemployment rate	11.52 (4.38) 0-30.51	11.27 (4.30) 0-31.91
Mortgage [c]	Continuous: Percentage of housing units with mortgages	77.11 (7.26) 42.35-100	76.91 (7.19) 7.87-100
Safety and Built environmental Characteristics			
Crime density	Continuous: [=total number of crimes during 2008-2009 (2011-2012) / total acres of a buffer in the 2010 (2013) sample]	0.06 (0.33) 0-12.94	0.12 (0.61) 0-25.40
Crash density	Continuous: [=total number of crashes during 2008-2009 (2011-2012) / total acres of a buffer in the 2010 (2013) sample]	0.17 (0.19) 0-2.20	0.15 (0.18) 0-1.50
Residential density	Continuous: [=total residential units / total acres in a buffer]	4.76 (1.44) 0.99-21.36	4.76 (1.46) 0.64-20.90
Average speed limits	Continuous: [=sum of (speed limit × street length) / total street lengths in a buffer]	24.90 (2.82) 13.92-44.75	25.01 (2.81) 9.93-40.82
Bike lanes	Binary: 1=presence of bike lanes in a buffer	2983 (22.20%)	3424 (23.61%)
	0=otherwise	10455 (77.80%)	11078 (76.39%)
Highway	Binary: 1=presence of highways in a buffer	3200 (23.81%)	3491 (24.07%)
	0=otherwise	10238 (76.19%)	11011 (75.93%)

Table 2. Continued

Variables	Descriptions	2010 (N=13,438) Mean/Freq. (S.D./%) Min.-Max.	2013 (N=14,502) Mean/Freq. (S.D./%) Min.-Max.
Railroad	Binary: 1=presence of railroads in a buffer	615 (4.58%)	615 (4.24%)
	0=otherwise	12823 (95.42%)	13887 (95.76%)
Bus stop	Binary: 1=presence of bus stops in a buffer	7627 (56.76%)	7794 (53.74%)
	0=otherwise	5811 (43.24%)	6708 (46.26%)
Parks	Binary: 1=presence of parks in a buffer	2123 (15.80%)	2364 (16.30%)
	0=otherwise	11315 (84.20%)	12138 (83.70%)
Neighboring foreclosures			
Foreclosures	Continuous: Number of single-family foreclosures in a buffer from the two-year time period	19.23 (15.45) 0-118	8.99 (6.92) 0-52
Neighborhood Walkability			
Walkability (continuous)	Continuous: Walk Score (0-100)	52.53 (20.62) 0-95	52.29 (21.09) 0-97
Walkability (categorical)	Three categories: Walk Score		
	1=car-dependent (0-49)	5026 (37.40%)	5466 (37.69%)
	2=walkable (50-69)	5608 (41.73%)	5926 (40.86%)
	3=very walkable (70-100)	2804 (20.87%)	3110 (21.45%)

Note: Frequency and percentage are calculated for categorical variables. Highway and railroad are measured within a 1/2 mile buffer. All the other environmental measures are based on a 1/4 mile buffer.

[a] The calculation of measuring the median household income in a buffer follows, sum of (proportion of block group area overlapping within a buffer × median household income at the block group level).

[b] The calculation of measuring unemployment rate in a buffer follows, sum of [(proportion of residential area of block group overlapping within a buffer × unemployed population at the block group level) / (proportion of residential area of block group overlapped within a buffer × total population in labor at the block group level)]

[c] The calculation of measuring percentage of housing units with a mortgage in a buffer follows, sum of [(proportion of residential area of block group overlapping within a buffer × owner occupied housing units with a mortgage at the block group level) / (proportion of residential area of block group overlapping within a buffer × the total owner occupied housing units at the block group level)]

4.4.2 Structural and Socioeconomic Factors Predicting Property Sales Value during Recession versus Recovery Periods

The main results are presented in Table 3. These estimates are direct effects from the spatial hedonic models. Most variables were generally significant with the expected direction of associations consistent with the literature. The coefficients of property structural characteristics were mostly positive, indicating that properties having a larger lot size, more recent year built, more beds and baths, two or more stories, a pool, and a garage tend to be sold at higher prices. Homes in neighborhoods having a higher median household income and lower unemployment rate have higher sales values. The estimated size of the depressed sale variable for 2010 was larger than for 2013, indicating that the own-price discount was severer during the economic downturn, and this may have caused more exposure to foreclosure spillovers on the housing market in neighborhoods. The month and location indicators were included in all models, but the estimated coefficients are not reported for brevity.

Table 3. Walkability, Foreclosure, and Other Factors Associated Property Value during the Recession and Recovery Periods

Variables	**2010 sample**			**2013 sample**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All income	**Lower income**	**Higher income**	**All income**	**Lower income**	**Higher income**
Property characteristics						
Log (lot size)	0.2265***	0.2302***	0.2201***	0.2349***	0.2514***	0.2288***
Year built	0.0012***	2.5E-05	0.0007**	0.0012***	0.0013**	0.0012***
Beds	0.0190***	0.0384***	0.0185***	0.0189***	0.0388***	0.0164***
Baths	0.1263***	0.0783***	0.1299***	0.1243***	0.0760***	0.1276***
Story	0.0813***	0.0745**	0.0771***	0.0716***	0.1561***	0.0640***
Pool	0.0785***	0.0731*	0.0773***	0.0750***	0.0983*	0.0745***
Garage	0.1015***	0.2168***	0.0780***	0.0699***	0.1705***	0.0510***
Financial characteristics						
Depressed sale	-0.1675***	-0.1807***	-0.1620***	-0.1536***	-0.1370***	-0.1559***
Socio-demographics						
Median income (Reference=low/moderate)						
Middle	0.1080***	N/A	N/A	0.1388***	N/A	N/A
High	0.3012***	N/A	0.1786***	0.3466***	N/A	0.1965***
Unemployment	-0.0085***	-0.0046*	-0.0096***	-0.0062***	-0.0010	-0.0078***
Mortgage	-0.0017**	-0.0017	-0.0017*	-0.0022***	0.0005	-0.0028***
Neighboring foreclosures						
Foreclosures	-0.0129***	-0.0004	-0.0134***	-0.0212***	0.0019	-0.0216***
Neighborhood Walkability						
Walk Score	0.0006*	0.0017	0.0012***	0.0012***	0.0027	0.0016***

Table 3. Continued

Variables	2010 sample			2013 sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	All income	**Lower income**	**Higher income**	**All income**	**Lower income**	**Higher income**
Built environments						
Crime density	0.0193	-0.0609**	0.0418**	0.0057	-0.0331**	0.0149*
Crash density	-0.1250***	-0.0213	-0.1430***	-0.0862***	-0.0189	-0.0922**
Net residential density	-0.0089**	-0.0305***	-0.0094**	-0.0005	-0.0209*	-0.0009
Average speed limits	-0.0005	0.0004	-0.0001	0.0010	-0.0006	0.0009
Bike lane	-0.0307***	-0.0075	-0.0388***	-0.0310**	0.0155	-0.0403***
Highway	-0.0328**	-0.0389*	-0.0297***	-0.0408***	-0.0372	-0.0389***
Rail road	-0.1221***	-0.0852***	-0.1813***	-0.0456*	-0.0345	-0.0369
Bus stop	-0.0105	-0.0283	-0.0038	-0.0094	-0.0307	-0.0048
Park	-0.0116	-0.0376	-0.0017	0.0196*	0.0071	0.0214*
Interaction with neighboring foreclosures						
Walk Score × Foreclosure	0.0001***	-3.4E-05	7.7E-05***	0.0002***	-8.0E-05	1.4E-04***
Spatial lag variable	0.0179***	N/A	0.0201***	0.0161***	N/A	0.0162***
Spatial error variable	0.4862***	0.3186***	0.4810***	0.4862***	0.2472***	0.5000***
Sample size	13438	2152	11286	14502	2035	12467
Pseudo R^2	0.76	0.53	0.73	0.69	0.44	0.64

Note: The sub-samples by all income, low/moderate income (below 79% of the metropolitan median income) and middle/high income (80% or over of the metropolitan median income) groups were estimated respectively; For all income and middle/high income groups, the Cliff-Ord model was used, but for the low/moderate income group, the spatial error model was used because the LM diagnostic for spatial lagged dependent variable was insignificant; The results of constant, locational and monthly variables were not included for the brevity; * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

4.4.3 Foreclosure Spillover Effect during Recession versus Recovery Periods

The estimated spillover effects of neighboring foreclosures were significant in both 2010 and 2013 samples even after the inclusion of the various neighborhood controls and the spatially lagged dependent and error term.[14] An additional foreclosure in a neighborhood was found to reduce the value by 0.73% in the 2010 sample and 1.13% in the 2013 sample, controlling for other variables at the mean value.[15] The different market conditions between the recession in 2010 and the recovery in 2013 may have generated the differential impact of spillover effects. During the recession, neighboring foreclosures may have had a weaker deleterious effect on property values because the overall housing market was depressed.

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[14] This study found the estimated size of the foreclosure and walkability impacts were attenuated when the Cliff-Ord spatial regression is employed. The negative spillover effects of the ordinary least square (OLS) regression model (shown in Equation (4.1)) were 0.80% in the 2010 sample and 1.58% in the 2013 sample. The estimated size of walkability premiums were 0.31% in the 2010 sample and 0.36% in the 2013 sample. The sign and significance of other variables were similarly estimated. The results of the OLS regression are reported in Appendix B.

[15] The results from the models excluding the interaction term were not reported in the tables. The estimated coefficients of foreclosure were -0.0073 ($p<0.001$) for 2010 and -0.0113 ($p<0.001$) for 2013.

4.4.4 Walkability Effect during Recession versus Recovery Periods

The walkability premiums were significant in both the 2010 and 2013 samples. A one unit increase in WS raised property values by 0.19% in 2010 and 0.23% in 2013, controlling for other variables at the mean value.[16] As shown in Columns (1) and (4) in Table 3, the interactions between neighboring foreclosures and neighborhood walkability for all income groups were positive and statistically significant for both 2010 and 2013. The marginal spillover effects of foreclosure were attenuated by 54.26-69.77% for 2010 and 66.04-84.91% for 2013 in very walkable neighborhoods (WS: 70-95), 38.76-53.49% for 2010 and 47.17-65.09% for 2013 in somewhat walkable neighborhoods (WS: 50-69), and 0-37.98% for 2010 and 0-46.22% for 2013 in car-dependent neighborhoods (WS: 0-49).[17]

For a more straightforward interpretation, this study replicated the analyses in Columns (1) and (4) of Table 3 by using the categorical WS variable and the corresponding results are presented in Table 3. Relative to car-dependent neighborhoods, the size of foreclosure impacts were attenuated by 32.22% for 2010 and 38.29% for 2013 in walkable neighborhoods. The interaction of the foreclosure with the very walkable category was not significant and the size was smaller than that in walkable neighborhoods. The coefficients of other control variables for all income groups were similar to the results of the model (Table 3) that used a continuous WS variable.

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[16] The estimated coefficients of walkability were 0.0019 ($p<0.001$) for 2010 and 0.0023 ($p<0.001$) for 2013.
[17] For example, in the 2010 sample (column (2) in Table 3), the calculation for the attenuation of price spillover in very walkable neighborhoods (WS: 70-95) follows, $0.0001 \times 70\ (95) / 0.0129 = 54.26\ (69.77)$.

4.4.5 Walkability-Foreclosure Interaction Effect by Income Groups

As seen in Table 3 (Columns (2), (3), (5) and (6)), this study further examined whether the interaction effects differed between lower and higher income groups. This study found that the interaction effects were significant only for the higher income group. Similar patterns were also found in Table 4 when categorical walkability variables were used. Interestingly, the spillover effects were insignificant in lower income neighborhoods. While the evidence of income-based disparities in foreclosures and physical environments has been documented in the literature, the findings may provide further evidence of income-based disparities in resiliency power of walkability on the price spillovers of foreclosures. Although lower income communities might be more likely to be featured with more compact and accessible environments (such as greater density, mixed land-use, and connected streets), other environmental qualities might be less conducive to walking due to a high crime rate, low social capital, and poor condition of streets and sidewalks. These spatial inequalities may exacerbate existing deleterious foreclosure effects, which tend to be more commonly observed in disadvantaged communities.

4.4.6 Safety and Other Built Environmental Effects during Recession versus Recovery Periods

While crime safety in a neighborhood was not significantly associated with property values, properties benefited from the neighborhood with higher traffic-related safety (lower crash density) in both samples. This study found price premiums on properties without highways and railroads located within the buffer in both the 2010 and 2013 samples. However, neighborhoods having higher residential density and lower speed limits did not lead to property value increase, but the significance of both variables were somewhat inconsistent across the models. Interestingly, the results showed that bike lane and park variables were negatively related to property values although the majority of relevant studies have shown that a bike lane and a park offer a good use of physical environments (C. Lee & Moudon, 2004). However, the benefits of a bike lane and/or a park might depend on its design and maintenance conditions, and it is possible that quality factors might be explained in negative associations with property values (Kovacs, 2012).

Table 4. Regression Results of Categorical Walkability Variable

	2010 sample			2013 sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	All income	Lower income	Higher income	All income	Lower income	Higher income
Neighboring foreclosures						
Foreclosure	-0.0090***	-0.0049**	-0.0099***	-0.0141***	-0.0048**	-0.0148***
Neighborhood walkability (Ref: Car-dependent)						
Walkable (50-69)	0.0124	-0.0223	0.0387**	0.0092	-0.0186	0.0340*
Very walkable (70-100)	0.0854***	0.0275	0.1257***	0.1350***	0.0267	0.1784***
Interaction with neighboring foreclosures						
Walkable (50-69) × Foreclosure	0.0029***	0.0018	0.0015*	0.0054***	0.00175	0.0027*
Very walkable (70-100) × Foreclosure	0.0010	0.0003	-0.0004	0.0013	0.00025	-0.0032
Pseudo R^2	0.76	0.53	0.73	0.69	0.44	0.65

Note: The results of this table were estimated based on the same modeling approach for Table 3, expect that categorical variables of walkability were utilized; The estimated coefficients of the key variables are only reported; Full results are reported in Appendix B. * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

4.5 Conclusions and Policy Implications

This study quantitatively assessed the neighborhood walkability premium and its association with the negative spillover effects of foreclosure on property values. This study found that walkable neighborhoods tended to be more resilient to the negative spillover effects of foreclosure on property values, but the mitigating effects of walkability were more significant in higher income communities. This study also suggested that walkability was more effective in maintaining neighborhood stability during the housing recovery market of 2011-2013, compared to the housing market crash of 2008-2010. These findings suggest that the income disparity issue exists in its resiliency power as well. More vulnerable groups face greater risks from economic crisis, and undergo harder times before recovery.

This research is subject to the following limitations. First, this study estimated the walkability premiums on single-family properties only, as dominant in housing markets and most commonly investigated in foreclosure literature. The moderating effect of walkability on spillovers may be different for other property types such as condominiums and multi-family homes. Second, this study only focused on the city of Los Angeles; therefore, the findings of this dissertation may not be generalizable to other study settings. Third, due to data availability, some variables, such as the time-on-market (TOM), other property characteristics (e.g. physical condition) and neighborhood physical conditions, were missing. The physical quality of the environment may be able to provide further details for the disparity in built environments. This could be a potential venue for future research.

Despite these limitations, I believe that this study makes several meaningful contributions to the literature. First, to my knowledge, no prior study has investigated the mitigation effects of walkability on foreclosure spillovers. This study found not only the impacts of neighborhood walkability for resiliency in the housing market but also income related disparities in such impacts. By considering the built-environment factors that have not been thoroughly examined in previous foreclosure literature, this study improves the model specifications; incorporating built environmental characteristics could potentially lead to improved estimated results for future foreclosure and walkability related studies. This study also advanced foreclosure measurements using a street network based buffer, which can more accurately reflect the actual setting and walkability of neighborhoods than the simpler airline buffer used in most previous studies.

Second, by focusing on environmental factors, this study attempted to draw more easily implementable policy and environmental interventions to mitigate the negative foreclosure spillover effects on communities and stimulate the stabilization of neighborhoods. Responding to the need for minimizing negative spillover effects of foreclosures, governments have developed policy strategies (such as Neighborhood Stabilization Program, U.S. Treasury's Home Affordability Modification Program) that focus on modifying financial lending options and preventing falling into or staying in foreclosure status (Immergluck, 2009). However, these efforts may not be sufficient to remedy problems from foreclosure spillovers, which can spread harms to other local communities. One central question lies in how we can enhance resilience and stabilization of the neighborhoods, and an answer to this question requires consideration of the larger contextual factors such as the neighborhood environments. More comprehensive efforts to improve environmental quality beyond foreclosure itself especially in low-SES communities are needed to strengthen the communities' resiliency from the various negative impacts from economic crises.

Third, the findings suggest that a link exists between the built environment and economic activities. It has become a prominent issue as the physical environments embrace social and economic benefits as Jane Jacobs emphasized the importance of understanding the relationship between physical built environments (e.g. walkable environments, especially safe and multi-use streets) and social lives. While many strategies to support pedestrian-oriented neighborhood design have been discussed, limited evidence exists from empirical studies. By demonstrating how walkable communities bring additional economic benefits by mitigating negative externalities from foreclosures, this study provides urban planners and local governments with new insights to better handle neighborhood stress and to create healthy and livable communities.

CHAPTER V

WALKABLE BUILT ENVIRONMENTS, FORECLOSURE DENSITY, AND FORECLOSURE DURATION

One strategy for reducing neighborhood dilapidation is to control foreclosed properties, particularly those which remain vacant or unmaintained. A number of studies have found that foreclosures tend to be disproportionally clustered in ethnic minority and low-income communities. However, while underlying neighborhood inequalities yield uneven foreclosure rates, few existing studies have examined whether the inequalities of built environments also impact foreclosures differently. By examining how walkability-related built environments are associated with foreclosure-related events, this study aims to provide supporting evidence that a walkable environment alleviates the density of foreclosures and reduces the duration of foreclosure sales.

5.1 Introduction

The consequences of the foreclosure crisis that began in 2007 have been examined as a source of risk factors for communities. Foreclosures have led to deterioration of the quality of neighborhoods through an increase in social disorder, including crime and vandalism (Ellen et al., 2013; Katz et al., 2013). Such crime-related risk factors can, in turn, jeopardize the wellbeing of neighborhood residents (Cagney et al., 2014; Houle, 2014; Libman, Fields, & Saegert, 2012) through their perceived loss of control (Downey & Van Willigen, 2005; Prohaska & Lichtenstein, 2014) and increased psychological stress (Hill et al., 2005). Foreclosures have also had an influence on migration patterns and boosted racial transition, driving social segregation (Hall et al., 2015). Since unequal access to the mortgage market led to unequal foreclosure events (Bocian et al., 2008; Rugh & Massey, 2010; Williams, Reynold, & Eileen Diaz, 2005), the evidence suggests that foreclosures were disproportionally clustered in communities composed of ethnic minorities (e.g. Latino and black) and low-income residents (Chan, Gedal, Been, & Haughwout, 2013; Pfeiffer & Molina, 2013). Research has also found that properties in such communities experienced a longer duration on the market for REO sales (Y. Li & Walter, 2013; Pfeiffer & Molina, 2013). However, while the underlying socioeconomic inequalities yield uneven foreclosure rates, a knowledge gap remains as regards whether the inequalities of built environments also have an uneven impact on foreclosures.

It has been suggested that built environmental factors bring “value” to a community, in that built environments are associated with walking behaviors (Saelens & Handy, 2008), social cohesion (Leyden, 2003; S. H. Rogers et al., 2011), clean environments (Frank et al., 2006), and economic value (W. Li et al., 2015). Walkability, in particular, has been associated with the maintenance of these values in communities. Sustaining the value of a place equipped with built environments more conducive to walkability may help properties gain marketability and prevent falling property values. The negative home equity from the decline of house prices has been shown to be one of the key determinants of mortgage default risk (Quercia & Stegman, 1992), which has the potential to increase foreclosures (Gerardi, Shapiro, & Willen, 2007). Built environmental factors related to walkability may therefore play a major role in the deterrence of foreclosure, bolstering strategies aimed at preventing the slide of neighborhoods into deterioration.

The current research investigated how built environments conducive to walkability are associated with two foreclosure-related outcomes, especially for foreclosures owned by lenders (known as REO) [18]: density of REO filings (defined here as REO density) and the length of time a property remains in REO status before being sold (defined here as REO duration). Important government interventions proposed by researchers and policy makers include reducing the likelihood of foreclosures and shortening the length of time a property spends in foreclosure status (Immergluck, 2008; Wassmer, 2011). This research aims to provide valuable information related to neighborhood characteristics for policy interventions designed to prevent REO events, and reduce the negative impacts on neighborhoods by shortening the duration of an REO sale.

[18] Given the dynamic nature of the foreclosure process (pre-foreclosure, auction, and REO), REO is one foreclosure type in the last stage of the process, which may induce more severe impacts on a neighborhood than any other types of foreclosure. A study (Capozza and Thomson, 2006) found that nearly 79% of the defaulted properties transitioned into the REO stage. Therefore, it might be appropriate to focus on REO properties.

5.2 Literature Review

5.2.1 Walkable Built Environments

Researchers in the fields of transportation and health have investigated the elements of the built environment associated with non-motorized behaviors such as walking or bicycling. Built environments, composed of physical, social, behavioral, and natural components designed for the purpose of human activities (Dannenberg et al., 2011), involve physical infrastructure, land use patterns, and design characteristics that either encourage or frustrate walking behavior (Frank, Engelke, & Schmid, 2003; Frumkin et al., 2004). Literature reviews and frequently-cited articles (Brownson, Hoehner, Day, Forsyth, & Sallis, 2009; Ewing & Cervero, 2001; C. Lee & Moudon, 2004; Saelens & Handy, 2008; Saelens, Sallis, & Frank, 2003) have identified the built environmental correlates of walking. The specific components include accessibility to destinations (such as parks), mixed land use, density, aesthetics, pedestrian infrastructure (such as sidewalks), connectivity of routes, and safety.

Among three broad categories of measurements of built environments (perceived, observational, and objective measures),[19] this research used the measure based on Geographic Information Systems (GIS). The use of GIS is becoming increasingly widespread, due to its ability to capture a number of different environmental characteristics. GIS data can also be measured at various geographic scales. In this

[19] Brownson et al. (2009) provided a comprehensive examination of three types of built environment measures used for research of physical activity: perceived measures by self-reported surveys or interviews, observational measures by audit instruments for trained observers to assess built environments, and objective measures by GIS-based data.

research, five domains of built environments were identified for estimating the impacts of walkability: residential density, land-use mix, street connectivity, access to recreational areas, and safety. These variables have been discussed in previous research as consistent correlates of walking (Saelens & Handy, 2008), and were also included in the constructs framed by Ewing and Cervero (2001), which are related to the so-called D variables (density, diversity, and design). These variables will be discussed in more detail in the methods section.

5.2.2 Walkable Neighborhoods and Foreclosure

Only a few studies have associated foreclosure probability with particular characteristics of the built environment. An early study by Blackman and Krupnick (2001) estimated a mortgage default risk of location-efficient homes. The concept of location efficiency includes less automobile dependency in denser residential areas and more accessible to public transport (Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002). However, this study did not use a direct measure for walkability, and was limited to including measures of certain characteristics representing the concept of location efficiency. In addition, the study did not find that location efficiency had a significant impact on the likelihood of default.

Rauterkus et al. (2010) offered the Walk Score as a proxy variable for measuring location efficiency in three metropolitan areas: Chicago, Jacksonville, and San Francisco. They explored the impact of environmental characteristics on the likelihood of mortgage default. They found that the risk of a mortgage default was reduced with a higher Walk Score in both Chicago and San Francisco, but increased in Jacksonville. The study noted regional differences in the risk of a mortgage default. Using the interaction terms between Walk Score and income, the authors also found that a higher Walk Score was significantly associated with a decrease in the risk of mortgage defaults, but that the results were only applicable in high-income areas.

A recent study by Pivo (2014) examined the associations between neighborhood walkability and the probability of mortgage default in multi-family properties. The study found a non-linearity in the effects of walkability on the default risk, using approximately 37,000 multifamily mortgages and three categories of Walk Scores with cut-points of 8 and 80. The study found that the default risk of a property decreased by 60.3% when the property was located in an area with a Walk Score of 80 or above. The author also noted that better loan terms may be offered for walkable properties, which could reduce the default risk.

Another recent study by Gilderbloom et al. (2015) used an ordinary least square (OLS) regression to investigate the association between neighborhood walkability (measured as Walk Score) and the number of foreclosure sales in the period between 2004 and 2008 in 170 census tracts as the unit of analysis. The study found that neighborhood walkability was significantly associated with fewer foreclosure sales. They also examined the significant impact of walkability on higher home values and lower level of crime, indicating that walkability can strengthen neighborhood resiliency.

While these studies focused only on the Walk Score as a measure of walkable environments, Pivo (2013) investigated the impacts of sustainability features on the mortgage default risk in multifamily housing. Pivo identified sustainable features such as commute time and mode of transport (e.g., public transit, walking, etc.), presence of retail establishments and a freeway, affordable housing standards, and proximity to protected open space. Using a logistic regression, this study found that less commuting time, more retail establishments, and the absence of a freeway contributed to lower default risk, holding other factors constant.

Overall, despite the limited number of existing studies on this subject, it seems likely that greater accessibility and compactness of neighborhoods reduce the risk of mortgage default or foreclosures. This dissertation builds on previous research by specifying elements of a walkable built environment associated with foreclosure. Although Pivo (2013) study employed several elements defined as sustainable features, no existing study has sought to investigate how multi-dimensional elements of the built environment are associated with foreclosures. In addition, prior research has focused on either mortgage defaults or foreclosure sales. In a mortgage default, a property has not yet started the foreclosure process, and in the foreclosure sale, the foreclosure process is completed. Using a rich data set, this dissertation analyzes a specific type of foreclosure in the process, REO. Finally, the spatial dependency among neighborhood observations, which has not been considered in previous research, was adjusted in this study.

5.2.3 Duration of REO Foreclosures

Reducing the market duration of foreclosed properties is an important policy intervention for neighborhood stability. Foreclosed properties are often vacant (Whitaker, 2011), and long-term vacant foreclosures can generate a large negative externality effect on neighborhood quality by increasing social disorder and crimes (Cui & Walsh, 2015; Skogan, 1990). Research also found that properties in foreclosure for over a year had a larger negative impact on nearby property values (Kobie & Lee, 2010).

Although multiple studies have focused on housing attributes, pricing strategies, mortgage rates, and seller motivations as determinants of market duration (Anglin, Rutherford, & Springer, 2003; Glower, Haurin, & Hendershott, 1998; Knight, 2002), little is known about the associations between neighborhood characteristics and market duration, especially for REO properties. Only a few studies have estimated the effects of neighborhood characteristics on the amount of time before an REO property is sold. (Immergluck, 2012; Y. S. Lee & Immergluck, 2012; Y. Li & Walter, 2013; Pfeiffer & Molina, 2013). Y. Li and Walter (2013) demonstrated that REOs were less likely to be sold if they were located in neighborhoods with a higher percentage of black and Hispanic populations and a lower homeownership rate. Pfeiffer and Molina (2013) found that a higher proportion of black residents in a given area, especially in inner-city neighborhoods, was associated with an REO property in that area being on the market for longer. However, existing research has only captured the socioeconomic characteristics of neighborhoods, while largely ignoring the ways in which built environmental factors influenced the duration of an REO foreclosure. This dissertation makes a contribution to the research by investigating the impacts of built environments on the market durations of properties in REO status.

Prior research has also analyzed the duration in REO status for specific housing submarkets, particularly lower-value properties, which is an issue that may require further policy attention. Low-value foreclosures can be targeted for speculative gain by investors, who may be more lax in maintenance duties than are owner-occupants (Immergluck, 2012). These foreclosures may therefore contribute to neighborhood disorder. Also, low-value properties are generally clustered in low-income and minority areas where the neighborhoods are more likely to be hit by a foreclosure surge (Ellen, Madar, & Weselcouch, 2015). In the literature analyzing REO duration during the period of the U.S. foreclosure crisis, Y. S. Lee and Immergluck (2012) found that low-value REO properties, mostly located in lower-income and minority neighborhoods, were sold more quickly due to fear of further decline in property values. Immergluck (2012) noted that lenders' decisions to sell or hold an REO may depend on expectations of increased equity and generated liquidity from the property. REOs in low-income neighborhoods may have greater rates of depreciation in property value. On the other hand, Y. Li and Walter (2013) found that REO properties appraised as low or high took a longer time to sell than did mid-value REO properties. They observed that many low-value REOs were located in low-income areas.

This dissertation suggests that the built environmental characteristics of areas in which REO properties are located might provide further insight into the duration of REO status of low-value properties. By examining the built environments and the duration in

REO status across property values, it examines how the durations of low-value REOs can be differentiated according to levels (lower, middle, and upper) of built environmental attributes (residential density, land-use mix, and street connectivity), thereby helping policy makers to implement appropriate policy decisions.

5.3 Methods

5.3.1 Study Area and Data

The study area, Los Angeles (LA) County, California includes diverse neighborhoods with various race/ethnic groups and street and land use patterns. The diversity of Los Angeles may provide a adequate setting in which to investigate the impacts of the neighborhood and built environment. According to the 2010 Census, the total population of LA County was estimated at 9.8 million, comprising 47.7% Hispanic or Latino, 50.3% White, 13.7% Asian, and 8.7% African American. LA County has 2,345 census tracts, a median household income ranging from $10,290 to $227,014, and a population density (persons per acre in a census tract) ranging from 0 to 160.3.

Table 5 provides the variable descriptions and summary statistics. Two separate analyses were conducted for each dependent variable: REO density and REO duration. Two data sets (sales and foreclosure data) obtained from private database vendors, DataQuick and Property Radar, were used to measure REO density and REO duration. The sales data included sales prices, transaction dates from January 2008 to December 2013, and property attributes (square footage of building, year of construction, and number of bedrooms). The foreclosure data included the dates on which properties entered each phase of the foreclosure process (pre-foreclosure, auction, and REO) from January 2008 to December 2013, property attributes, loan amounts, and appraised values. Incomplete sales records and non-market transactions were removed for the purposes of the analysis. After merging these two sets of data, the data set was reshaped from a long format to a wide format. From the final data set, the number of REO properties and the number of days in REO status could be obtained by analyzing the date a property entered REO status and the date it was sold, during the period between 2008 and 2013. The data was geocoded by matching each property to GIS-based parcels. The final dataset included 75,256 REO properties.

Table 5. Variable Descriptions and Summary Statistics

Variables	Descriptions	REO Density [a]	REO Duration [a]
		Mean/Freq. (S.D./%) Min.-Max.	Mean/Freq. (S.D./%) Min.-Max.
Dependent variables			
REO density	total number of single-family REO units / total number of residential units in the census tract	0.013 (0.015) 0-0.130	N/A
REO duration	Days REOs are on the market until an REO is sold	N/A	280.54 (333.33) 4-2190
Property characteristics			
Property value	Assessed property value (/ $10,000)	46.05 (31.24) 8.84-481.60	38.40 (26.60) 2.2E-03-1071
Building sqft	Square footage of building	1526.48 (508.90) 604.50-6190	1589.55 (756.21) 65-14835
Beds	Number of bedrooms	3.00 (0.62) 0-10	3.15 (0.91) 0-25
Year built	Year built	1954.39 (21.13) 1895-2008	1959.11 (25.20) 1833-2012
Loan-to-value	Combined loan-to-value ratio	0.66 (0.17) 0-2.59	1.22 (50.24) 0-13679.41
Socioeconomic characteristics of neighborhoods			
Median income	1=low/moderate household income group	718 (34.03%)	21225 (28.20%)
	2=middle household income group	674 (31.94%)	30642 (40.72%)
	3=high household income group	718 (34.03%)	23389 (31.08%)
Hispanic	% of Hispanic population	22.29 (17.13) 0-75.22	23.60 (15.83) 0-75.22

Table 5. Continued

Variables	Descriptions	REO Density [a] Mean/Freq. (S.D./%) Min.-Max.	REO Duration [a] Mean/Freq. (S.D./%) Min.-Max.
Black	% of Black population	8.411 (13.55) 0-88.50	11.97 (15.60) 0-88.50
Asian	% of Asian population	13.36 (15.47) 0-88.50	9.14 (10.95) 0-88.02
Pop18	% of population under age 18	24.24 (6.76) 0.23-46.99	26.77 (5.97) 0.76-46.99
Pop65	% of population over age 65	11.44 (5.36) 1.54-37.35	10.47 (4.52) 0-37.35
Owner	% of owner occupied units	49.99 (25.20) 0-100	60.84 (20.16) 0-100
Unemployment	% of unemployed among population 16 years and over	11.69 (4.60) 0-35.6	12.53 (4.51) 0-66.7
Vacancy	% of vacant housing units	6.01 (4.09) 0-55.40	6.39 (4.19) 0-55.40
Mortgage	% of housing units with mortgage	2.47 (2.50) 0-31.75	3.28 (2.75) 0-31.75
Active Commuting			
Active	% of those who commute (walk or bike) to work	3.28 (3.77) 0-48.13	2.07 (2.48) 0-48.13

Table 5. Continued

Variables	Descriptions	REO Density [a] Mean/Freq. (S.D./%) Min.-Max.	REO Duration [a] Mean/Freq. (S.D./%) Min.-Max.
Safety and Built environmental Characteristics			
Crime density	Yearly average crime density=total number of crimes during 8 years (2006-2013) / acre of the census tract / 8	0.28 (0.60) 0-5.25	0.39 (0.61) 0-5.25
Crash density	Yearly average crash density=total number of crashes during 8 years (2006-2013) / acre of the census tract / 8	0.09 (0.08) 1.2E-04-0.63	0.06 (0.06) 1.2E-04-0.60
Residential density	total residential units / acre of residential area in the census tract	3.94 (2.31) 6.4E-03-18.11	3.88 (2.33) 0.006-18.11
Land-use mix [b]	$-\sum(\frac{P_i}{A}(\ln(\frac{P_i}{A}))/\ln N$ (see note)	0.56 (0.21) 0-0.99	0.48 (0.20) 0-0.99
Street connectivity	total number of street intersections (4+) / acre of the census tract	0.24 (0.13) 3.2E-04-1.26	0.21 (0.11) 3.2E-04-1.08
Bike lane availability	0=none 1=having a bike lane in the census tract	930 (44.08%) 1180 (55.92%)	32087 (42.64%) 43169 (57.36%)
Park availability	0=none 1=having a park in the census tract	1056 (50.05%) 1054 (49.95%)	37244 (49.49%) 38012 (50.51%)

Note:

[a] For REO density, the property characteristics were measured as the median value of property value, square footage, bedroom, year built, and loan-to-value ratio at the census tract level. For REO duration, each property's characteristics were measured.

[b] Based on Frank et al. (2006), the land-use mix was measured as:

P_1=area of single-family residential land uses, P_2=area of multifamily residential land uses, P_3=area of commercial land uses, P_4=area of education land uses, P_5=area of office land uses, P_6=area of recreational land uses; A=total area of P_1-P_6; N=number of land uses present

5.3.2 Variables and Measurement

5.3.2.1 REO Density

The census tract is used as the unit of analysis. From the data set, the REO density was created by dividing the total number of single-family properties entering REO status in 2008 by the total number of residential units in each census tract. The total number of single-family REOs in 2008 was 26,816. The final sample has 2,110 tracts. The medians of property attributes in the census tracts were included as control variables: median sales value of all transactions during 2008, median square footage of buildings, median number of bedrooms, median year built, and median loan-to-value ratio (=loan amount divided by appraised property value).

5.3.2.2 REO Duration

The parcel-level property is the unit of analysis. To obtain a duration for REO sales, the number of days on the market was calculated by taking the difference between the date a property entered REO and the date that it was sold. The data set contains 75,256 properties that entered REO status between 2008 and 2013. Of these, 96.1% were sold, while the others were not sold during this time period. The sold properties have an average market value of $383,439 and the unsold properties $407,652. The property attributes of each property were included as control variables: assessed property value, square footage of buildings, number of bedrooms, year built, and loan-to-value ratio.

The average number of days across property-value classes is illustrated in Figure 7. Based on the classification used by Y. Li and Walter (2013), the assessed property value was classified into eight categories: less than $100,000, $100,001-$150,000, $150,001-$250,000, $250,001-$400,000, $400,001-$600,000, $600,001-$800,000, $800,001-$1,200,000, and higher than $1,200,001. As shown in Figure 7, on average, higher-value REO properties stayed on the market for longer than lower-value REO properties. A similar upward trend was also found in previous studies (Y. S. Lee & Immergluck, 2012).

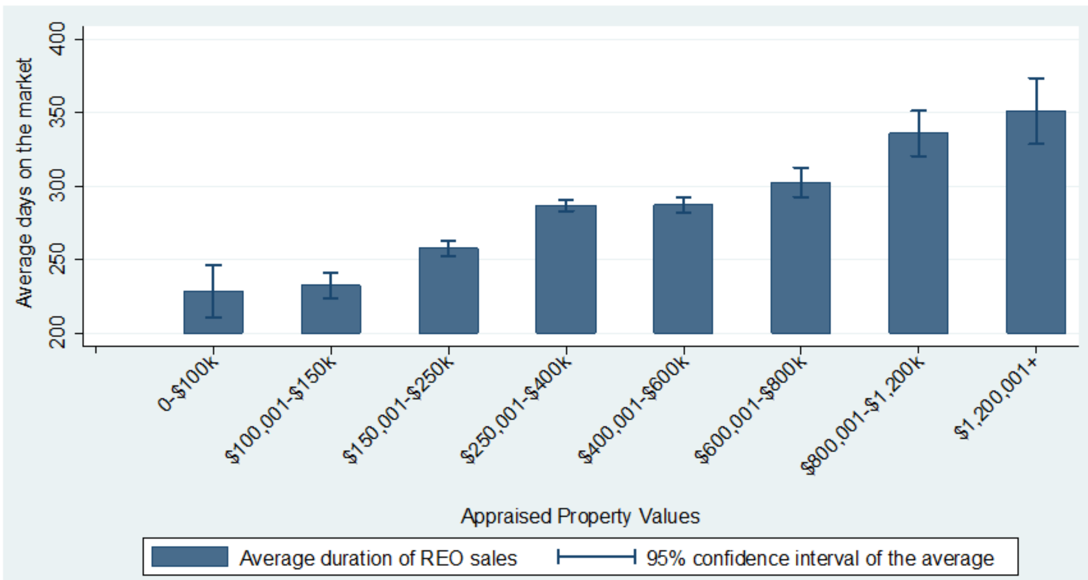

Figure 7. Average Duration of REO Sales by Property-Value Classes

5.3.2.3 Neighborhood Characteristics and Built Environments

The socio-economic status (SES) of neighborhoods at the census-tract level was drawn from the 2013 American Community Survey (ACS) 5-year (2008-2013) estimates. These included the median household income, the race/ethnicity composition of the population (percentage of Hispanics, blacks, and Asians), the age composition of the population (percentage of population under 18 and over 65), the percentage of vacant housing units, the percentage of housing units with mortgages, and the percentage of commuters who walk or bike to work.

The spatial characteristics of walkable environments are the main independent variables. All GIS data (e.g. streets, land uses, parks, crimes, and car-crashes) were collected from the Department of Regional Planning in Los Angeles County (planning.lacounty.gov). Based on the D-variable framework developed by Cervero and Kockelman (1997) , three core domains related to walkable environments were assessed:

(1) *Density*, such as residential density, measured as the number of residential units per acre in the census tract;

(2) *Diversity*, such as land-use mix, measured by an entropy index calculated as Land-Use Mix = $-\sum R_i(\ln R_i / \ln N)$, where R_i is a ratio of different land use types in the census tracts, and N is the number of different land uses;

(3) *Design*, such as street connectivity, measured as the number of intersections (four or more) per acre in a census tract.

Each domain was classified into three categories based on a percentile for the sample: lower (0-25), middle (26-74), and upper (75+) levels. Additional dimensions of built environments for neighborhood walkability were also included: bike lane availability, trip destination (park availability in the census tract) and neighborhood safety (yearly averaged crime density between 2008 and 2013 and yearly averaged crash density between 2008 and 2013).

Other SES variables, such as poverty level and education, and built environment variables, such as the local street density and retail density, were identified, but were ultimately excluded from the analysis due to a multicollinearity problem. All variables were measured using ArcGIS 10.2. All detailed measures are described in Table 5.

5.3.3 Analytical Methods

5.3.3.1 Statistical Method for REO Density

I started with the OLS regression to test for the relationships between built environments and the dependent variables for REO density. Since the null-hypothesis of spatial independency was rejected, the spatial lag and error models were considered for the statistical analysis.[20] However, the coefficient of spatially lagged error variable was not significant when both spatially lagged and error variables were included in the model. The separate models for each spatially lagged dependent and error variables were estimated and had very similar results, but the spatial lag model had a better model fit.[21] In addition, Robust LM-lag test was 105.29 ($p<0.0001$), and Robust LM-error test was 0.093 ($p=0.76$). Therefore, the spatial lag model was employed as the final model for correcting the spatial dependency between neighboring census tracts. The model specification is written as (Anselin & Rey, 2014):

$$\mathbf{y} = \boldsymbol{\alpha} + \mathbf{P} \cdot \boldsymbol{\beta} + \mathbf{N} \cdot \boldsymbol{\gamma} + \mathbf{B} \cdot \boldsymbol{\delta} + \boldsymbol{\lambda} \cdot \mathbf{W} \cdot \mathbf{y} + \mathbf{u} \quad (5.1)$$

$$\mathbf{u} \sim \mathbf{N}(\mathbf{0},\ \boldsymbol{\sigma}^{2}\mathbf{I})$$

---

[20] Both the Moran's I and LM statistics were used to test spatial dependency. The value of Moran's I statistics was 14.00 ($p<0.0001$). The values of LM statistics were LM-lag test=295.48 ($p<0.0001$) and LM-error test=190.29 ($p<0.0001$).

[21] The results from the spatial error model were included in Appendix C.

where $\boldsymbol{y}$ is a vector of the dependent variable; **P** is a matrix of variables for property characteristics and loan-to-value ratio; **N** is a matrix of variables for socioeconomic characteristics; **B** is a matrix of variables for built environmental characteristics; $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\delta}$ are a matrix of the estimated parameters; and $\mathbf{u}$ is the error term. The spatially lagged dependent variable is included in the form of $\mathbf{W} \cdot \mathbf{y}$; $\mathbf{W}$ is the spatial weighting matrix; λ denotes the spatial dependence parameter to be estimated; and v is the i.i.d. disturbance. To create a spatial weighting matrix, the contiguity approach with areal data can best represent spatial relationships among neighboring census tracts. Commonly considered is the queen spatial weight matrix; regions are considered to be correlated if they share any common boundaries. With respect to built environmental effects, the nonlinear function of built environment variables may be more reasonable in accounting for the relationships with the outcomes. Therefore, the quadratic terms of land use mix, residential density, street density and street connectivity were also examined. GeoDa Space (Arizona State University, Tempe, AZ) was used in the spatial regression analyses.

5.3.3.2 Statistical Method for REO Duration

In this study, the second dependent variable is the number of days until the REO property is sold. A hazard model is widely used for the time-to-event data, which is censored (i.e. observations are only available during the research time period). The Cox hazard proportion model was employed to estimate the built environmental effects on the market duration of REO sales.[22] Based on the distribution of the probability of a property being sold within a time interval given that the REO sale has not occurred, the Cox hazard model is estimated conditionally on property and neighborhood characteristics. The Cox hazard model is written as (Cox, 1972):

$$h(t, x) = h_0(t) \cdot \exp(\mathbf{X\beta}) \tag{5.2}$$

where $h(t, x)$ is the hazard function of the probability of being sold at a time, t, given the conditions of the x variables; $h_0(t)$ is the baseline hazard function which is not conditional on the x variables; **X** is the matrix of explanatory variables for property characteristics, socio-economic neighborhood characteristics, and built environment characteristics; $\boldsymbol{\beta}$ is the matrix of the estimated coefficients. To ascertain the different impacts of built environmental characteristics on the REO duration across property values, the interaction terms between the property value and the built environments were also included in the matrix of **X**. Stata 13 (StataCorp LP, College Station, TX) was used for estimating the Cox hazard model.

[22] For the robust check, the results from the Weibull Hazard Model was also included in Appendix D.

5.4 Results and Discussions

5.4.1 Distribution of REO Outcomes and Built Environments

The REO density, SES of neighborhoods, and built environmental characteristics were spatially distributed to explore the geographic patterns as shown in Figures 8 and 9. As illustrated in Figure 8, the density of REO properties appears to be higher in most lower-income neighborhoods. In such neighborhoods, the assessed property value of REO properties seems to be lower than in other areas. Figure 9 shows the distributions of residential density, land-use mix, and street connectivity. The maps of residential density and street connectivity show some clusters in the mid-south area of the county, and similar patterns are also evident in high REO density and low median household income.

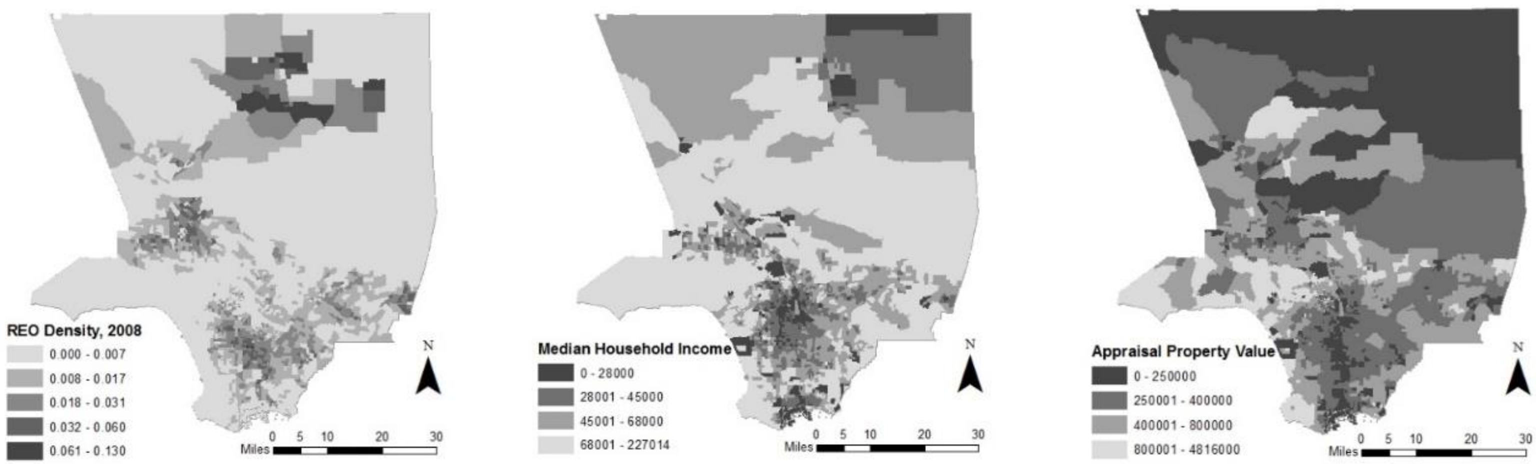

Figure 8. Spatial Patterns of REO Density and Socio-Economic Characteristics

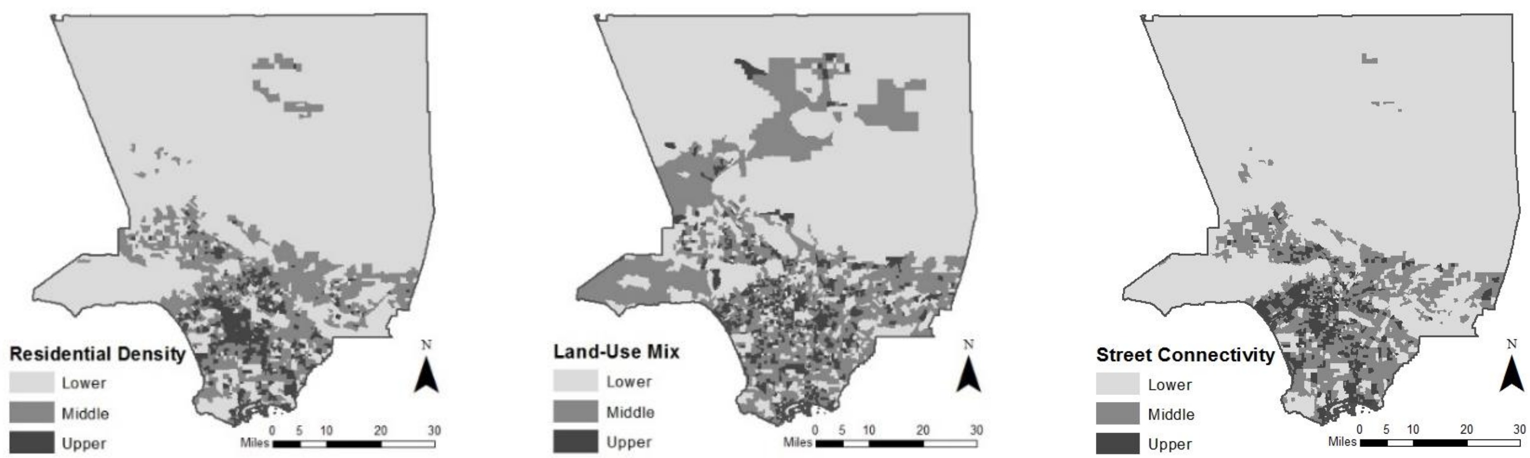

Figure 9. Spatial Patterns of Residential Density, Land-Use Mix, and Street Connectivity

Figure 10 presents the distribution of the average number of days to REO sales across the levels of built environments and property-value classes. For the lower level of built environments, the average number of days to REO sales tended to increase with the increase of property-value classes. However, in upper level residential density and street connectivity, the average number of days was shown to be higher for lower-valued REO properties. The average number of days decreased until the property value reached approximately $250,000, and then increased.

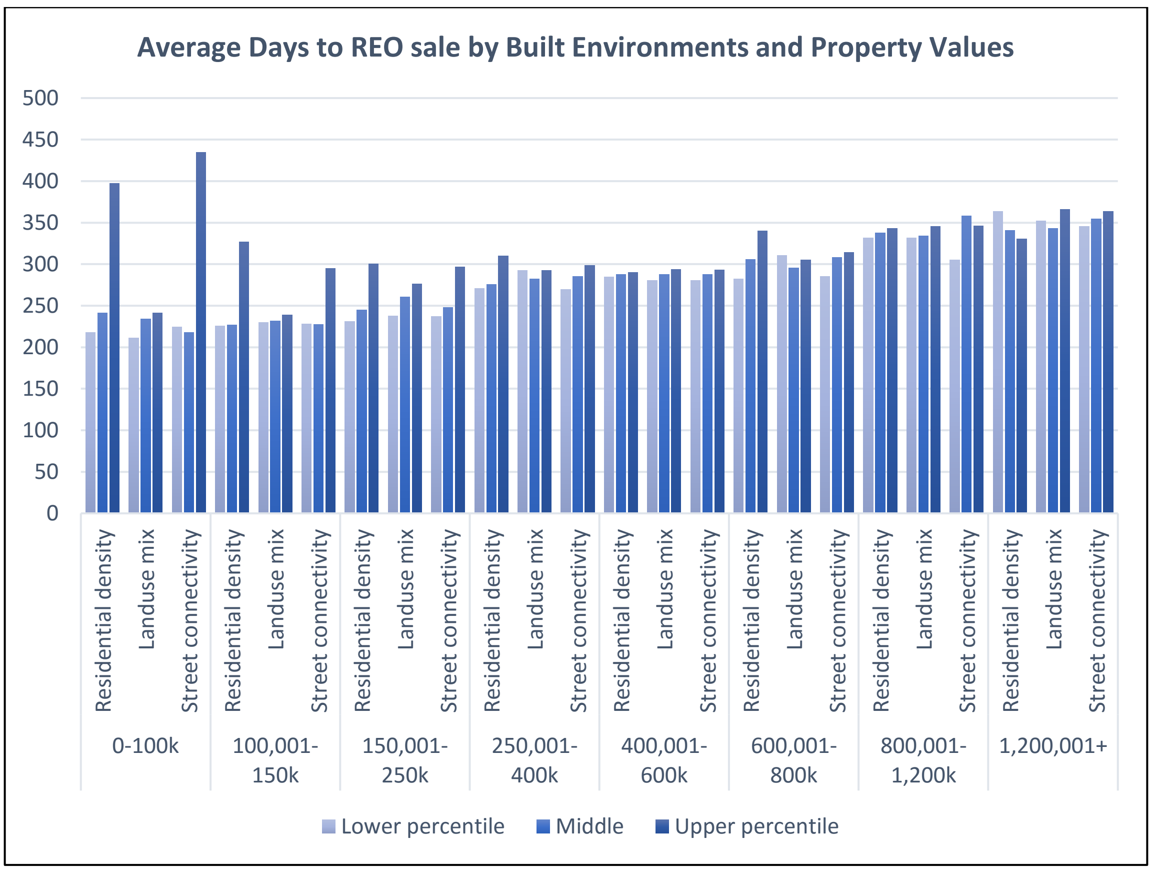

Figure 10. Average Days to REO Sale by Built Environments and Property Values

5.4.2 REO Density

Table 6 shows the results of the spatial lag model. The higher density of REOs in census tracts was significantly associated with property characteristics representing a lower median property value, a larger number of bedrooms, and more recent year of construction. Unexpectedly, the sign of the estimated loan-to-value (LTV) variable was negative, indicating that neighborhoods with a higher median loan-to-value ratio were correlated with a lower density of REOs.

Consistent with the literature (Allen, 2011; Immergluck, 2010a), neighborhoods with a higher percentage of black residents, a lower percentage of Asian residents, a lower median household income, and a higher unemployment rate have significant associations with a higher density of REOs. The results indicate that underprivileged communities with unemployed low-income and minority (especially black) residents experienced more REOs. While the literature showed a significant result for Hispanics in higher foreclosures (Aka, 2012), the Hispanic variable was not significant in this result. Hispanics are a major population group in LA, and this may help explain why. Other socio-demographic characteristics in census tracts were included in the current study. Neighborhoods with populations consisting of a higher number of residents aged 65 and over were found to have a lower REO density. On the other hand, neighborhoods containing higher percentages of residents under the age of 18 had a higher REO density. Households with more family members may have higher expenses given their income level, meaning that reducing the level of family income may not keep them from falling further into the process of foreclosure (Morton, 1975). As expected, a higher rate of vacant lands was significantly correlated with a higher REO density. In turn, REO properties are more likely to remain vacant, and therefore, the negative impact of REO properties could be cumulative (Immergluck, 2010a). The results showed that a higher rate of mortgaged housing units increased REO density. As mentioned in the literature (Immergluck, 2010b), this result may also imply that the high-risk lending activity in neighborhoods needs to be regulated in order to reduce further foreclosure activities.

The variable for active commuting to work was negatively associated with REO density, indicating that neighborhoods with a higher percentage of residents who walk or bike to work were less likely to experience foreclosures. One possible interpretation of this result is that neighborhood environments that foster active living have a role in the deterrence of foreclosures. The physical built environments supporting walkability were also significantly associated with REO density. The coefficients of land-use mix and street connectivity were significant and negative, indicating that more diverse and accessible neighborhoods had a lower density of REO properties. Residential density was shown to be positively associated with REO density in Model 1, but a nonlinear association with REO density was also found in Model 2; beyond a certain level of residential density (when residential density is $10 = 0.002/0.0001/2$), REO density became negatively associated with the increase in residential density.[23] Although bike lane and park can provide adequate infrastructure for walkability, they were found not to

[23] The calculation is based on the coefficients of the single term (0.002) and the square term (-0.0001) of residential density. The value, 10, is located approximately in the 99th percentile of residential density. More accurately, one can infer that REO density decreases in extremely highly dense residential areas.

be statistically significant for reducing REO density. Among the measures of neighborhood safety (crime, crash, and average speed limit), crime density was the only significant variable for an increase in REO density.

Table 6. Spatial Regression Results of REO Density and Built Environments

Variables	Model 1		Model 2	
	Coeff.	**S.E.**	**Coeff.**	**S.E.**
Property value (/$10,000)	-0.0008***	1.3E-04	-0.0007***	0.0001
Sqft (/100)	-7.4E-05	8.5E-05	-0.0001	0.0001
Beds	0.0016**	0.0005	0.0014**	0.0005
Year built	6.5E-05***	1.5E-05	0.0001***	0.0000
LTV	-0.0040**	0.0014	-0.0037**	0.0014
Median income				
Middle	0.0016*	0.0007	0.0013†	0.0007
High	-0.0021*	0.0009	-0.0022*	0.0009
Hispanic (/10)	0.0002	0.0002	0.0001	0.0002
Black (/10)	0.0008***	0.0002	0.0008***	0.0002
Asian (/10)	-0.0008***	0.0002	-0.0009***	0.0002
Pop18 (/10)	0.0042***	0.0005	0.0042***	0.0005
Pop65 (/10)	-0.0011†	0.0006	-0.0014*	0.0006
Unemployment (/10)	0.0033***	0.0006	0.0033***	0.0006
Vacancy (/10)	0.0027***	0.0006	0.0030***	0.0006
Mortgage (/10)	0.0038***	0.0011	0.0037***	0.0010
Active living (/10)	-0.0026***	0.0007	-0.0027***	0.0007
Crime density	0.0013**	0.0004	0.0012**	0.0004
Crash density	-0.0022	0.0037	0.0013	0.0037
Residential density	0.0009***	0.0002	0.0020***	0.0003
Square (Residential density)	N/A		-0.0001**	0.0000
Land-use mix	-0.0104***	0.0013	-0.0047	0.0047
Square (land-use mix)	N/A		-0.0043	0.0043
Street connectivity	-0.0179***	0.0038	-0.0278**	0.0084
Square (street connectivity)	N/A		0.0291	0.0195
Bike lane availability	0.0003	0.0005	0.0003	0.0005
Park availability	-0.0008	0.0005	-0.0007	0.0005

Table 6. Continued

	Model 1		Model 2	
	Coeff.	**S.E.**	**Coeff.**	**S.E.**
Constant	-0.1277***	0.0297	-0.1190***	0.0298
Spatial lag coefficient	0.3808***	0.0236	0.3819***	0.0235
Pseudo R^2	0.50		0.51	
Log-likelihood	6595.70		6602.11	

Notes: The spatial lag model was employed for both Model 1 and Model 2. Model 1 only included single terms of explanatory variables. Model 2 included the square terms of residential density, land use mix, and street connectivity. The units of Property Value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active Living were adjusted to obtain valid coefficients. The reference group of the median income is the low/moderate income group. The OLS results are reported in Appendix C. N=2110; † P<0.1, * P<0.05, ** P<0.01, *** P<0.001.

5.4.3 REO Duration

5.4.3.1 REO Duration, Property Value, and Built Environment

Table 7 and 8 shows the analytical results of the Cox proportional hazard model. In addition to the hazard ratio, the hazard coefficient was also included to aid the interpretation of the results. Table 7 presents the results for all samples. Consistent with the literature (Pfeiffer & Molina, 2013), the coefficients on square footage, the number of bedrooms, and year built are significant. An increase in the square footage of a building by 100 and the number of bedrooms decreased the likelihood of selling REOs by 0.3% and 2.17% respectively. An increase in the year of construction increased the likelihood of an REO being sold by 0.2%.

Among the socio-economic attributes of neighborhoods, the race/ethnicity (Hispanic, black, and Asian) was found to be significant. When the population of Hispanics and blacks in neighborhoods increased by 10 percentage points, the likelihood of REO properties being sold was lowered by 1.1% and 3.0%, respectively. Conversely, the likelihood of an REO being sold increased by 2.04% when the population of Asians in neighborhoods increased by 10 percentage points. These results are consistent with the literature, showing that the racial/ethnic composition of neighborhoods significantly influences the length of time REO properties remain on the market (Y. Li & Walter, 2013; Pfeiffer & Molina, 2013). However, Y. S. Lee and Immergluck (2012) found that minority communities experienced faster sales. They noted that lower-valued REOs were more likely to be sold, and that such properties were generally located in minority communities. While the previous study (Y. S. Lee & Immergluck, 2012) found that properties in neighborhoods with a higher median household income increased the likelihood of being sold, this study did not find any statistical significance for median household income. Somewhat unexpectedly, a percentage increase of vacant units in a neighborhood increase the likelihood of an REO being sold by 3.77%. A possible explanation is that neighborhood vacancies may relate to negative home equity, and the decrease in home values might be positively associated with the likelihood of selling REOs.

Consistent with the literature, the results show that REO properties with a higher property value were less likely to be sold. The estimated hazard ratio of the property value variable was 0.9973, meaning that when a property value increases by $10,000, an REO property has a 0.27% lower likelihood of being sold, when holding other factors constant. Previous research indicated that investors were more likely to purchase low-value properties because of their high absorption rate in the market (Immergluck, 2012; Immergluck & Law, 2014).

For residential density, land-use mix, and street connectivity, the estimated hazard ratios were found to be significant almost exclusively in the upper percentile category. The single terms of those three domains were estimated as negative, indicating that REOs in more compact, mixed and accessible neighborhoods were less likely to be sold. However, the interaction terms with property value were estimated as positive, indicating that the effects of compact, mixed, and accessible neighborhoods on REO duration increase with property value. Compared to the middle level of residential density, REOs in the upper level of residential density had a 4.2% lower likelihood of being sold at the mean of the samples; however, the likelihood of being sold increased by 0.17 of a percentage point with the increase in property value. The likelihood of being sold became positive when a property value reached nearly $640,000.[24] REOs in the upper level of mixed land-use areas had a 1.13% lower likelihood of being sold at the mean of the samples.[25] The estimated interaction effect of land-use mix with property value was not statistically significant. Upper-level street connectivity was also estimated as negative in the single term and positive in the interaction term with property value. Upper-level street connectivity increased the hazard ratio by 0.12 of a percentage point with every $10,000 increase in property value.

For other built environmental attributes, the results found that the likelihood of REOs being sold was 2.38% greater in neighborhoods with bike lanes. Neighborhood

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[24] Based on the hazard coefficients, the property value (PV) of $640,000 was derived from the following calculation: PV = 0.1082/0.0017. The coefficient of the upper percentile of residential density was -0.1082, and the coefficient of the interaction was 0.0017.
[25] The mean property value of the samples was $384,000.

safety influenced the likelihood of an REO being sold; however, crash-related safety had a significant hazard ratio of 0.60, meaning that REOs located in areas with higher crash rates were 40% less likely to be sold when the crash rate increased by one crash per acre. The estimated coefficient of park availability was positive but not significant.

Table 7. Results of REO Duration and Built Environments for All REOs

Variables	**Coeff. (S.E.)**	**Haz. Ratio (S.E.)**	**Z**	**P-value**
2009	**-0.1728 (0.0098)**	**0.8414 (0.0083)**	**-17.70**	**0.000**
2010	**-0.2407 (0.0107)**	**0.7861 (0.0084)**	**-22.61**	**0.000**
2011	**-0.1150 (0.0121)**	**0.8915 (0.0108)**	**-9.54**	**0.000**
2012	**0.0456 (0.0173)**	**1.0467 (0.0181)**	**2.65**	**0.008**
2013	**0.3516 (0.0475)**	**1.4213 (0.0675)**	**7.41**	**0.000**
Sqft (/100)	**-0.0031 (0.0010)**	**0.9970 (0.0010)**	**-3.34**	**0.001**
Beds	**-0.0220 (0.0057)**	**0.9783 (0.0056)**	**-3.90**	**0.000**
Year built	**0.0020 (0.0003)**	**1.0020 (0.0003)**	**8.47**	**0.000**
Loan-to-value	0.0001 (0.0001)	1.0001 (0.0001)	0.66	0.512
Median income				
Middle	-0.0152 (0.0122)	0.9850 (0.0121)	-1.24	0.214
High	-0.0176 (0.0175)	0.9826 (0.0172)	-1.01	0.313
Hispanic (/10)	**-0.0080 (0.0032)**	**0.9921 (0.0032)**	**-2.48**	**0.013**
Black (/10)	**-0.0140 (0.0031)**	**0.9862 (0.0030)**	**-4.59**	**0.000**
Asian (/10)	**0.0202 (0.0041)**	**1.0204 (0.0042)**	**4.95**	**0.000**
Pop18 (/10)	0.0128 (0.0112)	1.0129 (0.0114)	1.14	0.252
Pop65 (/10)	-0.0145 (0.0138)	0.9857 (0.0136)	-1.05	0.293
Ownership (/10)	0.0068 (0.0036)	1.0068 (0.0037)	1.88	0.060
Unemployment (/10)	0.0118 (0.0103)	1.0119 (0.0104)	1.15	0.249
Vacancy (/10)	**0.0370 (0.0100)**	**1.0377 (0.0104)**	**3.72**	**0.000**
Mortgage (/10)	0.0163 (0.0161)	1.0164 (0.0163)	1.01	0.311
Active living (/10)	-0.0146 (0.0175)	0.9856 (0.0173)	-0.83	0.405
Crime density	-0.0017 (0.0069)	0.9984 (0.0069)	-0.24	0.809
Crash density	**-0.5043 (0.0880)**	**0.6040 (0.0532)**	**-5.73**	**0.000**

Table 7. Continued

Variables	Coeff. (S.E.)	Haz. Ratio (S.E.)	Z	P-value
Property Value (PV) (/ $10,000)	**-0.0029 (0.0004)**	**0.9973 (0.0004)**	**-7.17**	**0.000**
Residential density				
Lower level	0.0086 (0.0200)	1.0086 (0.0202)	0.43	0.670
Upper level	**-0.1082 (0.0243)**	**0.8976 (0.0218)**	**-4.47**	**0.000**
PV × Residential density				
Lower level	-0.0005 (0.0005)	0.9996 (0.0005)	-1.07	0.286
Upper level	**0.0017 (0.0006)**	**1.0017 (0.0006)**	**2.76**	**0.006**
Land-use mix				
Lower level	-0.0162 (0.0172)	0.9840 (0.0169)	-0.94	0.346
Upper level	**-0.0421 (0.0192)**	**0.9588 (0.0184)**	**-2.20**	**0.028**
PV × Land-use mix				
Lower level	0.0002 (0.0004)	1.0002 (0.0004)	0.44	0.657
Upper level	0.0008 (0.0005)	1.0008 (0.0005)	1.62	0.106
Street connectivity				
Lower level	**-0.0655 (0.0205)**	**0.9367 (0.0192)**	**-3.21**	**0.001**
Upper level	-0.0403 (0.0226)	0.9606 (0.0217)	-1.79	0.074
PV × Street connectivity				
Lower level	**0.0017 (0.0005)**	**1.0017 (0.0005)**	**3.63**	**0.000**
Upper level	**0.0012 (0.0006)**	**1.0012 (0.0006)**	**2.15**	**0.032**
Bike lane availability	**0.0235 (0.0080)**	**1.0238 (0.0082)**	**2.94**	**0.003**
Park availability	0.0002 (0.0082)	1.0002 (0.0082)	0.02	0.981

Notes: N=73837, LR-Chi2=1704.87 ($p<0.0001$), Log-likelihood=-735576.78; The units of Property value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active living were adjusted to obtain valid coefficients and hazard ratios; Bold texts represent the statistical significance at the 0.05 level.

Figure 11 presents the plots of the estimated log hazards for the assessed property value, given the different percentile levels of built environmental attributes. The lines for the residential density and street connectivity showed similarities in trends. With the increase in property value, the estimated log hazards decreased in the low and middle levels of residential density and street connectivity. For the upper level, the slope of the lines was rare, and above certain property values, the estimated log hazards were higher than in the lower and middle levels. The plots for the upper level of residential density and street connectivity indicate that the likelihood of being sold increased with property values for REO properties located in compact and accessible neighborhoods. Land-use mix did not show any significant differences in the levels of built environments.

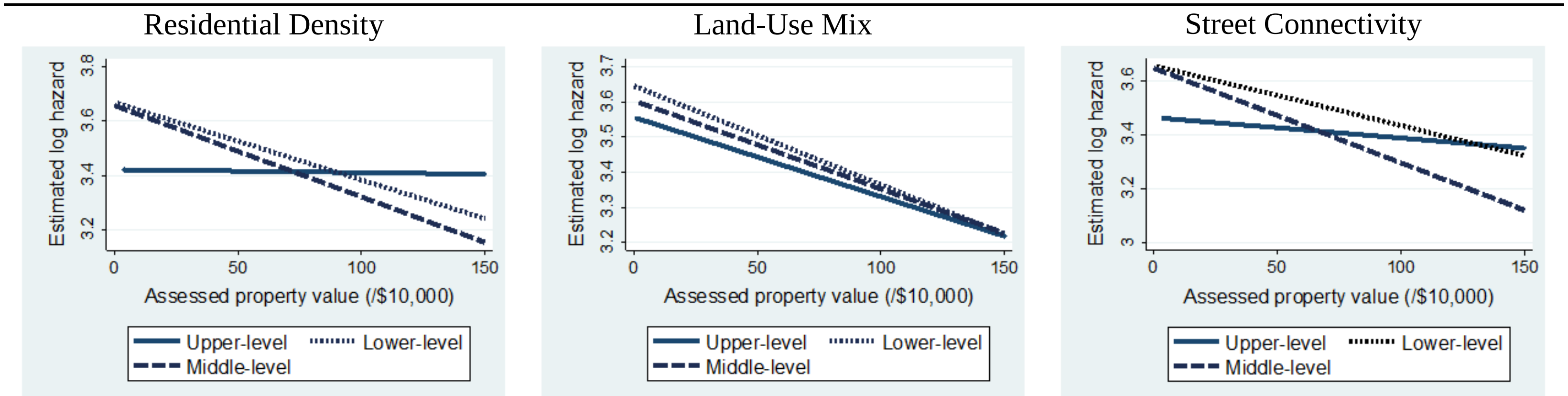


Figure 11. Estimated Log Hazard Plots by Different Levels of Built Environmental Attributes

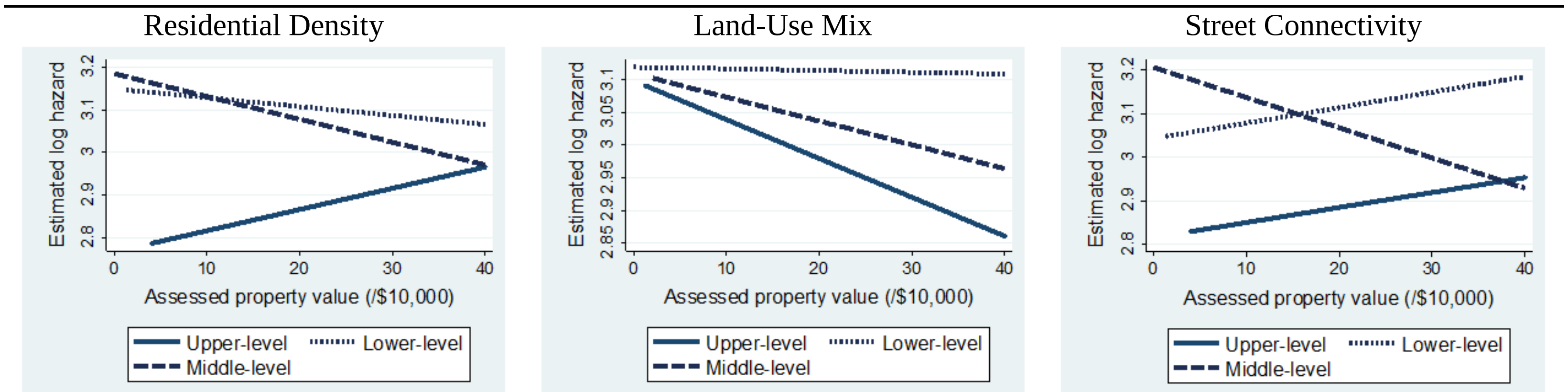


Figure 12. Estimated Log Hazard Plots by Different Levels and Attributes of Built Environments for Low-Value REOs

5.4.3.2 REO Duration and Built Environment for Lower-Value REO Properties

Table 8 shows the results of the subsample of REO properties valued at less than $250,000. Based on the distribution in Figure 10, $250,000 can be regarded as the cut-off point for the subsample, which needs further investigation. The property value of $250,000 was located below the 25th percentile in all samples. Compared with the results of all samples in Table 7, fewer variables were found to be significant in Table 8. The estimated coefficients of property and neighborhood characteristics were similar to the results of Table 7. Among property attributes, the square footage and year built were found to be significant. A hundred unit increase in the square footage decreased the likelihood of being sold by 1.81%. A one year increase in the year of construction increased the likelihood of being sold by 0.17%. From the significant variables in the socio-economic characteristics, the estimated hazard ratio of the Black population was 0.9847, meaning that the increase of 10 percentage points in the share of the Black population in a given neighborhood decreased the likelihood of an REO being sold by 1.53%.

For built environmental characteristics, residential density and street connectivity were found to be significant. Low-value REO properties in upper-level residential density had a 12.23% lower likelihood of being sold than those in middle-level residential density at the mean of the samples.[26] The effect of high residential density was a decrease in the likelihood of lower-value REO properties being sold. Low-value

[26] The mean property value for low-value REOs was $178,600.

REO properties in the lower level of street connectivity had a 1.05% lower likelihood of being sold at the mean of the samples. The bike lane and park availability variables showed no differences in direction or significance.

Figure 12 shows different patterns of the plots from those in Figure 11. The plot of the upper level of residential density and street connectivity is upward, with increasing property values; however, the estimated log hazards are lower than in the lower and middle levels. For any given levels of land-use mix, the estimated log hazard decreased with property value. The plot of the lower level of land-use mix is fairly close to a horizontal line, and the estimated log hazard is higher than in the middle and upper levels.

Table 8. Results of REO Duration and Built Environment for Low-Value REOs

Variables	Coeff. (S.E.)	Haz. Ratio (S.E.)	Z	P-value
2009	**-0.1001 (0.0187)**	**0.9048 (0.0169)**	**-5.36**	**0.000**
2010	**-0.1935 (0.0207)**	**0.8242 (0.0171)**	**-9.36**	**0.000**
2011	**-0.0609 (0.0231)**	**0.9410 (0.0217)**	**-2.64**	**0.008**
2012	-0.0048 (0.0331)	0.9953 (0.0330)	-0.14	0.886
2013	**0.4083 (0.0848)**	**1.5043 (0.1276)**	**4.81**	**0.000**
Sqft (/100)	**-0.0184 (0.0025)**	**0.9819 (0.0025)**	**-7.37**	**0.000**
Beds	0.0123 (0.0126)	1.0124 (0.0127)	0.98	0.328
Year built	0.0017 (0.0005)	1.0017 (0.0005)	**3.53**	**0.000**
Loan-to-value	0.0001 (0.0001)	1.0001 (0.0001)	0.63	0.528
Median income				
Middle	0.0051 (0.0209)	1.0051 (0.0210)	0.24	0.810
High	-0.0371 (0.0397)	0.9637 (0.0383)	-0.93	0.350
Hispanic (/10)	-0.0051 (0.0059)	0.9950 (0.0058)	-0.87	0.384
Black (/10)	**-0.0155 (0.0078)**	**0.9847 (0.0077)**	**-1.98**	**0.048**
Asian (/10)	0.0096 (0.0214)	1.0097 (0.0216)	0.45	0.653
Pop18 (/10)	0.0222 (0.0245)	1.0224 (0.0251)	0.90	0.366
Pop65 (/10)	0.0244 (0.0349)	1.0247 (0.0358)	0.70	0.485
Ownership (/10)	0.0070 (0.0080)	1.0070 (0.0081)	0.87	0.384
Unemployment (/10)	0.0125 (0.0195)	1.0126 (0.0198)	0.64	0.521
Vacancy (/10)	0.0344 (0.0181)	1.0350 (0.0188)	1.90	0.058
Mortgage (/10)	-0.0041 (0.0331)	0.9961 (0.0329)	-0.12	0.904
Active living (/10)	-0.0008 (0.0429)	0.9993 (0.0429)	-0.02	0.986
Crime density	0.0171 (0.0128)	1.0172 (0.0130)	1.34	0.180
Crash density	-0.3721 (0.2265)	0.6893 (0.1561)	-1.64	0.100
Property Value (PV) (/$10,000)	-0.0043 (0.0033)	0.9958 (0.0033)	-1.31	0.192
Residential density				
Lower percentile	0.0404 (0.0874)	1.0412 (0.0910)	0.46	0.644
Upper percentile	**-0.2627 (0.1292)**	**0.7691 (0.0994)**	**-2.03**	**0.042**
PV × Residential density				
Lower percentile	-0.0006 (0.0047)	0.9995 (0.0047)	-0.11	0.912
Upper percentile	0.0074 (0.0064)	1.0074 (0.0064)	1.16	0.245
Land-use mix				
Lower percentile	-0.0274 (0.0712)	0.9731 (0.0693)	-0.38	0.701
Upper percentile	0.0053 (0.0758)	1.0054 (0.0762)	0.07	0.944

Table 8. Continued

Variables	Coeff. (S.E.)	Haz. Ratio (S.E.)	Z	P-value
PV × Land-use mix				
Lower percentile	0.0039 (0.0040)	1.0039 (0.0040)	0.98	0.329
Upper percentile	-0.0026 (0.0040)	0.9975 (0.0040)	-0.65	0.515
Street connectivity				
Lower percentile	**-0.2664 (0.0888)**	**0.7663 (0.0680)**	**-3.00**	**0.003**
Upper percentile	-0.1903 (0.1241)	0.8268 (0.1026)	-1.53	0.125
PV × Street connectivity				
Lower percentile	**0.0155 (0.0048)**	**1.0156 (0.0049)**	**3.23**	**0.001**
Upper percentile	0.0061 (0.0062)	1.0061 (0.0062)	0.98	0.326
Bike lane availability	**0.0449 (0.0170)**	**1.0459 (0.0178)**	**2.64**	**0.008**
Park availability	-0.0109 (0.0183)	0.9892 (0.0181)	-0.60	0.551

Notes: N=20174, LR-Chi2=479.63 ($p<0.0001$), Log-likelihood=-175574.94; The sub-sample for lower-valued REOs (less than $250,000) was estimated; The units of Property value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active living were adjusted to obtain valid coefficients and hazard ratios; Bold texts represent the statistical significance at 0.05 level.

5.5 Conclusions and Policy Implications

One public policy approach for resolving foreclosure problems would be to reduce REO activity and the length of time a property remains in REO status. While "double triggers" (negative individual life events and negative home equity) may be the key to increasing mortgage default risk (Foote et al., 2008), the marketability of a property may depend more on the bundle of structural and environmental characteristics of the property. The literature has shown the importance of the environment in raising the marketability of a property. For example, walkable urban forms that provide greater accessibility place a price premium on a property. In this sense, walkable environments can help properties exit the foreclosure process by being sold to a new owner. This research utilized the D-variable (density, diversity, and design) framework, which provides measurable constructs for spatial characteristics of walkable neighborhoods, in order to establish whether and how walkable environments can help reduce REO density and duration. Although a growing number of studies argue that neighborhood context, with a particular focus on socio-economic characteristics, should be taken into consideration in designing foreclosure policies, no study has yet examined built environmental impacts on REO density and duration.

The findings highlight that not only socioeconomic conditions but also built environmental characteristics have significant associations with REO density and REO duration. A larger percentage of blacks, unemployed, vacancies, and mortgaged homes increased the density of REOs. In REO duration, relatively few variables, such as Hispanic and black, were significant. Vacancy was also significant, but increased the likelihood of the sale of an REO. Safer neighborhoods and more accessible and diverse settings of the built environment, encouraging walkability, were important considerations in reducing REO filings. Denser and more accessible settings of the built environment increased the likelihood of a sale, but only in cases of higher-value REOs. The findings indicate that the walkable environments contribute to a strategy for increasing the marketability of properties and reduce the slide of REOs into deterioration.

In the REO duration analyses, this research revealed further implications through testing the interaction terms between assessed property values and built environmental attributes. Holding built environmental factors constant at the middle level, this study found that low-value REOs tended to be sold more quickly, which is a similar finding to previous research on the relationship between market value and REO duration. However, in neighborhoods with a high density of residents and street connections, low-value REOs were less likely to be sold, but high-value REOs usually sold faster. This finding may reflect the fact that denser and more accessible neighborhoods translate inequitably into the marketability of properties. In addition, foreclosure disparities may exist in an inequitable distribution of market-supported environments. The samples used in this research also showed that the geographic distribution of lower-valued REO properties was more concentrated in low-income and minority communities. It is possible that the quality of built environmental resources is less desirable in such communities, and that the resources are less available, even though those communities have the same spatial structures of built environmental attributes as high-income communities. The evidence has shown that low-income and minority communities are generally disadvantaged in neighborhood safety such as crimes and crashes, and in environmental features such as esthetics and recreational areas and facilities (Sallis et al., 2011; Zhu & Lee, 2008). This research emphasizes the gap in policy intervention, which requires further attention on built environmental attributes.

The findings of this research are constrained by the following limitations. First, due to the data availability, this research did not include profiles of sellers and brokers. Because of the seller's motivation, an REO property might be held off as "shadow inventory" until the market condition recovers or "dumped" because of a difficult market condition. A broker's ability may also influence the REO sales (Y. Li & Walter, 2013). Most covariates (such as property attributes and neighborhood characteristics) used in this research were estimated consistently with the previous literature, but the omitted variables would merit further investigation in future research. Second, this research focused on REO properties, but the data did not divulge information on whether REO properties are vacant or tenant-occupied. Third, due to the geographical (LA County) and temporal (2008-2013) limitations, the findings may not apply to other contexts and other time periods. REO accumulation may vary across states where the foreclosure processes are different (Immergluck, 2010a). Last, this research did not include specific aspects of built environmental resources, such as the availability and quality of neighborhood amenities. This would be the potential for uncovering further relationship between built environments and foreclosures in future research.

To help local communities recover from the foreclosure crisis, policymakers and local governments focus on the effectiveness of existing policy interventions such as the Neighborhood Stabilization Program (NSP), to reduce vacancies and rehabilitate communities by encouraging the purchase of foreclosed homes. As strategic options for designing effective policies, further enforcement efforts for improving the quality of environmental attributes are also needed to help protect our neighborhoods from the impacts of foreclosures.

CHAPTER VI

CONCLUSION

This dissertation has examined how walkable environments alleviate foreclosure-related activities. This study advances the existing literature by incorporating built environmental factors into the examination of foreclosure spillover effects, foreclosure density, and foreclosure duration. Findings from this study provide important implications for future interventions to reduce the impacts of foreclosure.

6.1 Overview of Findings

Chapter III presented a comprehensive examination of the literature to identify methodological and content issues and improve understanding of foreclosure spillover effects on property values. This review highlighted a lack of a thorough examination of contextual neighborhood factors, such as built environmental effects. Previous evidence supports the economically sustainable benefits of the walkable environment as a result of accessible and compact urban design. Thus, the review discussed opportunities for future research that addresses environmental interventions to reduce the price spillover effects of foreclosures. The review also indicated that insufficient attention has been given to the dynamic and elaborate details of foreclosure measurement. Measuring specific foreclosure stages and statuses, property types, and property conditions may provide opportunities to disentangle the mechanisms affecting foreclosures and nearby property values. In addition, further research is suggested to examine the extent to which foreclosure spillover effects vary across neighborhood characteristics, housing market periods, and housing submarkets.

The research gaps addressed in Chapter III and Chapter IV examined how neighborhood walkability can weaken the negative foreclosure spillover effects on property values. By using the interaction terms between neighborhood walkability, measured as Walk Score (WS) and neighboring foreclosures, this chapter evaluated the degree to which neighborhood walkability lessens the intensity of foreclosure spillover effects on property values. Using separate models, the differential impacts of the walkability premium on price spillovers of foreclosures were also analyzed for two different income groups (low versus high) and market periods (the housing market crash of 2010 versus the housing market recovery of 2013). The results showed that the price spillover effects of foreclosure were significantly attenuated in very walkable neighborhoods (WS: 70-95) by 54.26-69.77% for 2010, and 66.04-84.91% for 2013; however, the mitigation effects were insignificant for low-income groups. This leads to the conclusion that potential income disparities in walkability impacts may exist, which ameliorate negative price spillovers of foreclosures.

Chapter V investigated the influence of walkability-related environments – residential density, land-use mix, and street connectivity – as represented by the D-variable frame (density, diversity and design), on real estate owned (REO) foreclosures. Two dependent variables were used: REO density and REO duration. This chapter highlighted a lower REO density in neighborhoods which are safer, more accessible, and have a diverse setting of built environments. By using interaction terms between the market value of REOs and built environmental factors, the study found that higher-value REOs in denser and more accessible neighborhoods were more likely to be sold; on the contrary, lower-value REOs were less likely to be sold. These findings help to explain inconsistent results regarding the duration of low-value REOs in the previous literature. This study implies the underlying disparity issues regarding environmental support for the marketability of foreclosed properties. Essentially, compact and accessible environments are not beneficial to low-income and minority communities.

Overall, this dissertation demonstrates that a walkable neighborhood has the potential to provide resilience benefits of enhancing neighborhood stability in the aftermath of an economic shock. In particular, this dissertation suggests that neighborhood walkability can help to boost recovery from a foreclosure crisis through producing economic benefits and reducing foreclosure-related events. As emphasized by Jane Jacobs (1961), the findings from this dissertation imply that more accessible and compact urban designs could help holistic planning strategies to enhance social and economic activities. While a growing demand for living in walkable communities with environmental improvements has been documented (Handy, Sallis, Weber, Maibach, & Hollander, 2008; Hollander, Martin, & Vehige, 2008), an increased concern for policy makers could be the decreasing affordability of housing as result (Haughey & Sherriff, 2011). To counteract this concern, the government may need to promote policies to encourage mixed-income and diverse housing development. It is also important to encourage policy initiatives such as financial and regulatory incentives in order to increase affordable housing in walkable communities.

The study findings also demonstrate new aspects of socioeconomic disparities in the recovery from the impact of foreclosure as a possible consequence of unequal environmental supports, in terms of neighborhood maintenance and aesthetics. Figure 13 illustrates street views in low-income and high-income areas in Los Angeles, and shows the explicit differences in visual appeals, sidewalk conditions, garden and lawn conditions, street trees, safe fences, and building façade. Undesirable quality in neighborhood environments may reduce the potential benefits from walkability in low-income areas, even when low-income areas have high levels of walkability (e.g., greater accessibility, compactness, and diversity.

High-walkability & Low-income area

High-walkability & High-income area

Figure 13. Illustrations of Compact and Accessible Environments in Low-Income versus High-Income Residential Areas
Note: Both areas are represented in the upper percentile level of residential density, land-use mix, and street connectivity, and the very walkable neighborhood (WS: 80). The images were captured by using Google Street View.

In summary, this dissertation suggests that a comprehensive effort is needed to design dense neighborhoods with a mixture of land uses and accessible destinations. This would not only benefit communities in terms of economic resilience during the economic downturn, but also provide an important opportunity to achieve a healthy way of living and well-being. More importantly, income-based disparities in such walkability impacts would be reduced by improving the quality of the neighborhood.

6.2 Policy Implications

Empirical evidence from this study brings attention to the potential for an environmental intervention to develop effective policies for reducing foreclosure impacts. The first implication is that strategies targeting investments for neighborhood revitalization should consider the contextual characteristics of neighborhoods. Since 2008, the federal Neighborhood Stabilization Program (NSP) has been implemented across the three rounds (NSP1, NSP2, and NSP3) to prevent further spread of foreclosure contagions. The revitalization activities include rehabilitation, demolition, land banking, and redevelopment of foreclosed or vacant properties (Schuetz, Spader, Buell, et al., 2015). However, the funds of such place-based policies are very limited relative to other refinancing and loan modification programs, such as the homebuyer tax credits and the Home Affordable Modification Program (Been, Chan, Ellen, & Madar, 2011; Immergluck, 2013). With limited public resources, strategic investments in adequate neighborhoods are important for ensuring the effectiveness of a policy intervention. The funding formulas are largely flexible in designing strategies by localities and generally based on housing market conditions and the prevalence of foreclosed and vacant properties (Schuetz, Spader, Buell, et al., 2015). Recent research on the investigation of neighborhood characteristics of the NSP2 tracts in seven counties noted that income status was not the primary determinant of NSP tract selection

(Schuetz, Spader, & Cortes, 2015). Regarding contextual characteristics such as residential density, this study argues that spatially clustered low-income and minority areas should have a high priority for revitalization programs.

This study also highlights the importance of walkability-related development as a larger strategy for stabilizing neighborhoods. The effectiveness of policy strategies for achieving neighborhood stabilization has shown mixed results with variations across geographical areas and market conditions (Galster, Tatian, & Accordino, 2006). Certainly, how we strategically implement effective investments in response to policy problems has always been a researchable question. In 2008, the NSP launched an initiative for reducing foreclosure effects which focused on strategic plans to acquire and rebuild or demolish foreclosed and vacant properties. However, this may not be enough to resolve the dilapidated neighborhood problems that result from foreclosures. Strategic policy efforts might need to be more grounded in establishing walkable and healthy communities that stem from the recognition that physical environments have an impact on social and economic activities. The results from this dissertation confirm the economically sustainable benefits of walkability-related built environments. Achieving healthy and livable neighborhoods requires well-designed and accessible neighborhood amenities, such as public parks and trails, pedestrian and bike facilities, and small-scale outlets and stores, for recreational and utilitarian purposes. To improve the operation of such built environmental resources, pedestrian-oriented urban designs, multi-modal transportation networks, good landscape and visual appeal, and neighborhood safety from crime and traffic are also needed. Such a development template for building healthy communities should be taken into account when developing policy interventions for neighborhood stabilization.

Additionally, the socio-economic disparities in the area of environmental support require more comprehensive efforts for resiliency from foreclosure impacts. As mentioned in Chapters IV and V, although low-income and minority communities have the same or even greater built environmental characteristics for achieving walkable environments that could lead to higher marketability of properties and investment returns, the poor quality and availability of built environmental resources could undermine the benefits of denser and more accessible neighborhoods. Low-income and minority communities are also disproportionately exposed to risk factors such as crimes, traffic, and environmental hazards (Sallis et al., 2011; Zhu & Lee, 2008). Although the literature has focused on foreclosure disparities, especially by socio-economic status, no study has thoroughly examined foreclosure impacts in conjunction with environmental disparities. In the light of the environmental disparities, the importance of environmental policy intervention requires further research to justify the equity issues and guide future policies.

6.3 Future Studies

With advanced measurement and methodology approaches, more rigorous research is suggested for future studies. First, future studies should elaborate the spillover effects on neighborhood through specifying foreclosure measures over time, which allows a consideration of the trajectory of foreclosed properties from a pre-foreclosure to an REO sale. Further inferences for causal mechanisms could be drawn by separating foreclosure externalities based on property types and conditions, as well as foreclosure stages and statuses. Second, future research needs to use different approaches such as the stated preference method to evaluate the impact of foreclosures. While the stated preference approach might be challenging and costly, it could be valuable to draw specific policy-related neighborhood specific initiatives. Third, future studies should identify micro-level measures of the built environment (e.g., audit measures), which were not captured in this dissertation. Fourth, future studies will build on current research on the foreclosure-crime relationship and the foreclosure-health relationship, linking them with walkability impacts. Finally, it is necessary to apply a longitudinal study design and an intervention-driven approach to the research on environmental support.

REFERENCES

Adamowicz, W. L., Louviere, J., & Williams, M. (1994). Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities. *Journal of Environmental Economics and Management, 26*(3), 271-292.

Aka, E. (2012). Foreclosure Disparities in Metropolitan Atlanta Counties Housing Market, 2000-2010: Implications for Policies and Planning. *International Journal of Interdisciplinary Social Sciences, 6*(6), 89-126.

Allen, R. (2011). Who Experiences Foreclosures? The Characteristics of Households Experiencing a Foreclosure in Minneapolis, Minnesota. *Housing Studies, 26*(6), 845-866.

Allison, P. D. (2010). *Survival Analysis Using SAS: a practical guide*: SAS Institute.

Anenberg, E., & Kung, E. (2014). Estimates of the Size and Source of Price Declines Due to Nearby Foreclosures. *American Economic Review*, *104*(8), 2527-2551.

Anglin, P. M., Rutherford, R., & Springer, T. M. (2003). The Trade-off Between the Selling Price of Residential Properties and Time-on-the-Market: The Impact of Price Setting. *The Journal of Real Estate Finance and Economics, 26*(1), 95-111.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models. by Luc Anselin*: Dordrecht : Springer Netherlands, 1988.

Anselin, L. (2003). Spatial Externalities, Spatial Multipliers, and Spatial Econometrics. *International Regional Science Review, 26*(2), 153-166.

Anselin, L., & Lozano-Gracia, N. (2008). Errors in variables and spatial effects in hedonic house price models of ambient air quality. *Empirical Economics*, *34*(1), 5-34.

Anselin, L., & Rey, S. J. (1991). Properties of Tests for Spatial Dependence in Linear Regression Models. *Geographical Analysis*, *23*(2), 112-131.

Anselin, L., & Rey, S. J. (2014). *Modern Spatial Econometrics in Practice : A Guide to GeoDa, GeoDaSpace and PySAL*: Chicago, IL : GeoDa Press LLC, [2014].

Apgar, W. C., Duda, M., & Gorey, R. N. (2005). The municipal cost of foreclosures: A Chicago case study. *Minneapolis, MN: Homeownership Preservation Foundation*.

Avery, R. B. (1996). Credit Risk, Credit Scoring, and the Performance of Home Mortgages. *Federal Reserve Bulletin*, *82*(7), 621-648.

Bartholomew, K., & Ewing, R. (2011). Hedonic price effects of pedestrian-and transit-oriented development. *Journal of Planning Literature*, *26*(1), 18-34.

Basu, S., & Thibodeau, T. G. (1998). Analysis of Spatial Autocorrelation in House Prices. *The Journal of Real Estate Finance and Economics, 17*(1), 61-85.

Batson, C. D., & Monnat, S. M. (2015). Distress in the Desert: Neighborhood Disorder, Resident Satisfaction, and Quality of Life During the Las Vegas Foreclosure Crisis. *Urban Affairs Review, 51*(2), 205-238.

Baxter, V., & Lauria, M. (2000). Residential mortgage foreclosure and neighborhood change. *Housing Policy Debate*, *11*(3), 675-699.

Been, V., Chan, S., Ellen, I. G., & Madar, J. R. (2011). Decoding the foreclosure crisis: Causes, responses, and consequences. *Journal of Policy Analysis & Management, 30*(2), 388-396.

Benefield, J. D., & Hardin, W. G. (2013). Does Time-on-Market Measurement Matter? *The Journal of Real Estate Finance and Economics, 50*(1), 52-73.

Biswas, A. (2012). Housing submarkets and the impacts of foreclosures on property prices. *Journal of Housing Economics, 21*(3), 235-245.

Blackman, A., & Krupnick, A. (2001). Location-Efficient Mortgages: Is the Rationale Sound? *Journal of Policy Analysis and Management*(4), 633.

Bocian, D. G., Ernst, K. S., & Li, W. (2008). Race, ethnicity and subprime home loan pricing. *Journal of Economics and Business, 60*(1–2), 110-124.

Bocian, D. G., Smith, P., & Li, W. (2012). Collateral damage: The spillover costs of foreclosures: Durham, NC: Center for Responsible Lending.

Boyle, A., Barrilleaux, C., & Scheller, D. (2014). Does Walkability Influence Housing Prices? *Social Science Quarterly (Wiley-Blackwell), 95*(3), 852-867.

Boyle, K. J. (2003). Introduction to Revealed Preference Methods. In P. Champ, K. Boyle & T. Brown (Eds.), *A Primer on Nonmarket Valuation* (Vol. 3, pp. 259-267): Springer Netherlands.

Brownson, R. C., Hoehner, C. M., Day, K., Forsyth, A., & Sallis, J. F. (2009). Measuring the built environment for physical activity: state of the science. *American journal of preventive medicine, 36*(4), S99-S123. e112.

Cagney, K. A., Browning, C. R., Iveniuk, J., & English, N. (2014). The Onset of Depression During the Great Recession: Foreclosure and Older Adult Mental Health. *American Journal of Public Health, 104*(3), 498-505 498p.

Callaghan, E. G., & Colton, J. (2008). Building sustainable & resilient communities: a balancing of community capital. *Environment, Development and Sustainability, 10*(6), 931-942.

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced Sales and House Prices. *American Economic Review, 101*(5), 2108-2131.

Capozza, D. R., & Thomson, T. A. (2006). Subprime Transitions: Lingering or Malingering in Default? *The Journal of Real Estate Finance and Economics, 33*(3), 241-258.

Carr, L. J., Dunsiger, S. I., & Marcus, B. H. (2010). Walk Score™ As a Global Estimate of Neighborhood Walkability. *American journal of preventive medicine, 39*(5), 460-463.

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

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment, 2*(3), 199-219.

Chan, S., Gedal, M., Been, V., & Haughwout, A. (2013). The role of neighborhood characteristics in mortgage default risk: Evidence from New York City. *Journal of Housing Economics, 22*(2), 100-118.

Cheung, R., Cunningham, C., & Meltzer, R. (2014). Do homeowners associations mitigate or aggravate negative spillovers from neighboring homeowner distress? *Journal of Housing Economics, 24*, 75-88.

Clauretie, T. M., & Daneshvary, N. (2009). Estimating the House Foreclosure Discount Corrected for Spatial Price Interdependence and Endogeneity of Marketing Time. *Real Estate Economics, 37*(1), 43-67.

Clauretie, T. M., & Sirmans, G. S. (2010). *Real Estate Finance: Theory & Practice: Theory and Practice* (6 ed.): Cengage Learning.

Cleves, M. A., Gould, W. W., Gutierrez, R. G., & Marchenko, Y. U. (2008). *An introduction to survival analysis using Stata* (2nd ed.): College Station, Tex. : Stata Press, [2008].

Cliff, A. D., & Ord, J. K. (1972). Testing for Spatial Autocorrelation Among Regression Residuals. *Geographical Analysis, 4*(3), 267-284.

Cliff, A. D., & Ord, J. K. (1981). *Spatial processes: Models & Applications* (Vol. 44): London: Pion.

Cox, D. R. (1972). Regression Models and Life-Tables. *Journal of the Royal Statistical Society. Series B (Methodological), 34*(2), 187-220.

Cui, L., & Walsh, R. (2015). Foreclosure, vacancy and crime. *Journal of Urban Economics, 87*, 72-84.

Daneshvary, N., & Clauretie, T. M. (2012). Toxic neighbours: foreclosures and short-sales spillover effects from the current housing-market crash. *Economic Inquiry, 50*(1), 217-231.

Daneshvary, N., Clauretie, T. M., & Kader, A. (2011). Short-Term Own-Price and Spillover Effects of Distressed Residential Properties: The Case of a Housing Crash. *The Journal of Real Estate Research, 33*(2), 179-207.

Dannenberg, A. L., Frumkin, H., & Jackson, R. (2011). *Making healthy places : designing and building for health, well-being, and sustainability*: Washington, D.C. : Island Press, [2011].

Diao, M., & Ferreira Jr, J. (2010). Residential property values and the built environment: empirical study in the Boston, Massachusetts, Metropolitan Area. *Transportation Research Record: Journal of the Transportation Research Board*(2174), 138-147.

Dormann, C. F., McPherson, J. M., Araújo, M. B., Bivand, R., Bolliger, J., Carl, G., . . . Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography, 30*(5), 609-628.

Downey, L., & Van Willigen, M. (2005). Environmental Stressors: The Mental Health Impacts of Living Near Industrial Activity. *Journal of Health and Social Behavior, 46*(3), 289-305.

Dubin, R. A. (1988). ESTIMATION OF REGRESSION COEFFICIENTS IN THE PRESENCE OF SPATIALLY AUTOCORRELATED ERROR TERMS. *Review of Economics & Statistics, 70*(3), 466.

Dubin, R. A. (2003). Robustness of Spatial Autocorrelation Specifications: Some Monte Carlo Evidence. *Journal of Regional Science, 43*(2), 221-248.

Duncan, D. T., Aldstadt, J., Whalen, J., Melly, S. J., & Gortmaker, S. L. (2011). Validation of Walk Score® for Estimating Neighborhood Walkability: An Analysis of Four US Metropolitan Areas. *International Journal of Environmental Research and Public Health*(11).

Duncan, M. (2010). The Impact of Transit-oriented Development on Housing Prices in San Diego, CA. *Urban Studies*.

Ellen, I. G., Lacoe, J., & Sharygin, C. A. (2013). Do foreclosures cause crime? *Journal of Urban Economics, 74*, 59-70.

Ellen, I. G., Madar, J., & Weselcouch, M. (2015). The Foreclosure Crisis and Community Development: Exploring REO Dynamics in Hard-Hit Neighborhoods. *Housing Studies, 30*(4), 535-559.

Eppli, M. J., & Tu, C. C. (1999). *Valuing the new urbanism: The impact of the new urbanism on prices of single-family homes*: Washington, DC : Urban Land Institute, [1999].

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board, 1780*, 87-114.

Ewing, R., & Cervero, R. (2010). Travel and the built environment. *Journal of the American Planning Association*, *76*(3), 265-294.

Farr, D. (2008). *Sustainable urbanism : urban design with nature*: Hoboken, N.J. : Wiley, [2008].

Foote, C. L., Gerardi, K., & Willen, P. S. (2008). Negative equity and foreclosure: Theory and evidence. *Journal of Urban Economics, 64*(2), 234-245.

Foster, S., & Giles-Corti, B. (2008). The built environment, neighborhood crime and constrained physical activity: An exploration of inconsistent findings. *Preventive Medicine, 47*(3), 241-251.

Fotheringham, A. S., & Rogerson, P. (2009). *The SAGE handbook of spatial analysis. edited by A. Stewart Fotheringham and Peter A. Rogerson*: Los Angeles, [Calif.] ; London : SAGE, 2009.

Frame, W. S. (2010). Estimating the Effect of Mortgage Foreclosures on Nearby Property Values: A Critical Review of the Literature. *Economic Review - Federal Reserve Bank of Atlanta, 95*(3), II,1-9.

Frank, L. D., Engelke, P. O., & Schmid, T. L. (2003). *Health and community design : the impact of the built environment on physical activity. Lawrence D. Frank, Peter O. Engelke, Thomas L. Schmid*: Washington, DC : Island Press, [2003].

Frank, L. D., Sallis, J. F., Conway, T. L., Chapman, J. E., Saelens, B. E., & Bachman, W. (2006). Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality. *Journal of the American Planning Association, 72*(1), 75-87.

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010). The development of a walkability index: application to the Neighborhood Quality of Life Study. *British journal of sports medicine, 44*(13), 924-933.

Frank, L. D., Stone Jr, B., & Bachman, W. (2000). Linking land use with household vehicle emissions in the central puget sound: methodological framework and findings. *Transportation Research Part D: Transport and Environment, 5*(3), 173-196.

Frumkin, H., Frank, L. D., & Jackson, R. (2004). *Urban sprawl and public health : designing, planning, and building for healthy communities*: Washington, D.C. : Island Press, [2004].

Galster, G., Tatian, P., & Accordino, J. (2006). Targeting Investments for Neighborhood Revitalization. *Journal of the American Planning Association, 72*(4), 457-474.

Garber, R., Kim, J., Sullivan, K., & Dowell, E. (2008). $60 Million and Counting: The Cost of Vacant and Abandoned Properties to Eight Ohio Cities: Columbus: Community Research Partners.

Garrod, G., & Willis, K. G. (1999). *Economic valuation of the environment : methods and case studies. Guy Garrod, Kenneth G. Willis*: Cheltenham, UK ; Northampton, MA : Edward Elgar, [1999].

Gehl, J. (1987). *Life between buildings : using public space. Jan Gehl ; translated by Jo Koch*: New York : Van Nostrand Reinhold, [1987].

Gerardi, K., Rosenblatt, E., Willen, P. S., & Yao, V. (2015). Foreclosure externalities: New evidence. *Journal of Urban Economics, 87,* 42-56.

Gerardi, K., Shapiro, A. H., & Willen, P. S. (2007). *Subprime Outcomes: Risky Mortgages, Homeownership Experiences, and Foreclosures*. Working Paper. Federal Reserve Bank of Boston.

Ghent, A. C., & Kudlyak, M. (2011). Recourse and Residential Mortgage Default: Evidence from US States. *Review of Financial Studies*.

Gilderbloom, J. I., Riggs, W. W., & Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. *Cities, 42*(Part A), 13-24.

Glower, M., Haurin, D. R., & Hendershott, P. H. (1998). Selling Time and Selling Price: The Influence of Seller Motivation. *Real Estate Economics, 26*(4), 719-740.

Grambsch, P. M., & Therneau, T. M. (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika, 81*(3), 515-526.

Greene, W. H. (2012). *Econometric analysis. 7th ed. William H. Greene* (7th ed.): Boston : Prentice Hall, [2012].

Groves, J. R., & Rogers, W. H. (2011). Effectiveness of RCA Institutions to Limit Local Externalities: Using Foreclosure Data to Test Covenant Effectiveness. *Land Economics, 87*(4), 559.

Guo, S. (2010). *Survival analysis. Shenyang Guo*: New York : Oxford University Press, 2010.

Hall, M., Crowder, K., & Spring, A. (2015). Neighborhood Foreclosures, Racial/Ethnic Transitions, and Residential Segregation. *American Sociological Review, 80*(3), 526-549.

Halvorsen, R., & Pollakowski, H. O. (1981). Choice of functional form for hedonic price equations. *Journal of Urban Economics, 10*(1), 37-49.

Han, H.-S. (2014). The Impact of Abandoned Properties on Nearby Property Values. *Housing Policy Debate, 24*(2), 311-334.

Handy, S., Sallis, J. F., Weber, D., Maibach, E., & Hollander, M. (2008). Is Support for Traditionally Designed Communities Growing? Evidence From Two National Surveys. *Journal of the American Planning Association, 74*(2), 209-221.

Harding, J. P., Rosenblatt, E., & Yao, V. W. (2009). The contagion effect of foreclosed properties. *Journal of Urban Economics, 66*(3), 164-178.

Hartley, D. (2014). The effect of foreclosures on nearby housing prices: Supply or dis-amenity? *Regional Science and Urban Economics, 49*, 108.

Haughey, R., & Sherriff, R. (2011). *Challenges and policy options for creating and preserving affordable housing near transit and in other location-efficient areas*: DIANE Publishing.

Haurin, D. (1988). The Duration of Marketing Time of Residential Housing. *Journal of the American Real Estate & Urban Economics Association, 16*(4), 396-410.

Hill, T. D., Ross, C. E., & Angel, R. J. (2005). Neighborhood Disorder, Psychophysiological Distress, and Health. *Journal of Health and Social Behavior, 46*(2), 170-186.

Hipp, J. R., & Chamberlain, A. W. (2015). Foreclosures and crime: A city-level analysis in Southern California of a dynamic process. *Social Science Research, 51*, 219-232.

Hollander, M., Martin, S. L., & Vehige, T. (2008). The Surveys Are In! The Role of Local Government in Supporting Active Community Design. *Journal of Public Health Management and Practice*, *14*(3), 228-237.

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D., & Haas, P. (2002). Location Efficiency: Neighborhood and Socio-Economic Characteristics Determine Auto Ownership and Use - Studies in Chicago, Los Angeles and San Francisco. *Transportation Planning and Technology*, *25*(1), 1-27.

Hosmer, D. W., Lemeshow, S., & May, S. (2008). *Applied survival analysis : regression modeling of time-to-event data* (2nd ed.): Hoboken, N.J. : Wiley-Interscience, [2008].

Houle, J. N. (2014). Mental health in the foreclosure crisis. *Social Science & Medicine, 118*, 1-8.

Ihlanfeldt, K., & Mayock, T. (2014). The Impact of REO sales on Neighborhoods and Their Residents. *The Journal of Real Estate Finance and Economics*, 1-43.

Immergluck, D. (2008). From the Subprime to the Exotic: Excessive Mortgage Market Risk and Foreclosures. *Journal of the American Planning Association*, *74*(1), 59-76.

Immergluck, D. (2009). The Foreclosure Crisis, Foreclosed Properties, and Federal Policy: Some Implications for Housing and Community Development Planning. *American Planning Association. Journal of the American Planning Association*, *75*(4), 406-423.

Immergluck, D. (2010a). The accumulation of lender-owned homes during the US mortgage crisis: examining metropolitan REO inventories. *Housing Policy Debate, 20*(4), 619-645.

Immergluck, D. (2010b). Neighborhoods in the Wake of the Debacle: Intrametropolitan Patterns of Foreclosed Properties. *Urban Affairs Review, 46*(1), 3-36.

Immergluck, D. (2012). Distressed and Dumped: Market Dynamics of Low-Value, Foreclosed Properties during the Advent of the Federal Neighborhood Stabilization Program. *Journal of Planning Education and Research, 32*(1), 48.

Immergluck, D. (2013). Too Little, Too Late, and Too Timid: The Federal Response to the Foreclosure Crisis at the Five-Year Mark. *Housing Policy Debate, 23*(1), 199-232.

Immergluck, D., & Law, J. (2014). Investing in Crisis: The Methods, Strategies, and Expectations of Investors in Single-Family Foreclosed Homes in Distressed Neighborhoods. *Housing Policy Debate, 24*(3), 568-593.

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

Jackson, J. R., & Kaserman, D. L. (1980). Default Risk on Home Mortgage Loans: A Test of Competing Hypotheses. *The Journal of Risk and Insurance, 47*(4), 678-690.

Jacobs, J. (1961). *The death and life of great American cities* New York : Random House, [1961].

Joice, P. A. (2011). Neighborhood Stabilization Program. *Cityscape: A Journal of Policy Development and Research, 13*(1), 135-141.

Kashian, R., & Carroll, J. D. (2011). The Effect of Sheriff's Sales on Condominium Sub-market Property Values. *Journal of Regional Analysis and Policy, 41*(1), 70-81.

Katz, C. M., Wallace, D., & Hedberg, E. C. (2013). A Longitudinal Assessment of the Impact of Foreclosure on Neighborhood Crime. *Journal of Research in Crime and Delinquency, 50*(3), 359-389.

Kelejian, H. H., & Prucha, I. R. (1998). A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *The Journal of Real Estate Finance and Economics*, *17*(1), 99-121.

Kelejian, H. H., & Prucha, I. R. (1999). A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model. *International Economic Review, 40*(2), 509-533.

Kelejian, H. H., & Prucha, I. R. (2010a). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics, 157*(1), 53-67.

Kelejian, H. H., & Prucha, I. R. (2010b). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics, 157*(1), 53.

Kingsley, G. T., Smith, R., & Price, D. (2009). The impacts of foreclosures on families and communities. *Washington, DC: The Urban Institute*, 757-786.

Knight, J. R. (2002). Listing Price, Time on Market, and Ultimate Selling Price: Causes and Effects of Listing Price Changes. *Real Estate Economics, 30*(2), 213-237.

Kobie, T. F., & Lee, S. (2010). The Spatial-Temporal Impact of Residential Foreclosures on Single-Family Residential Property Values. *Urban Affairs Review, 47*(1), 3-30.

Koster, H. R. A., & Rouwendal, J. (2012). The impact of mixed land use on residential property values. *Journal of Regional Science, 52*(5), 733-761.

Kovacs, K. F. (2012). Integrating property value and local recreation models to value ecosystem services from regional parks. *Landscape and Urban Planning, 108*(2-4), 79-90.

Kupke, V., Rossini, P., & McGreal, S. (2012). Measuring the impact of higher density housing development. *Property Management, 30*(3), 274-291.

Lambie-Hanson, L. (2015). When does delinquency result in neglect? Mortgage distress and property maintenance. *Journal of Urban Economics, 90*, 1-16.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy, 74*(2), 132-157.

Lee, C., & Moudon, A. V. (2004). Physical activity and environment research in the health field: implications for urban and transportation planning practice and research. *Journal of Planning Literature, 19*(2), 147-181.

Lee, K.-y. (2008). Foreclosure's price-depressing spillover effects on local properties: a literature review. St. Louis: Federal Reserve Bank of St Louis.

Lee, Y. S., & Immergluck, D. (2012). Explaining the Pace of Foreclosed Home Sales during the US Foreclosure Crisis: Evidence from Atlanta. *Housing Studies, 27*(8), 1100-1123.

Leinberger, C., & Alfonzo, M. (2012). Walk this way: The economic promise of walkable places in metropolitan Washington, DC: The Brookings Institution.

Leonard, T., & Murdoch, J. C. (2009). The neighborhood effects of foreclosure. *Journal of Geographical Systems, 11*(4), 317-332.

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics. James LeSage, R. Kelley Pace*: Boca Raton : CRC Press, [2009].

Leyden, K. M. (2003). Social capital and the built environment: The importance of walkable neighborhoods. *American Journal of Public Health, 93*(9), 1546-1551.

Li, W., Joh, K., Lee, C., Kim, J.-H., Park, H., & Woo, A. (2014). From Car-Dependent Neighborhoods to Walkers' Paradise: Estimating Walkability Premiums in the Condominium Housing Market. *Transportation Research Record*(2453), 162-170.

Li, W., Joh, K., Lee, C., Kim, J.-H., Park, H., & Woo, A. (2015). Assessing Benefits of Neighborhood Walkability to Single-Family Property Values: A Spatial Hedonic Study in Austin, Texas. *Journal of Planning Education and Research, 35*(4), 471.

Li, Y., & Walter, R. (2013). Single-Family Housing Market Segmentation, Post-Foreclosure Resale Duration, and Neighborhood Attributes. *Housing Policy Debate, 23*(4), 643-665.

Libman, K., Fields, D., & Saegert, S. (2012). Housing and Health: A Social Ecological Perspective on the US Foreclosure Crisis. *Housing, Theory & Society, 29*(1), 1-24.

Lin, Z., Rosenblatt, E., & Yao, V. W. (2009). Spillover Effects of Foreclosures on Neighborhood Property Values. *Journal of Real Estate Finance and Economics, 38*(4), 387-407.

Lindblad, M. R., & Riley, S. F. (2015). Loan Modifications and Foreclosure Sales during the Financial Crisis: Consequences for Health and Stress. *Housing Studies, 30*(7), 1092-1115.

Linden, L., & Rockoff, J. E. (2008). Estimates of the Impact of Crime Risk on Property Values from Megan's Laws. *American Economic Review, 98*(3), 1103-1127.

Ling, D. C., & Archer, W. R. (2010). *Real estate principles : a value approach. 3rd ed. David C. Ling, Wayne R. Archer* (3rd Ed.): Boston : McGraw-Hill Irwin, [2010].

Lipscomb, C. A. (2006). An Alternative Spatial Hedonic Estimation Approach. *Journal of Housing Research, 15*(2), 143-160.

Litman, T. (2003). Economic Value of Walkability. *Transportation Research Record: Journal of the Transportation Research Board, 1828*, 3-11.

Lorenc, T., Clayton, S., Neary, D., Whitehead, M., Petticrew, M., Thomson, H., . . . Renton, A. (2012). Crime, fear of crime, environment, and mental health and wellbeing: Mapping review of theories and causal pathways. *Health & place, 18*(4), 757-765.

Loukaitou-Sideris, A., & Eck, J. E. (2007). Crime Prevention and Active Living. *American Journal of Health Promotion, 21*(4s), 380-389.

Malpezzi, S. (2003). Hedonic pricing models: a selective and applied review. *Section in Housing Economics and Public Policy: Essays in Honor of Duncan Maclennan*.

Manaugh, K., & El-Geneidy, A. (2011). Validating walkability indices: How do different households respond to the walkability of their neighborhood? *Transportation Research Part D, 16*, 309-315.

Matthews, J. W., & Turnbull, G. K. (2007). Neighborhood Street Layout and Property Value: The Interaction of Accessibility and Land Use Mix. *Journal of Real Estate Finance and Economics*, *35*(2), 111-141.

Mayer, C., Pence, K., & Sherlund, S. M. (2009). The Rise in Mortgage Defaults. *The Journal of Economic Perspectives*, *23*(1), 27-50.

Mendelsohn, R., & Olmstead, S. (2009). The economic valuation of environmental amenities and disamenities: methods and applications. *Annual Review of Environment and Resources, 34*, 325-347.

Militino, A. F., Ugarte, M. D., & García-Reinaldos, L. (2004). Alternative Models for Describing Spatial Dependence among Dwelling Selling Prices. *The Journal of Real Estate Finance and Economics, 29*(2), 193-209.

Moreno, A. (1995). The cost-effectiveness of mortgage foreclosure prevention. *Minneapolis: Family Housing Fund*.

Morton, T. G. (1975). A Discriminant Function Analysis of Residential Mortgage Delinquency and Foreclosure. *Real Estate Economics, 3*(1), 73-88.

Moudon, A. V., Lee, C., Cheadle, A. O., Garvin, C., Johnson, D., Schmid, T. L., . . . Lin, L. (2006). Operational definitions of walkable neighborhood: theoretical and empirical insights. *Journal of Physical Activity & Health, 3,* S99.

Nicholls, S., & Crompton, J. L. (2005). The Impact of Greenways on Property Values: Evidence from Austin, Texas. *Journal of Leisure Research, 37*(3), 321-341.

Pace, R. K., Barry, R., & Sirmans, C. F. (1998). Spatial Statistics and Real Estate. *The Journal of Real Estate Finance and Economics, 17*(1), 5-13.

Pennington-Cross, A. (2006). The Value of Foreclosed Property. *The Journal of Real Estate Research, 28*(2), 193-214.

Pfeiffer, D., & Molina, E. T. (2013). The Trajectory of REOs in Southern California Latino Neighborhoods: An Uneven Geography of Recovery. *Housing Policy Debate, 23*(1), 81-109.

Pivo, G. (2013). The Effect of Sustainability Features on Mortgage Default Prediction and Risk in Multifamily Rental Housing. *Journal of Sustainable Real Estate, 5*(1), 149-170.

Pivo, G. (2014). Walk Score: The Significance of 8 and 80 for Mortgage Default Risk in Multifamily Properties. *Journal of Sustainable Real Estate, 6*(2), 187-210.

Prohaska, A., & Lichtenstein, B. (2014). Losing a Home to Mortgage Foreclosure: Temporary Setback or Chronic Stressor? *Social Justice, 40*(3), 65-80.

Quercia, R. G., & Stegman, M. A. (1992). Residential Mortgage Default: A Review of the Literature. *Journal of Housing Research, 3*(2), 341.

Rauterkus, S. Y., Thrall, G. I., & Hangen, E. (2010). Location Efficiency and Mortgage Default. *Journal of Sustainable Real Estate, 2*(1), 117-141.

RealtyTrac. (2011). 2010 Year-End U.S. Metro Foreclosure Report. Retrieved from http://www.realtytrac.com/content/press-releases/2010-year-end-us-metro-foreclosure-report-6317

Rogers, S. H., Halstead, J. M., Gardner, K. H., & Carlson, C. H. (2011). Examining Walkability and Social Capital as Indicators of Quality of Life at the Municipal and Neighborhood Scales. *Applied Research in Quality of Life, 6*(2), 201-213.

Rogers, W. H. (2010). Declining foreclosure neighborhood effects over time. *Housing Policy Debate, 20*(4), 687-706.

Rogers, W. H., & Winter, W. (2009). The Impact of Foreclosures on Neighboring Housing Sales. *The Journal of Real Estate Research, 31*(4), 455-479.

Rogerson, R. J. (1999). Quality of Life and City Competitiveness. *Urban Studies, 36*(5-6), 969-985.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy, 82*(1), 34.

Rugh, J. S., & Massey, D. S. (2010). Racial segregation and the American foreclosure crisis. *American Sociological Review, 75*(5), 629-651.

Rutherford, R. C., & Chen, J. (2012). Foreclosure, quality and spillover in residential markets. *International Journal of Housing Markets and Analysis, 5*(1), 53-70.

Saelens, B. E., & Handy, S. L. (2008). Built environment correlates of walking: a review. *Medicine and science in sports and exercise, 40*(7 Suppl), S550-S566.

Saelens, B. E., Sallis, J. F., & Frank, L. D. (2003). Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures. *Annals Of Behavioral Medicine: A Publication Of The Society Of Behavioral Medicine*, *25*(2), 80-91.

Sallis, J. F., Slymen, D. J., Conway, T. L., Frank, L. D., Saelens, B. E., Cain, K., & Chapman, J. E. (2011). Income disparities in perceived neighborhood built and social environment attributes. *Health & place*, *17*(6), 1274-1283.

Sallis, J. F., Spoon, C., Cavill, N., Engelberg, J. K., Gebel, K., Parker, M., . . . Ding, D. (2015). Co-benefits of designing communities for active living: an exploration of literature. *International Journal of Behavioral Nutrition & Physical Activity*, *12*, 1-10.

Schabenberger, O., & Gotway, C. A. (2005). *Statistical methods for spatial data analysis. Oliver Schabenberger, Carol A. Gotway*: Boca Raton : Chapman & Hall/CRC, [2005].

Schuetz, J., Been, V., & Ellen, I. G. (2008). Neighborhood effects of concentrated mortgage foreclosures. *Journal of Housing Economics, 17*(4), 306-319.

Schuetz, J., Spader, J., Buell, J. L., Burnett, K., Buron, L., Cortes, A., . . . Whitlow, S. (2015). Investing in Distressed Communities: Outcomes From the Neighborhood Stabilization Program. *17*(2), 279-306.

Schuetz, J., Spader, J., & Cortes, A. (2015). Have Distressed Neighborhoods Recovered? Evidence from the Neighborhood Stabilization Program *Working Papers -- U.S.*

Federal Reserve Board's Finance & Economic Discussion Series (pp. 1-48): US Federal Reserve Board.

Sirmans, G. S., Macpherson, D. A., & Zietz, E. N. (2005). The Composition of Hedonic Pricing Models. *Journal of Real Estate Literature, 13*(1), 3-43.

Skogan, W. G. (1990). *Disorder and decline : crime and the spiral of decay in American neighborhoods.* : New York : Free Press ; Toronto : Collier Macmillan Canada ; New York : Maxwell Macmillan International, [1990].

Sohn, W. D., Moudon, V. A., & Lee, J. (2012). The economic value of walkable neighborhoods. *URBAN DESIGN International*, *17*(2), 115-128.

Song, Y., & Knaap, G.-J. (2004). Measuring the effects of mixed land uses on housing values. *Regional Science and Urban Economics, 34*(6), 663-680.

Stedman, R. C. (2003). Is It Really Just a Social Construction?: The Contribution of the Physical Environment to Sense of Place. *Society & Natural Resources, 16*(8), 671-685.

Sugiyama, T., Neuhaus, M., Cole, R., Giles-Corti, B., & Owen, N. (2012). Destination and Route Attributes Associated with Adults' Walking: A Review. *Medicine & Science in Sports & Exercise, 44*(7), 1275-1286 1212p.

Taylor, L. O. (2008). Theoretical Foundations and Empirical Developments in Hedonic Modeling. In A. Baranzini, J. Ramirez, C. Schaerer & P. Thalmann (Eds.), *Hedonic Methods in Housing Markets* (pp. 15-37): Springer New York.

Turner, R. K., Pearce, D. W., & Bateman, I. (1993). *Environmental economics : an elementary introduction. R. Kerry Turner, David Pearce and Ian Bateman*: Baltimore : Johns Hopkins University Press, 1993.

Valente, J., Wu, S., Gelfand, A., & Sirmans, C. F. (2005). Apartment Rent Prediction Using Spatial Modeling. *Journal of Real Estate Research, 27*(1), 105-136.

Wassmer, R. W. (2011). The recent pervasive external effects of residential home foreclosure. *Housing Policy Debate, 21*(2), 247-265.

Whitaker, S. (2011). Foreclosure-related vacancy rates. *Economic Commentary*(July).

Whitaker, S., & Fitzpatrick IV, T. J. (2013). Deconstructing distressed-property spillovers: The effects of vacant, tax-delinquent, and foreclosed properties in housing submarkets. *Journal of Housing Economics, 22*(2), 79-91.

Whitehead, J. C., Pattanayak, S. K., Van Houtven, G. L., & Gelso, B. R. (2008). Combining Revealed and Stated Preference Data to Estimate the Nonmarket Value of Ecological Services: An Assessment of the State of the Science. *Journal of Economic Surveys, 22*(5), 872-908.

Williams, R., Reynold, N., & Eileen Diaz, M. (2005). The Changing Face of Inequality in Home Mortgage Lending, 181.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.): Cambridge, Mass. : MIT Press, [2010].

Wooldridge, J. M. (2013). *Introductory econometrics : a modern approach* (5th ed.): Mason, Ohio : South-Western Cengage Learning, [2013].

Young, R. A. (2005). *Determining the economic value of water : concepts and methods. Robert A. Young*: Washington, D.C. : Resources for the Future, [2005].

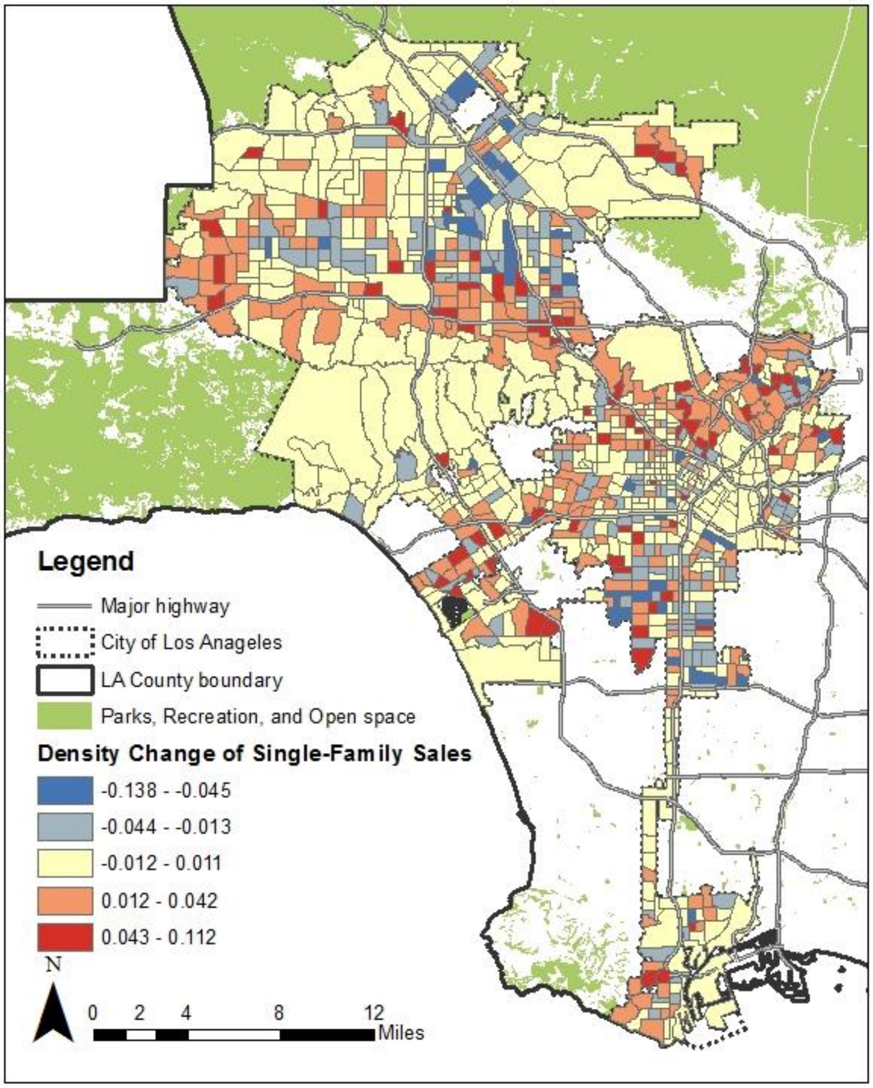
Zahabi, S., Miranda-Moreno, L., Patterson, Z., & Barla, P. (2013). Urban Transportation Greenhouse Gas Emissions and Their Link with Urban Form, Transit Accessibility, and Emerging Green Technologies. *Transportation Research Record: Journal of the Transportation Research Board, 2375*, 45-54.

Zhang, L., & Leonard, T. (2014). Neighborhood impact of foreclosure: A quantile regression approach. *Regional Science and Urban Economics, 48*, 133-143.

Zhu, X., & Lee, C. (2008). Walkability and Safety Around Elementary Schools: Economic and Ethnic Disparities. *American Journal of Preventive Medicine, 34*(4), 282-290.

APPENDIX A

DISTRIBUTION OF DENSITY CHANGE OF SINGLE-FAMILY HOME SALES



Note: The map illustrates the density change of single-family home sales between 2010 and 2013. The density change was based on the difference between the single-family home sales in 2010 and 2013 per acre in each census tract

APPENDIX B

EFFECTS OF NEIGHBORHOOD WALKABILITY AND FORECLOSURE

B-1 Results without Interaction Effects for the 2010 Sample

Variables	2010 sample (N=13438)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Property characteristics				
Log (lot size)	0.2196***	0.2635***	0.2511***	0.2330***
Year built	-3.90E-04	3.00E-04	2.10E-04	0.0007**
Beds	-0.0144**	-0.0162***	-0.0135**	0.0179***
Baths	0.1990***	0.1943***	0.1904***	0.1260***
Story	0.1276***	0.1423***	0.1394***	0.0827***
Pool	0.0979***	0.1049***	0.1036***	0.0799***
Garage	0.1922***	0.1858***	0.1724***	0.1007***
Financial characteristics				
Depressed sale	-0.2134***	-0.2109***	-0.2064***	-0.1681***
Socio-demographics				
Median income				
Middle	0.1238***	0.1302***	0.1201***	0.1068***
High	0.3182***	0.3478***	0.3310***	0.2946***
Unemployment	-0.0072***	-0.0077***	-0.0071***	-0.0088***
Mortgage	-7.90E-04	-0.0012**	-0.0011**	-0.0018**
Neighboring foreclosures				
Foreclosures	-0.0081***	-0.008***	-0.0088***	-0.0073***
Neighborhood Walkability				
Walk Score		0.0026***	0.0031***	0.0019***
Built environments				
Crime density			0.0170	0.0169
Crash density			-0.1158***	-0.1306***
Net residential density			-0.0020	-0.0108**
Average speed limits			-1.00E-03	0.0001
Bike lane			-0.0393***	-0.0332***
Highway			-0.0413***	-0.0400***
Rail road			-0.1223***	-0.1243***
Bus stop			-0.0106	-0.0097
Park			-0.0225**	-0.0116
Spatial lag variable				0.0171***
Spatial error variable				0.4860***
Constant	11.2100***	9.3660***	9.7450***	9.0220***
R^2 / Pseudo R^2	0.76	0.76	0.77	0.76
Mean VIF	1.90	1.91	1.82	1.82

Note: The OLS estimates were used for Model 1-3; The Cliff-Ord spatial regression model was used for Model 4. Monthly time trends and locational dummies were controlled for all models, but not reported; The spatial weight matrix was created based on 0.25 mile inverse distance weighting; * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

B-2 Results without Interaction Effects for the 2013 Sample

Variables	2013 sample (N=14502)			
	Model 1	Model 2	Model 3	Model 4
Property characteristics				
Log (lot size)	0.2027***	0.2521***	0.2599***	0.2388***
Year built	-7.7e-04**	4.10E-04	3.30E-04	0.0013***
Beds	-0.0186***	-0.0223***	-0.0201***	0.0182***
Baths	0.2079***	0.2020***	0.2007***	0.1247***
Story	0.1022***	0.1249***	0.1185***	0.0723***
Pool	0.0856***	0.0905***	0.0921***	0.0756***
Garage	0.1627***	0.1511***	0.1416***	0.0706***
Financial characteristics				
Depressed sale	-0.1912***	-0.1898***	-0.1880***	-0.1538***
Socio-demographics				
Median income (Ref: Low)				
Middle	0.1509***	0.1599***	0.1516***	0.1383***
High	0.3608***	0.3949***	0.3821***	0.3422***
Unemployment	-0.0039***	-0.0049***	-0.0047***	-0.0065***
Mortgage	-0.0010*	-0.0016***	-0.0017***	-0.0022***
Neighboring foreclosures				
Foreclosures	-0.0146***	-0.0148***	-0.0158***	-0.0113***
Neighborhood Walkability				
Walk Score		0.0033***	0.0036***	0.0023***
Built environments				
Crime density			7.10E-04	0.0049
Crash density			-0.0688**	-0.0906***
Net residential density			0.0124***	-0.0018
Average speed limits			0.0018	0.0013***
Bike lane			-0.0373***	-0.0339***
Highway			-0.0518***	-0.0454***
Rail road			-0.0632***	-0.0458*
Bus stop			-0.0228**	-0.0083
Park			0.0186*	0.0200*
Spatial lag variable				0.0158***
Spatial error variable				0.4886***
Constant	12.0800***	9.2320***	9.2790***	7.7370***
R^2 / Pseudo R^2	0.68	0.69	0.69	0.69
Mean VIF	1.93	1.93	1.84	1.84

Note: The OLS estimates were used for Model 1-3; The Cliff-Ord spatial regression model was used for Model 4. Monthly time trends and locational dummies were controlled for all models, but not reported; The spatial weight matrix was created based on 0.25 mile inverse distance weighting; * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

B-3 Robustness Check with Different Spatial Weight Matrices

Variables	2010 sample (N=13438)		2013 sample (N=14502)	
	K-nearest	**Binary**	**K-nearest**	**Binary**
Property characteristics				
Log (lot size)	0.1555***	0.2349***	0.1690***	0.2419***
Year built	0.0007***	0.0005*	0.0012***	0.0011***
Beds	0.0121***	0.0150***	0.0116***	0.0126**
Baths	0.1091***	0.1376***	0.1129***	0.1369***
Story	0.0710***	0.0927***	0.0486***	0.0744***
Pool	0.0600***	0.0813***	0.0508***	0.0797***
Garage	0.0752***	0.1148***	0.0554***	0.0877***
Financial characteristics				
Depressed sale	-0.1584***	-0.1732***	-0.1476***	-0.1564***
Socio-demographics				
Median income (Ref: Low)				
Middle	0.0380***	0.1219***	0.0529***	0.1494***
High	0.1045***	0.3283***	0.1312***	0.3727***
Unemployment	-0.0018***	-0.0092***	-0.0013*	-0.0066***
Mortgage	1.5E-05	-0.0014*	-0.0002	-0.0020**
Built environments				
Crime density	-0.0020	0.0202	-0.0039	0.0054
Crash density	-0.0648***	-0.1147***	-0.0267	-0.0730**
Net residential density	0.0086***	-0.0102**	0.0170***	0.0017
Average speed limits	-0.0022**	-0.0007	-0.0016	0.0009
Bike lane	-0.0117*	-0.0380***	-0.0125*	-0.0334***
Highway	-0.0012	-0.0369***	-0.0102	-0.0537***
Rail road	-0.0411***	-0.1288***	-0.0120	-0.0505*
Bus stop	-0.0012	-0.0096	-0.0075	-0.0126
Park	-0.0065	-0.0154	0.0105	0.0134
Neighboring foreclosures				
Foreclosures	-0.0045***	-0.0143***	-0.0077***	-0.0230***
Neighborhood Walkability				
Walk Score	0.0013***	0.0009**	0.0018***	0.0014***
Interaction with neighboring foreclosures				
Walk Score × Foreclosure	3.3E-05***	0.0001***	0.0001**	0.0002***
Spatial lag variable	0.5949***	0.0051***	0.5992***	0.0024**
Spatial error variable	-0.2175***	0.4190***	-0.2068***	0.4322***
Constant	2.1076***	9.5579***	0.7415	8.2773***
Pseudo R^2	0.85	0.76	0.81	0.69

Note: The Cliff-Ord spatial regression model was used; The K-nearest weight matrix was created based on four nearest neighbors, and the binary weight matrix was based on a 0.25-mile distance. Monthly time trends and locational dummies were controlled for all models, but not reported; * P < 0.05, ** P < 0.01, *** P < 0.001

B-4 Estimates of Categorical Walkability Variable for the 2010 Sample

Variables	2010 sample (N=13438)		
	All income	Lower income	Higher income
Property characteristics			
Log (lot size)	0.2247***	0.2271***	0.2184***
Year built	0.0005*	-4.3E-05	0.0006**
Beds	0.0185***	0.0392***	0.0183***
Baths	0.1275***	0.0782***	0.1301***
Story	0.0801***	0.0762**	0.0757***
Pool	0.0791***	0.0741*	0.0777***
Garage	0.1029***	0.2163***	0.0766***
Financial characteristics			
Depressed sale	-0.1678***	-0.1808***	-0.1624***
Socio-demographics			
Median income (Ref: Low)			
Middle	0.1111***		
High	0.2994***		0.1745***
Unemployment	-0.0087***	-0.0049*	-0.0097***
Mortgage	-0.0016**	-0.0018	-0.0017**
Built environments			
Crime density	0.0155	-0.0635***	0.0380**
Crash density	-0.1245***	-0.0133	-0.1460***
Net residential density	-0.0090**	-0.0307***	-0.0098**
Average speed limits	-0.0004	0.0003	0.0001
Bike lane	-0.0319***	-0.0045	-0.0390***
Highway	-0.0353***	-0.0405*	-0.0307**
Rail road	-0.1225***	-0.0834***	-0.1833***
Bus stop	-0.0078	-0.0278	-0.0008
Park	-0.0123	-0.0388*	-0.0037
Neighboring foreclosures			
Foreclosures	-0.0090***	-0.0039*	-0.0099***
Neighborhood Walkability			
Walkable (50-69)	0.0124	0.0024	0.0387**
Very walkable (70-100)	0.0854***	-0.0002	0.1257***
Interaction with neighboring foreclosures			
Walkable (50-69)×Foreclosure	0.0029***	0.0013	0.0015*
Very walkable (70-100)×Foreclosure	0.0010	0.0012	-0.0004
Spatial lag variable	0.0187***		0.0208***
Spatial error variable	0.4782***	0.3202***	0.4781***
Pseudo R^2	0.76	0.53	0.73

Note: The Cliff-Ord spatial regression model was used. Monthly time trends and locational dummies were controlled for all models, but not reported; The spatial weight matrix was created based on 0.25 mile inverse distance weighting; * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

B-5 Estimates of Categorical Walkability Variable for the 2013 Sample

Variables	2013 sample (N=14502)		
	All income	Lower income	Higher income
Property characteristics			
Log (lot size)	0.2321***	0.2511***	0.2261***
Year built	0.0012***	0.0013*	0.0012***
Beds	0.0192***	0.0403***	0.0167***
Baths	0.1244***	0.0757***	0.1273***
Story	0.0692***	0.1520***	0.0620***
Pool	0.0748***	0.1021**	0.0742***
Garage	0.0713***	0.1620***	0.0510***
Financial characteristics			
Depressed sale	-0.1548***	-0.1380***	-0.1571***
Socio-demographics			
Median income (Ref: Low)			
Middle	0.1420***		
High	0.3464***		0.1931***
Unemployment	-0.0061***	-0.0009	-0.0076***
Mortgage	-0.0022**	0.0006	-0.0029***
Built environments			
Crime density	0.0046	-0.0340***	0.0130*
Crash density	-0.0951***	-0.0091	-0.1047***
Net residential density	-0.0007	-0.0217*	-0.0017
Average speed limits	0.0008	-0.0014	0.0009
Bike lane	-0.0315***	0.0273	-0.0409***
Highway	-0.0383***	-0.0352	-0.0357**
Rail road	-0.0449*	-0.0341	-0.0370
Bus stop	-0.0064	-0.0293	-0.0018
Park	0.0183	0.0054	0.0197
Neighboring foreclosures			
Foreclosures	-0.0141***	-0.0140**	-0.0148***
Neighborhood Walkability			
Walkable (50-69)	0.0092	-0.1610**	0.0340*
Very walkable (70-100)	0.1350***	-0.0927	0.1784***
Interaction with neighboring foreclosures			
Walkable (50-69)×Foreclosure	0.0054***	0.0120**	0.0027*
Very walkable (70-100)×Foreclosure	0.0013	0.0116*	-0.0032
Spatial lag variable	0.0169***		0.0168***
Spatial error variable	0.4835***	0.2429***	0.4966***
Pseudo R^2	0.69	0.44	0.65

Note: The Cliff-Ord spatial regression model was used. Monthly time trends and locational dummies were controlled for all models, but not reported; The spatial weight matrix was created based on 0.25 mile inverse distance weighting; * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

APPENDIX C

ESTIMATION OF REO DENSITY

C-1 Results from OLS Model

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Property value (/$10,000)	-0.0002***	-0.0001***	-0.0001***	-9.9E-05***
Sqft (/100)	-8.9E-07	-5.0E-07	2.2E-07	7.30E-08
Beds	0.0030***	0.0022***	0.0018**	0.0016**
Year built	2.2E-05	0.0001***	0.0001***	0.0001***
LTV	-0.0001	-0.0048**	-0.0042**	-0.0039*
Median income				
Middle		0.0032***	0.0018*	0.0015*
High		0.0003	-0.0021*	-0.0023*
Hispanic (/10)		2.5E-05	2.1E-05	1.20E-05
Black (/10)		0.0001***	0.0001***	0.0001***
Asian (/10)		-0.0001***	-0.0001***	-0.0001***
Pop18 (/10)		0.0006***	0.0005***	0.0005***
Pop65 (/10)		-0.0001	-0.0001*	-0.0002*
Unemployment (/10)		0.0004***	0.0004***	0.0004***
Vacancy (/10)		0.0003***	0.0004***	0.0004***
Mortgage (/10)		0.0005***	0.0004***	0.0004***
Active living (/10)		-0.0005***	-0.0003***	-0.0003***
Crime density			0.0019***	0.0018***
Crash density			-0.0029	0.0004
Residential density			0.0009***	0.0021***
Square (Residential density)				-0.0001**
Land-use mix			-0.0123***	-0.0097
Square (land-use mix)				-0.0017
Street connectivity			-0.0079**	-0.0365***
Square (street connectivity)				0.0397
Bike lane availability			0.0007	0.0006
Park availability			-0.0011*	-0.0011*
Constant	-0.0285	-0.1184***	-0.2020***	0.2192***
R^2	0.17	0.40	0.42	0.46
Mean VIF	1.77	1.87	1.86	4.34

Notes: N=2110; Model 4 included the square terms of residential density, land use mix, and street connectivity. The units of Property Value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active Living were adjusted to obtain valid coefficients. The reference group of the median income is the low/moderate income group; † $P<0.1$, * $P<0.05$, ** $P<0.01$, *** $P<0.001$.

C-2 Results from Spatial Lag Model

Variables	Model 1	Model 2	Model 3	Model 4
Property value (/$10,000)	-0.0014***	-0.0006***	-0.0008***	-0.0007***
Sqft (/100)	-0.0002**	-0.0002*	-7.4E-05	-0.0001
Beds	0.0026***	0.0019***	0.0016**	0.0014**
Year built	-3.2E-05	1.4E-05	6.5E-05***	0.0001***
LTV	-0.0008	-0.0044**	-0.0040**	-0.0037**
Median income				
Middle		0.0026***	0.0016*	0.0013✝
High		-0.0004	-0.0021*	-0.0022*
Hispanic (/10)		0.0003	0.0002	0.0001
Black (/10)		0.0009***	0.0008***	0.0008***
Asian (/10)		-0.0009***	-0.0008***	-0.0009***
Pop18 (/10)		0.0050***	0.0042***	0.0042***
Pop65 (/10)		-0.0009	-0.0011✝	-0.0014*
Unemployment (/10)		0.0034***	0.0033***	0.0033***
Vacancy (/10)		0.0023***	0.0027***	0.0030***
Mortgage (/10)		0.0045***	0.0038***	0.0037***
Active living (/10)		-0.0040***	-0.0026***	-0.0027***
Crime density			0.0013**	0.0012**
Crash density			-0.0022	0.0013
Residential density			0.0009***	0.0020***
Square (Residential density)				-0.0001**
Land-use mix			-0.0104***	-0.0047
Square (land-use mix)				-0.0043
Street connectivity			-0.0179***	-0.0278**
Square (street connectivity)				0.0291
Bike lane availability			0.0003	0.0003
Park availability			-0.0008	-0.0007
Constant	0.0712**	-0.0281	-0.1277***	-0.1190***
Spatial lag coefficient	0.5187***	0.4168***	0.3808***	0.3819***
Pseudo R^2	0.36	0.47	0.50	0.51
Log-likelihood	6280.66	6514.65	6595.70	6602.11

Notes: N=2110; The spatial lag model approach was employed. The units of Property Value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active Living were adjusted to obtain valid coefficients. The reference group of the median income is the low/moderate income group; ✝ P<0.1, * P<0.05, ** P<0.01, *** P<0.001.

C-3 Results from Spatial Error Model

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Property value (/$10,000)	-0.0011***	-0.0004**	-0.0006***	-0.0006***
Sqft (/100)	-0.0004***	-0.0003***	-0.0002*	-0.0002*
Beds	0.0028***	0.0022***	0.0018***	0.0017**
Year built	-0.0001***	-7.9E-06	4.6E-05**	0.0001***
LTV	-0.0009	-0.0029*	-0.0025	-0.0024†
Median income				
Middle		0.0023**	0.0014†	0.0011
High		1.0E-05	-0.0015	-0.0018†
Hispanic (/10)		0.0005*	0.0005*	0.0004†
Black (/10)		0.0013***	0.0011***	0.0011***
Asian (/10)		-0.0008***	-0.0007***	-0.0008***
Pop18 (/10)		0.0053***	0.0046***	0.0045***
Pop65 (/10)		-0.0008	-0.0007	-0.0010
Unemployment (/10)		0.0030***	0.0032***	0.0030***
Vacancy (/10)		0.0015**	0.0019**	0.0023***
Mortgage (/10)		0.0045***	0.0040***	0.0038***
Active living (/10)		-0.0035***	-0.0025***	-0.0024**
Crime density			0.0021***	0.0020***
Crash density			-0.0040	-0.0002
Residential density			0.0010***	0.0020***
Square (Residential density)				-0.0001**
Land-use mix			-0.0087***	-0.0016
Square (land-use mix)				-0.0060
Street connectivity			-0.0272	-0.0262**
Square (street connectivity)				0.0294
Bike lane availability			-7.5E-05	-0.0001
Park availability			-0.0005	-0.0005
Constant	0.1705***	0.0129	-0.0893**	-0.1089***
Spatial error coefficient	0.5681***	0.5050***	0.4904***	0.4856***
Pseudo R^2	0.13	0.35	0.40	0.41
Log-likelihood	6278.40	6798.68	6571.74	6585.37

Notes: N=2110; The spatial error model approach was employed. Model 4 included the square terms of residential density, land use mix, and street connectivity. The units of Property Value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active Living were adjusted to obtain valid coefficients. The reference group of the median income is the low/moderate income group; † P<0.1, * P<0.05, ** P<0.01, *** P<0.001.

APPENDIX D

WEIBULL HAZARD MODEL

D-1 Full Sample Weibull Hazard Model

Variables	Coeff. (S.E.)	Haz. Ratio (S.E.)	Z	P-value
2009	-0.1649 (0.0098)	0.8481 (0.0083)	-16.95	0.000
2010	-0.1908 (0.0106)	0.8264 (0.0088)	-18.03	0.000
2011	-0.0350 (0.0120)	0.9657 (0.0116)	-2.91	0.004
2012	0.1493 (0.0172)	1.1610 (0.0200)	8.69	0.000
2013	0.4493 (0.0475)	1.5672 (0.0744)	9.46	0.000
Sqft (/100)	-0.0039 (0.0010)	0.9962 (0.0010)	-4.26	0.000
Beds	-0.0215 (0.0057)	0.9788 (0.0056)	-3.80	0.000
Year built	0.0019 (0.0003)	1.0019 (0.0003)	7.99	0.000
Loan-to-value	0.0001 (0.0001)	1.0001 (0.0001)	0.65	0.515
Median income				
Middle	-0.0155 (0.0122)	0.9847 (0.0121)	-1.27	0.206
High	-0.0213 (0.0175)	0.9790 (0.0171)	-1.22	0.223
Hispanic (/10)	-0.0064 (0.0032)	0.9937 (0.0032)	-1.98	0.048
Black (/10)	-0.0152 (0.0031)	0.9850 (0.0030)	-4.97	0.000
Asian (/10)	0.0217 (0.0041)	1.0219 (0.0042)	5.33	0.000
Pop18 (/10)	0.0166 (0.0112)	1.0167 (0.0114)	1.48	0.138
Pop65 (/10)	-0.0167 (0.0138)	0.9835 (0.0135)	-1.22	0.224
Ownership (/10)	0.0087 (0.0037)	1.0087 (0.0037)	2.40	0.016
Unemployment (/10)	0.0175 (0.0103)	1.0176 (0.0105)	1.71	0.088
Vacancy (/10)	0.0360 (0.0100)	1.0367 (0.0104)	3.62	0.000
Mortgage (/10)	0.0206 (0.0161)	1.0208 (0.0164)	1.28	0.200
Active living (/10)	-0.0138 (0.0175)	0.9864 (0.0173)	-0.78	0.433
Crime density	-0.0028 (0.0069)	0.9973 (0.0069)	-0.41	0.685
Crash density	-0.5252 (0.0879)	0.5915 (0.0520)	-5.98	0.000
Property Value (PV) (/ $10,000)	-0.0027 (0.0004)	0.9974 (0.0004)	-6.88	0.000
Residential density				
Lower level	0.0169 (0.0200)	1.0170 (0.0203)	0.85	0.397
Upper level	-0.1101 (0.0242)	0.8958 (0.0216)	-4.57	0.000
PV × Residential density				
Lower level	-0.0007 (0.0005)	0.9994 (0.0005)	-1.63	0.103
Upper level	0.0017 (0.0006)	1.0017 (0.0006)	2.84	0.005
Land-use mix				
Lower level	-0.0147 (0.0172)	0.9855 (0.0169)	-0.86	0.391
Upper level	-0.0462 (0.0191)	0.9549 (0.0183)	-2.42	0.016

Continued

Variables	Coeff. (S.E.)	Haz. Ratio (S.E.)	Z	P-value
PV × Land-use mix				
Lower level	0.0001 (0.0004)	1.0001 (0.0004)	0.16	0.875
Upper level	0.0009 (0.0005)	1.0009 (0.0005)	1.82	0.068
Street connectivity				
Lower level	-0.0727 (0.0204)	0.9300 (0.0190)	-3.57	0.000
Upper level	-0.0323 (0.0225)	0.9683 (0.0218)	-1.44	0.150
PV × Street connectivity				
Lower level	0.0018 (0.0005)	1.0018 (0.0005)	3.96	0.000
Upper level	0.0011 (0.0006)	1.0011 (0.0006)	1.95	0.051
Bike lane availability	0.0279 (0.0080)	1.0283 (0.0083)	3.49	0.000
Park availability	-0.0001 (0.0082)	1.0000 (0.0082)	0.00	0.996
Constant	-8.5979 (0.4420)	0.0002 (0.0001)	-19.46	0.000
/Ln_P	-0.0635 (0.0029)	-0.0635 (0.0029)	-22.51	0.000
P	0.9386 (0.0027)	0.9386 (0.0027)		
1/P	1.0656 (0.0031)	1.0656 (0.0031)		

Notes: N=73837, LR-Chi2=1739.51 (p<0.0001), Log-likelihood=-118118.28; P is the shape parameter of the Weibull distribution; The units of Property value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active living were adjusted to obtain valid coefficients and hazard ratios.

D-2 Sub-sample Weibull Hazard Model for Low-Value REOs

Variables	**Coeff. (S.E.)**	**Haz. Ratio (S.E.)**	**Z**	**P-value**
2009	-0.1147 (0.0187)	0.8918 (0.0167)	-6.15	0.000
2010	-0.1660 (0.0206)	0.8472 (0.0175)	-8.06	0.000
2011	0.0091 (0.0230)	1.0092 (0.0232)	0.39	0.693
2012	0.1068 (0.0331)	1.1127 (0.0368)	3.23	0.001
2013	0.5104 (0.0848)	1.6660 (0.1413)	6.02	0.000
Sqft (/100)	-0.0215 (0.0025)	0.9788 (0.0025)	-8.65	0.000
Beds	0.0089 (0.0126)	1.0090 (0.0127)	0.71	0.479
Year built	0.0017 (0.0005)	1.0017 (0.0005)	3.42	0.001
Loan-to-value	0.0001 (0.0001)	1.0001 (0.0001)	0.70	0.486
Median income				
Middle	0.0009 (0.0209)	1.0009 (0.0209)	0.04	0.968
High	-0.0599 (0.0397)	0.9420 (0.0374)	-1.51	0.131
Hispanic (/10)	-0.0072 (0.0059)	0.9929 (0.0058)	-1.23	0.220
Black (/10)	-0.0202 (0.0078)	0.9801 (0.0077)	-2.60	0.009
Asian (/10)	-0.0007 (0.0214)	0.9994 (0.0214)	-0.03	0.976
Pop18 (/10)	0.0367 (0.0246)	1.0374 (0.0255)	1.49	0.135
Pop65 (/10)	0.0340 (0.0350)	1.0346 (0.0362)	0.97	0.331
Ownership (/10)	0.0109 (0.0080)	1.0109 (0.0081)	1.35	0.175
Unemployment (/10)	0.0145 (0.0195)	1.0147 (0.0198)	0.74	0.457
Vacancy (/10)	0.0509 (0.0181)	1.0522 (0.0191)	2.81	0.005
Mortgage (/10)	-0.0020 (0.0331)	0.9981 (0.0331)	-0.06	0.953
Active living (/10)	-0.0101 (0.0430)	0.9901 (0.0426)	-0.23	0.816
Crime density	0.0268 (0.0128)	1.0271 (0.0131)	2.11	0.035
Crash density	-0.3719 (0.2259)	0.6895 (0.1558)	-1.65	0.100
Property Value (PV) (/ $10,000)	-0.0010 (0.0033)	0.9991 (0.0033)	-0.28	0.779
Residential density				
Lower level	0.0516 (0.0870)	1.0529 (0.0916)	0.59	0.553
Upper level	-0.3317 (0.1283)	0.7178 (0.0921)	-2.59	0.010
PV × Residential density				
Lower level	-0.0002 (0.0047)	0.9999 (0.0047)	-0.04	0.966
Upper level	0.0098 (0.0063)	1.0099 (0.0064)	1.55	0.120
Land-use mix				
Lower level	-0.0006 (0.0710)	0.9995 (0.0710)	-0.01	0.994
Upper level	0.0105 (0.0756)	1.0105 (0.0763)	0.14	0.890

Continued

Variables	Coeff. (S.E.)	Haz. Ratio (S.E.)	Z	P-value
PV × Land-use mix				
Lower level	0.0030 (0.0039)	1.0030 (0.0040)	0.75	0.451
Upper level	-0.0029 (0.0040)	0.9972 (0.0040)	-0.72	0.471
Street connectivity				
Lower level	-0.2723 (0.0884)	0.7617 (0.0673)	-3.08	0.002
Upper level	-0.1977 (0.1231)	0.8207 (0.1010)	-1.61	0.108
PV × Street connectivity				
Lower level	0.0158 (0.0048)	1.0159 (0.0049)	3.31	0.001
Upper level	0.0066 (0.0062)	1.0066 (0.0062)	1.07	0.287
Bike lane availability	0.0518 (0.0170)	1.0531 (0.0179)	3.04	0.002
Park availability	-0.0099 (0.0183)	0.9903 (0.0181)	-0.54	0.590
Constant	-8.0908 (0.9142)	0.0004 (0.0003)	-8.85	0.000
/Ln_P	-0.0866 (0.0054)	-0.0866 (0.0054)	-16.23	0.000
P	0.9171 (0.0049)	0.9171 (0.0049)		
1/P	1.0905 (0.0059)	1.0905 (0.0059)		

Notes: N=20174, LR-Chi2=552.33 ($p<0.0001$), Log-likelihood=-32557.66; P is the shape parameter of the Weibull distribution; The units of Property value, Sqft, Hispanic, Black, Asian, Pop18, Pop65, Unemployment, Vacancy, Mortgage, and Active living were adjusted to obtain valid coefficients and hazard ratios.