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Author(s): Meagan Cahill, Ph.D., Kathy Pettit, M.P.P., Avi Bhati, Ph.D., Mitch Downey, Leah Hendey, Dwight Pope, Sophie Litschwartz

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RESEARCH REPORT

Foreclosures and Crime

A Space-Time Analysis

Meagan Cahill, Ph.D.
URBAN INSTITUTE

Kathy Pettit, MPP
URBAN INSTITUTE

Avi Bhati, Ph.D.
MAXARTH, LLC

with Mitch Downey, Leah Hendey, Dwight Pope, and Sophie Litschwartz

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In addition, we would like to thank the local housing and community experts in Washington, DC and Miami-Dade County, FL who provided essential insight into the foreclosure crisis in each metropolitan area, and the residents who participated in focus groups, giving us an insider's view to living in hard-hit neighborhoods.

Finally, we thank our grant monitor, Joel Hunt of the National Institute of Justice, for his unending patience, encouragement, and support of this work.

Abstract

Despite growing attention to the negative consequences of foreclosures in neighborhoods, very little systematic research on the outcomes of the foreclosure crisis was being conducted on the topic through the late 2000s. In 2010, the National Institute of Justice funded the Urban Institute's Justice Policy Center to fill that gap with a systematic assessment of the impacts of foreclosures and crime levels on each other.

Four questions guided the present research:

1) What is the effect of foreclosures on the levels of crime in a neighborhood and how does that relationship change over time? Do the two phenomena have a circular relationship (where each affects the other simultaneously)?

2) Do foreclosures in one area have a "spillover" effect, increasing crime in a neighboring area at an immediate or later time period?

3) How do the effects of foreclosures on crime differ in the short-, medium-, and long-term?

4) What are the perceptions of key informants and residents on foreclosures and crime in their neighborhoods, on the impact of foreclosures on the crime rate, and on the best approaches to addressing the spillover effects of the foreclosure crisis?

Data:
The relationship between crime data and foreclosures was modeled at the census tract level for two sites:

- Washington, DC
  - 188 census tracts
  - Over the period Q1 2003 through Q4 2010
- Miami, FL
  - 329 census tracts
  - Over the period Q4 2003 through Q1 2011
- Total of 6,016 data points in the DC data and a total of 9,870 data points in the Miami data.

Results:
- Effect of foreclosures on crime:
  - Statistically significant in only one model: Miami model of foreclosure sales and violent crime.
  - One percent increase in foreclosures would result in a 0.0157 percent increase in violent crimes – small enough to be considered non-existent.
- In other models, the effect of foreclosures on crime was very small *and* non-significant
- The effect of nearby foreclosures (spatially lagged foreclosures) was very small *and* not significant in any of the models

The analysis suggests that any observed relationship between foreclosures and crime exists, more or less, because both foreclosures and crime happen in disadvantaged neighborhoods. Given this evidence, there is no reason to conclude that concentrated foreclosures, at least to the extent experienced in DC or Miami in the late 2000s, led to significant increases in crime on their own.

The relationship between foreclosures and crime is complex, and indeed, in many ways, the two are related. However, evidence from a number of sources explored as part of this research—maps of the foreclosures and crime in both cities before and after the foreclosure crisis hit, reports from local experts and residents in both cities, descriptive analysis of foreclosures and crime data, and complex statistical models—suggests that the relationship is not direct, and is instead built on each event's relationships with other factors, like neighborhood characteristics that were in place before foreclosures spiked, such as poverty or other types of disadvantage.

On a very small scale, such as by individual property or by block, a relationship between foreclosures and crime could exist, but if it does, we do not expect that it is widespread. Policies should not be designed to address these two phenomena alone. Instead, any policy responses should be designed to address wider community problems or disadvantage that likely lead to both higher foreclosures and higher crime.

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Executive Summary

The housing bubble of the early-to-mid 2000s dominated the media's coverage of housing and real estate issues for several years: low and no-interest loans, bidding wars, exponential growth in housing values, and larger numbers of homeowners than ever before in U.S. history were all top stories of the period. After the housing bubble burst in the mid-to-late 2000s, however, the ongoing mortgage foreclosure crisis became a mainstay of the popular media. At the same time, stories that suggested crime was infiltrating areas hard-hit by foreclosures started to emerge, raising fears among both individual homeowners and communities (Leinberger, 2008).

By the end of 2013, the economy had shown signs of recovery and the crisis had abated somewhat, but foreclosures still remained problematic in many of the hardest-hit places, like parts of Florida, Nevada, Michigan, and Ohio (CoreLogic, 2014). Furthermore, the question of whether communities in these areas suffered widespread negative effects, like increased crime, from the foreclosure crisis remained.

Background

Despite growing attention to the negative neighborhood-level consequences of foreclosures, very little systematic research on the outcomes of the foreclosure crisis was being conducted through the late 2000s.[1] In 2010, the National Institute of Justice funded the Urban Institute's Justice Policy Center to fill that gap with a systematic assessment of the impacts of foreclosures and crime levels on each other, using sophisticated spatial analysis methods, informed by qualitative research on the topic.

Four central research questions guided the present research:

1) What is the effect of foreclosures on the levels of crime in a neighborhood and how does that relationship change over time? Do the two phenomena have a circular relationship (where each affects the other simultaneously)?

2) Do foreclosures in one area have a "spillover" effect, increasing crime in a neighboring area at an immediate or later time period?

3) How do the effects of foreclosures on crime differ in the short-, medium-, and long-term?

4) What are the perceptions of key informants and residents on foreclosures and crime in their neighborhoods, on the impact of foreclosures on the crime rate, and on the best approaches to addressing the spillover effects of the foreclosure crisis?

[1] A notable exception to this dearth of research was the work of Immergluck & Smith (2006), discussed in the next chapter.

Using data on foreclosures and crime in Washington, DC (DC) and Miami-Dade County, FL (Miami) over a nearly ten-year period, the present research considers the effects of the two phenomena on each other through a dynamic systems approach. This approach involves simultaneously modeling the temporal and spatial effects of foreclosures on neighborhood crime levels and of crime on neighborhood foreclosure rates. The effects of crime on foreclosures were modeled to control for a possible effect in that direction—a direct effect of crime on foreclosures is not theoretically supported but by affecting property values, increased crime levels can increase foreclosure risk for remaining homeowners in hard-hit areas.

THEORETICAL FOUNDATIONS

Three theories, all ecological in nature, inform the present work linking foreclosures and crime in neighborhoods: 1) social disorganization theory; 2) broken windows theory; and 3) routine activities theory. The key overlapping element of each of these theories is the social component—the guardianship that residents of and visitors to a neighborhood provide, and the collective efficacy that emerges when residents work together towards a common goal—in this case, preventing crime.

Common theoretical postulates drawn from these ecological theories relate to (1) residents' ability to work together toward a common goal, (2) visual cues regarding the social nature of an area and its level of social control, and (3) the unmaintained, vacant houses that attract criminals and criminal events. Based on these postulates, areas of concentrated foreclosures are expected to experience rising levels of crime.

Indeed, Wilson and Paulsen's (2010, p. 1) review of the theoretical underpinnings linking neighborhood conditions and crime suggest that "foreclosures have the potential to be a catalyst from which persistent crime patterns can take root." Wilson and Paulsen identify a two-stage process of foreclosure-related decline: first, homeowners under financial stress are unable to maintain their properties, foregoing needed repairs and spending less time on upkeep of the exterior of the house as well (creating "broken windows"). Vacant homes may also be rendered permanently or temporarily uninhabitable due to structural damage or poor upkeep, further reducing the chance that new buyers will purchase them. Second, homes become vacant as the foreclosure process is completed and homeowners move out, leaving fewer guardians (routine activities) and fewer contributors to the neighborhood's collective efficacy (social disorganization). If new buyers cannot be found for a foreclosed property, the problems engendered by a vacant home will remain and may influence crime rates in the area.

Some rigorous research has been conducted on the effects of foreclosures on crime very recently. We identified ten studies published since 2010 that employed measures of completed foreclosures, or REO properties. Nine of those studies found some level of positive relationships between foreclosures and crime, although most with some caveats, including inconsistent findings across space (i.e., results varied from place to place). On balance, the set of evidence, initially showing a positive relationship, is actually quite mixed. The question of whether a relationship exists between foreclosures and crime, then, is far from settled.

Sites

Chapters 3 and 4 present the contexts in which foreclosures and crime occur in the two study sites. In ***Washington, DC***, the foreclosure crisis, like housing values and race in the city, had a distinct geographic pattern. Average housing sales prices in DC rose 77 percent between 2000 and 2007 (NeighborhoodInfo DC,2012), and while the foreclosure crisis tempered housing prices in the late 2000s, the price drop experienced in the city was not as extreme as it was in other metropolitan areas. By December 2009, one year into the foreclosure crisis, DC's foreclosure inventory for single-family and condominium homes had climbed to about 1.6 times the foreclosure inventory from early 2007 (NeighborhoodInfo DC, 2010).

For more insight on the city's experience with foreclosures and crime, we conducted expert interviews and a focus group with residents. These efforts provided useful insight into the foreclosure and crime relationships in DC, but also suggested that the link between these two phenomena was weak at best. While foreclosures may have been a small part of the recent story of the neighborhood situations, they certainly were not the cause of or even a major factor in the quality or crime levels of the neighborhoods where they occurred.

In DC we constructed three foreclosure measures, using data from the city's Recorder of Deeds and the DC Office of Tax and Revenue: foreclosure starts, inventory, and sales. The research team also obtained address-level crime incident data for DC from the Metropolitan Police Department (MPD). Both datasets were collected for the period January 2003 through December 2010.

Miami-Dade County, FL, along with many other fast-growing markets across the country, was disproportionately impacted by the housing crisis of the 2000s. The foreclosure crisis in Florida broadly, and more specifically in Miami, was caused by the confluence of a number of factors. Some of these factors affected cities nationwide, like loose lending regulations, low mortgage interest rates, and buyers over-reaching to purchase homes they couldn't afford. Others, like a new housing construction boom, uniquely affected Florida and similar states.

In Miami, local individuals well-informed on housing issues and the local policy context did not connect the foreclosure crisis with an increase in crime in hard hit (or other) areas. The situations reported in the local and national media on the connection between crime and foreclosures appeared to be isolated or outliers.

Foreclosure data were obtained from the Clerk of Courts for Miami-Dade County and county-wide parcel data and property sales data for the period August 2003 through April 2011 were obtained from the Miami-Dade County Property Appraiser. These data sources were used to construct county-wide foreclosure sales measures. The research team obtained address-level crime incident data from the Miami-Dade County Police Department and the City of Miami Police Department for August 2003 through June 2011.

Methods

Discussed in Chapter 5, models were developed for geographic units—census tracts—that were used to approximate neighborhoods. This approach allowed us to determine how one neighborhood's (census tract's) levels of foreclosures and crime may affect those of a nearby neighborhood. Our analyses were framed under a dynamic systems approach that modeled both temporal and spatial aspects of the foreclosures and crime relationship simultaneously.

We hypothesized that the relationship between the two phenomena would represent a feedback loop, so that an initial shock of foreclosures in a neighborhood may lead to increased crime, but increased levels of crime may in turn lead to decreased property values and waning desirability of the area, leading to additional foreclosures. Those additional foreclosures contribute to even more crime and the cycle continues, escalating as the ability of remaining residents to stem the tide of neighborhood deterioration decreases. We further hypothesized that areas with high levels of foreclosure and crime may have negative effects on nearby areas, spreading neighborhood deterioration to adjacent (or further) neighborhoods.

Models of the relationship between foreclosures and crime rapidly become very complex when the feedback loop and temporal and spatial aspects are added. The combination of the discrete nature of the outcomes (in counts rather than rates), simultaneous nature of crime and foreclosures (the feedback loops), and panel nature of the data (with temporal and spatial dependence incorporated) made the estimation problem unique and nontrivial. The framework used here is an extension of the standard Poisson count model, which builds on earlier applications to the problem of studying rare events (Bhati, 2005, 2008).

Thus, the estimated models included spatial lags, temporal lags, cross-spatial and cross-temporal lag terms, unobserved heterogeneity, simultaneous system modeling, and fixed effects. Because the resulting models were very complex, the objective functions often failed to converge (i.e., no solution is found). Therefore, a two-step EM (expectation-maximization) algorithm, which simplifies the estimation problem and provides results for the parameters of interest, was used.

Results

Chapter 5 discusses the relationship between crime data and foreclosures, modeled at the census tract level for DC and Miami. Crime counts and foreclosures were aggregated at the census tract level by quarter. This allowed the creation of panel datasets with measures of crime and foreclosures varying with time and cross-sectional unit. Data from DC spanned the periods Q1 2003 through Q4 2010 while data for Miami spanned the period Q4 2003 through Q1 2011. There were 188 census tracts in DC and 329 census tracts in Miami. This resulted in a total of 6,016 data points in the DC data and a total of 9,870 data points in the Miami data.

First, correlations and spatial lag regression models were examined to better understand the basic relationships between foreclosures and crime. The correlation analysis suggested that the relationship between foreclosures and crime was very weak and typically not statistically distinct from the null effect (no relationship), except in the case of violent crime. Even the statistically significant coefficients, however, were small in most cases. Findings from the spatial lag models—that crime in one tract is significantly affected by crime nearby—supported our inclusion of spatially lagged terms in the dynamic models for both crime and foreclosures.

As part of the dynamic modeling effort, we tested a number of models with a different set of parameters for estimation, including different numbers of temporal and spatial lags and combinations of foreclosure and crime measures. However, we found very little of statistical significance in any of the models. We therefore selected three sets of models (for a total of nine models) to highlight here: foreclosure inventory and each crime measure (violent, property, total) in DC; foreclosure sales and each crime measure (violent, property, total) in DC; and foreclosure sales and each crime measure (violent, property, total) in Miami.

Because the models are in log-log form (i.e., the outcome measure is logged and the foreclosures measures are also logged) the coefficients are interpreted as elasticities. Elasticities reflect a percent change in the outcome measure for a percent change in the predictor.

The first main effect of interest was the direct effect of foreclosures on crime; this effect was statistically significant in only one of the models (Miami sales-violent crime). In this model, the coefficient for current foreclosures is equal to 0.0157, suggesting that a one percent increase in foreclosures results in a 0.0157 percent increase in violent crimes. Despite its significance, then, the effect size is small enough to be considered non-existent. In other models, this coefficient, in addition to being non-significant, was also extremely small.

The second main effect of interest was the spatially lagged foreclosure measure. None of the coefficients on the spatially lagged foreclosure measures were statistically significant in any of the models, and similarly, the effect sizes were extremely small. The results suggest a weak or non-existent effect of foreclosures on crime.

The research team also examined other model parameters for insight into the data and the relationship between foreclosures and crime. In all of the models, the fixed effect terms were statistically significant, suggesting that there were sufficient time-stable effects in the census tracts. If these effects are ignored, then time-stable differences may be mistaken for substantive effects. In other words, it is likely that there are other elements—neighborhood characteristics, for example—that have a significant effect on both crime and foreclosure levels. Without accounting for these unmeasured but significant effects, the model results may have led the research team to believe that the direct effects of foreclosures and crime on each other was significant and greater than their true relationship.

Conclusions

The relationship between foreclosures and crime is complex, and indeed, in many ways, the two are related, by virtue of being symptoms of similar neighborhood conditions. However, evidence from a number of sources—maps of the two phenomena in both study areas before and after the foreclosure crisis hit, insight from local experts and residents in both study areas, descriptive analysis of foreclosures and crime data, and complex statistical models—suggests that the relationship is not direct, and is instead built on each phenomenon's mutual relationships with other factors, like pre-existing and relatively stable neighborhood characteristics.

The modeling results suggest that any observed relationship between foreclosures and crime exists, more or less, because both phenomena happen in disadvantaged neighborhoods. Given this evidence, there is no reason to conclude that concentrated foreclosures, at least to the extent experienced in DC or Miami in the late 2000s, led to significant increases in crime on their own.

While there remains the possibility that on a micro-scale, such as by individual property or by block, a relationship between foreclosures and crime exists, we do not expect that such a relationship is widespread, nor that medium or large scale policies can be designed to address these two phenomena alone. Instead, policies should be designed to address wider community problems or disadvantage that likely lead to higher incidences of both foreclosures and crime.

Introduction

"I thought I'd bought a home in Pleasantville. I never imagined in my wildest dreams that something like this would happen."

-Laurie Talbot, resident of Charlotte, NC neighborhood where more than 60% of the homes are in foreclosure and whose house was hit by a stray bullet.[2]

The housing bubble of the early-to-mid 2000s dominated the media's coverage of housing and real estate issues for several years: low and no-interest loans, bidding wars, exponential growth in housing values, and larger numbers of homeowners than ever before in U.S. history were all top stories of the period. After the housing bubble burst in the mid-to-late 2000s however, the ongoing mortgage foreclosure crisis became a mainstay of the popular media. At the same time, stories that suggested crime was infiltrating areas hard-hit by foreclosures started to emerge, raising fears among both individual homeowners and communities (Leinberger, 2008).

By the end of 2013, the economy had shown signs of recovery and the crisis had abated somewhat, but foreclosures still remained problematic in many of the hardest-hit places, like parts of Florida, Nevada, Michigan, and Ohio (CoreLogic, 2014). And the question of whether communities in these areas suffered widespread negative effects, like increased crime, from the foreclosure crisis remained.

Causes and consequences of the crisis

There is broad consensus that the early stages of the foreclosure crisis were precipitated by the growth in the number of subprime loans—with their looser standards for borrowers—as well as loan-to-value ratios that increased sharply as the housing bubble burst. These increasing ratios were largely the result of declining housing values (Ong & Pfeiffer, 2008), which left many homeowners with home purchase loans greater than the cost of their house, commonly referred to as "underwater mortgages." Other factors include the structure of the lending industry, a lack of regulation for making mortgage loans, rising mortgage rates, and significant debt among borrowers holding delinquent or foreclosed mortgages (Schloemer, Li, Ernst, & Keest, 2006). Economic instability and higher unemployment rates exacerbated the crisis:

[2] As quoted in Leinberger, 2008.

foreclosures became increasingly common not only in the subprime, but also in the prime mortgage markets. Foreclosures in the prime market were driven by loss of income rather than onerous loan terms (as was frequently the case with subprime loans) (Pettit et al., 2009).

Foreclosures incur high costs borne not only by the borrowers and lenders, but also by municipalities, neighborhoods, and taxpayers. Getter (Getter, 2008) reports that the overall cost of a single foreclosure is close to $80,000, some of which is associated with either repairing, maintaining, and selling a property, or demolishing it. Foreclosed properties are also less attractive to some buyers (Wilson & Paulsen, 2010), especially if they have been "stripped" of fixtures, appliances, or anything sale-worthy. This practice of stripping homes has become increasingly common among homeowners vacating a foreclosed property (Rudolf, 2009). Vacant housing represents one of the clearest markers of physical and social decay in a community (Taylor, 2010), and may have an ongoing negative effect on the housing market of a neighborhood. Increased demand for social services by foreclosed homeowners adds to the expense incurred by foreclosure (Aalbers, 2009; Setterfield, 1997). Given these challenges, it is not surprising that researchers have found that foreclosures have a spillover effect on housing prices, decreasing the value of nearby houses (Immergluck & Smith, 2006).

The mechanism by which foreclosed houses influence property values is still being evaluated. Gerardi and Willen (Gerardi & Willen, 2008) suggest that the presence of foreclosed homes is less important to the housing prices in an area than the condition of those foreclosed houses: reduced investment by owners of foreclosed houses reduces the condition of the property and lowers housing prices for other homes in the area. As foreclosures decrease the value of properties in general, municipalities will also sustain losses in tax revenue over time. With state and local budget deficits due to lost revenue increasing across the country, municipalities will be challenged to provide more for their citizens with fewer financial resources.

CRIME AS A CONSEQUENCE OF FORECLOSURES

At the time the current foreclosure crisis was recognized as such—usually considered to be mid-2008 (HUD, 2009), little academic attention or research had been dedicated to understanding what connection, if any, foreclosures had with crime. What limited research did exist focused mainly on the financial aspects of foreclosures rather than on the individual or neighborhood impacts of foreclosures. Patterns in lending, interest rates, and types of mortgages were—and remain—popular topics among researchers studying the relationship of crime and foreclosure. As the crisis deepened through the end of the 2000s, however, and more and more homeowners were at risk of losing, or had lost, their homes, researchers began to consider what these high numbers of concentrated foreclosures could do to a neighborhood. What effects could such rapid neighborhood change have on the social fabric and physical space of communities? And what other social ills would follow foreclosures: vacancies, crime, drug use, drug sales?

Anecdotal evidence emerged that blocks—even whole neighborhoods—were all but abandoned as homeowners in distress left and banks either wouldn't or couldn't sell the properties. Houses on mostly-vacant blocks with properties falling into disrepair saw plummeting home values, further eroding the wealth of remaining homeowners. Because foreclosures, especially in the hardest hit areas, occurred quickly and to so many homeowners, the crisis created a situation of rapid neighborhood change. Such rapid change had historically not been observed in such a broad context, and had the potential to lead to increasing neighborhood crime, making it hard for homeowners or local service networks to stem the tide of neighborhood deterioration. Crime has been identified as a negative outcome of concentrated foreclosures (Bess, 2008; Gerardi & Willen, 2008; Immergluck & Smith, 2006).

Research questions

Despite growing attention to the negative neighborhood-level consequences of foreclosures, very little systematic research on the outcomes of the foreclosure crisis was being conducted through the late 2000s. The present research fills this gap by analyzing the impacts of foreclosures and crime levels on each other using sophisticated spatial and temporal analysis methods that are informed by qualitative research on the topic.

A circular relationship between foreclosures and crime may also exist. It is possible that as crime in a neighborhood increases, property values may decline more rapidly than they were falling, and residents already at risk for foreclosure in that neighborhoods may have fewer options for avoiding foreclosure. Declining house values may reduce a homeowner's ability to sell a home for the mortgaged amount, or banks may be less likely to agree to short sales if the value of the home is significantly less than that of the mortgage. Therefore, the effects of foreclosures on crime cannot be considered without simultaneously considering the effects of crime on foreclosures. In addition, the spatial aspects of the influence of foreclosures on crime cannot be ignored: one community's crime levels may be affected by foreclosures or crime occurring in neighboring areas.

Four central research questions guided development of the present research:

1) What is the effect of foreclosures on the levels of crime in a neighborhood and how does that relationship change over time? Do the two phenomena have a circular relationship (where each affects the other simultaneously)?

2) Do foreclosures in one area have a "spillover" effect, increasing crime in a neighboring area at an immediate or later time period?

3) How do the effects of foreclosures on crime differ in the short-, medium-, and long-term?

4) What are the perceptions of key informants and residents on foreclosures and crime in their neighborhoods, on the impact of foreclosures on the crime rate, and on the best approaches to addressing the spillover effects of the foreclosure crisis?

Using data on foreclosures and crime in Washington, DC (DC) and Miami-Dade County, FL (Miami)[3] over a nearly ten-year period, the present research considers the effects of the two phenomena on each other through a dynamic systems approach. This approach involves simultaneously modeling the temporal and spatial effects of foreclosures on neighborhood crime levels and of crime on neighborhood foreclosures. We model the effects of crime on foreclosures to explore the possibility of such a circular relationship—a direct effect of crime on foreclosures is not theoretically supported but by affecting property values, increased crime levels can increase foreclosure risk for remaining homeowners in hard-hit areas.

There are very few examples of rigorous research conducted on the effects of foreclosures on crime, and this research broadens a sparse field. The research also contributes a unique approach to studying these two phenomena simultaneously in order to control for possible spurious effects of crime on foreclosure. This demonstrates the utility and necessity of the dynamic system approach to studying this type of relationship. While we consider spatial relationships to be more important than temporal ones for accurately modeling the effects of foreclosures on crime (e.g., foreclosures in one area may influence crime levels in a neighboring area), we include temporal lags in our model to ensure that we are controlling for a possible spurious relationship. The modeling approach demonstrates the importance of including temporal terms in spatial models of the relationship between foreclosures and crime.

Chapter 2 describes the foreclosure process and explicates the theoretical foundation supporting the hypothesis that foreclosures can lead to crime at the neighborhood level. Chapter 2 also details the most recent research on foreclosures and the foreclosure crisis—most having been completed after 2010. Chapters 3 and 4 focus on DC and Miami, respectively, providing contextual information on foreclosures and neighborhoods in the city. These site-specific chapters also describe the qualitative and quantitative data collection efforts for each site and provide descriptive analysis on foreclosures and crime in each site.

Chapter 5 presents the results of the statistical analyses for each site, and Chapter 6 provides a discussion and concluding thoughts given the findings presented.

[3] We use "Miami" here to refer to the entire study area, unless otherwise specified.

Linking Foreclosures and Crime

Foreclosure is a complex and often lengthy process, the nuances of which are governed by state law. Understanding the context within which foreclosures take place—the process by which foreclosures happen, how long they take, and how they fit into broader neighborhood conditions and change processes—is important to understanding how foreclosures might contribute to crime, and how crime might contribute to foreclosures. This chapter first details the foreclosure process in each of the study sites (DC and Miami). It then discusses the theory underlying our hypotheses that foreclosures might exacerbate or even create public safety problems in high-foreclosure neighborhoods, and how crime might, in turn or concurrently, exacerbate the foreclosure crisis.

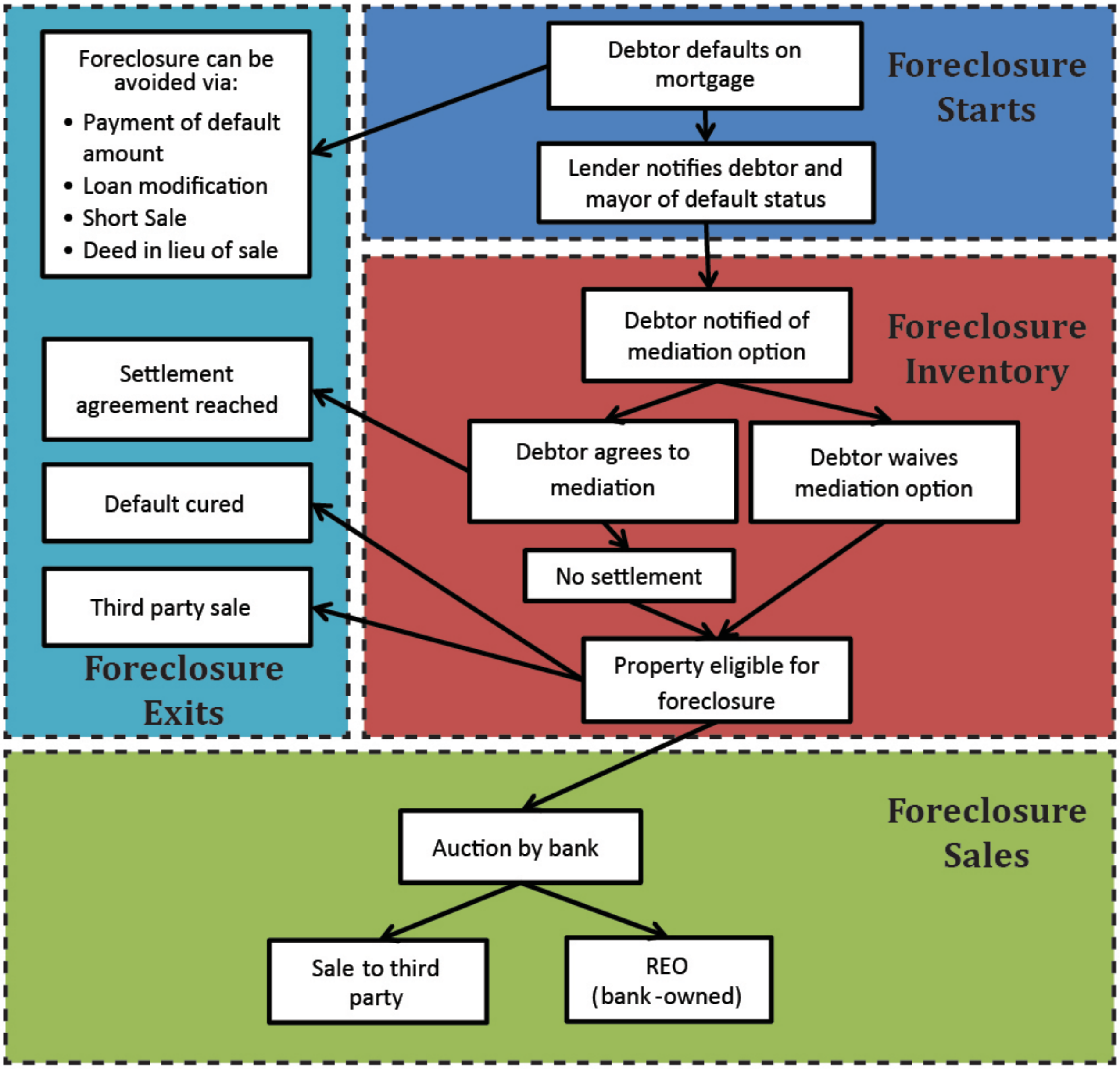
The length (at least 6 years, beginning in 2008) and scale of the current crisis —in December 2013, even as foreclosure rates were continually dropping nationwide, over one million housing units were in some stage of foreclosure (CoreLogic, 2014)—have attracted the attention of researchers. Research in this field seeks to understand what caused the crisis and to quantify the negative effects of foreclosures, including understanding the direction of the relationship between crime and foreclosure—and vice versa. Current research is helping to inform approaches that local municipalities, counties, and states might implement to alleviate the negative effects of foreclosures and crime. Research in this area has thus expanded considerably since 2010, but the results of the various analyses have not been consistent. This chapter concludes with an overview of this current research and discusses possible reasons for the variation in results.

The foreclosure process

The process of each foreclosure varies based on the characteristics of the borrower, the loan or loans used to purchase a property, and whether state foreclosures follow a "*judicial foreclosure*" or "*power-of-sale*" (also referred to as "non-judicial") process (Getter, 2008). Judicial foreclosures require that a judge make the final ruling on foreclosure. Foreclosures in power-of-sale states, on the other hand, do not *require* court proceedings, although the final outcome may be reviewed by a court for legality. DC is a non-judicial, power-of-sale state, while Florida follows a judicial foreclosure process. A foreclosure can take anywhere from several months to two years to complete, and typically takes longer in states requiring judicial processes (Getter, 2008). Figure 1 and Figure 2 depict the typical steps involved in these two different types of foreclosure processes.

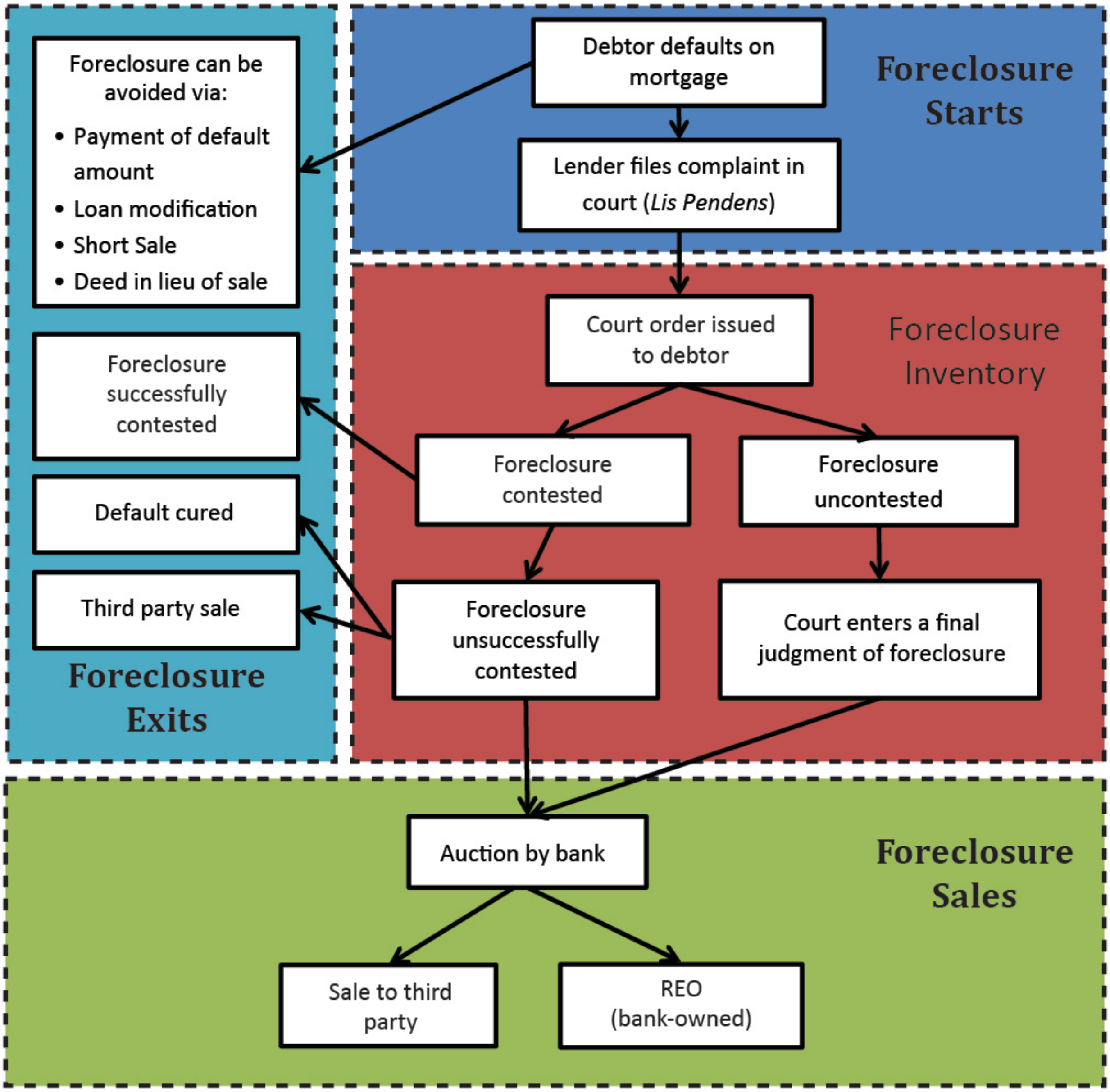
In both processes, foreclosures generally begin after a borrower is 90 days or more delinquent on loan payments (i.e., defaults). Lenders must follow a number of different procedures, including providing notification to the borrower and the appropriate government agency that the loan is in default; the first notice of default starts the foreclosure process. These actions are generally referred to as "foreclosure starts" but may also be referred to as a pre-foreclosure, foreclosure notice, or *lis pendens* (suit pending).[4]

FIGURE 1: POWER-OF-SALE (OR, NON-JUDICIAL) FORECLOSURE PROCESS (E.G., DC)



[4] Not all starts ultimately lead to foreclosure. If the homeowner can pay the default amount or make arrangements with the lender, foreclosure can be avoided. Thus, counting the number of foreclosure starts generally over-estimates the number of houses actually in foreclosure (Getter et al. 2008).

FIGURE 2: JUDICIAL FORECLOSURE PROCESS (E.G., MIAMI, FL)



If foreclosure is not avoided, the lender begins a procedure to take over the deed to the property. Often, the process ends with a public auction of the property. If the property is not purchased through auction, the property title is transferred to the lender and referred to as "real estate owned" or REO. The lender is then responsible for carrying the costs of the house (Getter, 2008). Home foreclosure contributes to vacancies in the community (Grover, Smith, & Todd, 2008)[5] and may lead to decreased property values and other forms of disinvestment (Hartley, 2010), as well as the social problems that result from high levels of home vacancy. These problems are often spatially concentrated.

Theorizing the crime-foreclosure link

Wilson and Paulsen (2010) proposed a theoretical foundation linking foreclosures and crime, paying close attention to the speed with which neighborhood change took place during the dramatic contraction of the housing market and the extensive social and economic costs borne by neighborhoods and localities as a result of concentrated foreclosures. Further, Taylor's (Taylor, 2010) review of existing theoretical models suggests that no one theory is sufficient to explain the link between foreclosures and crime rates, but that multiple ecological theories are important in understanding the relationship.

Three main schools of thought, all ecological in nature, inform the present work that links foreclosures and crime in neighborhoods: 1) social disorganization; 2) broken windows theory; and 3) routine activities theory. While each of these approaches to explaining crime at an ecological level has unique characteristics, elements of each theory are also intertwined, and help to explain the hypotheses underlying this work: that areas with rising levels of foreclosures are at risk for subsequent increases in crime, and that higher crime levels may contribute to additional foreclosures in an area. The key overlapping element of each of these theories is the social component—the guardianship that residents of and visitors to a neighborhood provide, and the collective efficacy that emerges when residents work together towards a common goal—in this case, preventing crime.

While not presenting a theory of crime in place explicitly, Jane Jacob's (1961) seminal work on cities and the relationships among their residents continues to inform work in this vein, including the present study. While published decades before theories like broken windows or routine activities, her work bridges many of the ideas in these separate theories, linking the related but distinct ideas about the social roles of people in a neighborhood who could, for example, serve as guardians, prevent broken windows from remaining broken for too long, or provide an informal level of social control in an area.

Jacobs' work emphasized the importance of "pavement" in cities— typically in the form of sidewalks. The pavement, or the sidewalk, Jacobs argued, is where the "eyes on the street" should be active at all times of the day and evening, in order to maintain safety and security of residents, visitors, and businesses, and most activity should be oriented street-ward. Jacobs also argued for a continuous population of the

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[5] Also see http://www.nytimes.com/2011/10/28/us/foreclosures-lead-to-crime-and-decay-in-abandoned-buildings.html?pagewanted=all

sidewalk with residents, visitors, and businesspeople (shopkeepers) and businesses alike, in order to maintain the safety of the city: "The sidewalk must have users on it fairly continuously, both to add to the number of effective eyes on the street and to induce the people in buildings along the street to watch the sidewalks in sufficient number."

Jacobs also suggested that the responsibility for safety of urban neighborhoods lies with the people in the neighborhood, not the police. While necessary, she argues, the police cannot secure every space, and security "is kept primarily by an intricate, almost unconscious, network of voluntary controls and standards among the people themselves, and enforced by the people themselves." Her ideas about the informal requirements of urban dwellers and visitors in order to maintain safety were precursors to theories on collective efficacy and routine activities, and provide a useful foundation to understanding the arguments put forth in the three theories guiding this work.

SOCIAL DISORGANIZATION THEORY

Social disorganization theories of crime have their roots in the Chicago School of sociology, which suggested that social disorganization was the inability of a community to realize the common values of its residents and support social order (Kornhauser, 1978; Shaw & McKay, 1942). This inability to maintain order and realize community goals was attributed to disrupted or weakened social networks linking friends, kin, and/or acquaintances (Sampson & Groves, 1989). Joseph and colleagues (Joseph, Chaskin, & Webber, 2007) identified the importance of interpersonal relationships in residents' ability to exert social control to improve safety and quality of life; many factors influence the number and strength of such interpersonal relationships.

However, early social disorganization theories failed to explain how social controls could develop in communities without strong social ties (Granovetter, 1983) or why strong social ties could promote crime as effectively as it could inhibit it (Pattillo, 1999; Venkatesh, 1997). Jacobs (1961) discussed, although not explicitly, the role of weak ties in the city, suggesting that the nature of relationships formed on the sidewalks with neighbors that one sees regularly, but briefly, requires less of a commitment to the relationship by either party. Being on friendly terms with many neighbors, without the obligations of a close friendship, actually provides both privacy (because neighbors are more acquaintances than friends) and security, through more eyes on the street, at the same time. But Jacobs' work did not fully theorize the development of these relationships or how they could contribute to social norms beyond providing more eyes on the street.

Collective efficacy theory was designed to address these gaps in early social disorganization and guardianship theories. A neighborhood's collective efficacy refers to its level of cohesion and shared expectations of social control. A neighborhood may have differing levels of collective efficacy with regards to specific tasks or goals (e.g., crime control, supporting community services) (Sampson, Raudenbush, &

Earls, 1997). For instance, residents in neighborhoods with high collective efficacy might support public order by confronting individuals who are loitering, monitoring neighbors' homes for suspicious activity, and reporting youth truancy. They might do this even if the social ties between neighbors are limited—Jacobs' concept of neighbor-acquaintances—so long as there are expectations of mutual support among neighbors regarding shared responsibilities for crime control.

Because communal standards and even weak social ties require time to develop, residential instability may impede this process, reducing a community's ability to identify and work toward collective goals. Empirical research indicates that collective efficacy is significantly and positively correlated with residential stability and significantly and negatively correlated with perceived violence, victimization, and homicide (Sampson et al., 1997). To the extent that residential stability is measured as the length of time residents have lived in a household and the number of owner-occupied housing units in a neighborhood (Graif & Sampson, 2009; Rhineberger-Dunn & Carlson, 2011; Turney & Harknett, 2010), foreclosures impact residential stability by removing residents from neighborhoods and weakening the shared standards and expectations for support that collective efficacy suggests may reduce crime in a neighborhood.

Foreclosures may also affect collective efficacy by restricting the resources that residents have at their disposal to maintain social control. Homeowners who are facing foreclosure are not likely to have significant resources (whether in the form of financial support, time, or emotional dedication to a cause) to commit to neighborhood maintenance or well-being. If foreclosures are concentrated in neighborhoods, their negative effects, such as dwindling individual and community-level resources, may be compounded. This lack of resources can lead residents to become disengaged in the community, weakening social ties and informal networks. In addition, going through foreclosure can cause significant stress for a homeowner, which may also keep him or her from fully engaging in neighborhood social ties.

Further, when deciding to remain in or move to an area, residents use visual cues to guess at relative housing values, neighborhood stability (Kruger, 2008), and the community's standards for socially acceptable behavior (Reiss, 1986). As a result, individuals who seek safety and social cohesion may avoid neighborhoods with highly visible physical and social decay, assuming that the social cohesion they value is similarly lacking. Conversely, even in neighborhoods with significant foreclosures, if residents can maintain shared expectations for social control, they may be able to mitigate the impact of foreclosures, for example by calling police or neighborhood groups to secure abandoned houses (Graves, 2012). When such neighborhood maintenance does not occur however, the resulting decay and disorder may signal to offenders that a neighborhood is suitable for criminal activity.

BROKEN WINDOWS THEORY

The idea from social disorganization theory that visitors and potential residents use visual cues to make assumptions about the social nature of a community is a natural segue into broken windows theory's related statements about physical and social disorder. While collective efficacy describes the social process that impacts a community's capacity to control crime, broken windows theory posits that indicators of physical and social disorder in a neighborhood, like decaying properties or panhandlers, are tied to a community's functioning and tolerance for criminal activity (Wilson & Kelling, 1982). Not only do signs of deterioration and social disorder suggest direct exposure to dangerous or unhealthy conditions (Kruger, 2008), they also provide information to potential offenders on residents' ability and willingness to monitor, control, defend, and improve their community (Homel & Clarke, 1997; Sampson & Raudenbush, 1999). Sampson and Raudenbush (1999) summarize the problem: "Evidence of disorder also gives a running account of the effectiveness of residents seeking neighborhood improvement, and that record may encourage or discourage future activism" (p. 604). Research on residents' perceptions of vacant houses confirms the view that vacant houses lower residents' option of the neighborhood and their sense of community (Graves, 2012). When there is evidence that neighborhoods are ineffective in controlling crime or enforcing social order, criminals may view that area as a more suitable site for committing offenses.

The "broken windows" problem is compounded in areas where more than one house is left in such a state. Foreclosed homes that have been left vacant are more likely to fall prey to thieves who steal valuable items from the homes, to homeless individuals looking for shelter, or to drug dealers looking for a location to conduct business. Police receive more calls for service from blocks with unsecured properties, and blocks with abandoned buildings have high rates of property crimes regardless of whether that property was used illegally (Spelman, 1993). As more homes enter this state the broken windows theory posits that crime and disorder are likely to increase. These houses may also deter potential residents who might otherwise stabilize the neighborhood from moving in.

ROUTINE ACTIVITIES THEORY

Routine activity theory posits that crime occurs when a motivated offender finds a suitable target that is unguarded (Cohen & Felson, 1979)—vacant houses may help to bring these elements together and encourage offending. Overgrown lawns and deteriorating physical conditions convey that the property is neglected. This environment may suggest that the community is not exercising guardianship over a particular property, making it a good site to commit an offense. Vacant lots have been found to have an impact on automobile thefts (Rice & Smith, 2002) and robberies (Roman, 2004). Abandoned, unsecured residential homes on a block have also been found to be related to crime broadly (Eck & Weisburd, 1995; Spelman, 1993). With more targets and unsecured locations available for offenders because of the proliferation of foreclosed, vacant houses, crime would be expected to increase. In this sense, foreclosed properties can be seen as crime attractors or generators.

Routine activities and broken windows may work in concert in a neighborhood with abandoned homes: motivated offenders, drawn to the area by the signs of physical and social disorder that vacant houses represent, may then either target those houses for property or disorder crimes, or may use the unguarded site a vacant property represents as a staging point for an offense.

BRINGING THE THEORIES TOGETHER

These three ecological theories of crime form the foundation of the present research. Common ecological theoretical postulates relate to (1) residents' ability to work together toward a common goal, (2) visual cues regarding the social nature of an area and its level of social control, and (3) the unmaintained, vacant houses that attract criminals and criminal events. Based on these postulates, areas of concentrated foreclosures are expected to experience rising levels of crime.

Wilson and Paulsen's (2010) review of the theoretical underpinnings linking neighborhood conditions and crime suggest that "foreclosures have the potential to be a catalyst from which persistent crime patterns can take root" (p. 1). They identify a two-stage process of foreclosure-related decline: first, homeowners under financial stress are unable to maintain their properties, foregoing needed repairs and spending less time on upkeep of the exterior of the house as well (creating "broken windows"). Vacant homes may also be rendered permanently or temporarily uninhabitable due to structural damage or poor upkeep, further reducing the chance that new buyers will purchase them. Second, homes become vacant as the foreclosure process is completed and homeowners move out, leaving fewer guardians (routine activities) and fewer contributors to the neighborhood's collective efficacy (social disorganization). If new buyers cannot be found for a foreclosed property, the problems engendered by a vacant home will remain and may influence crime rates in the area. The authors' review suggests that concentrated foreclosures that follow such a two-stage process can speed the decline of neighborhoods—which is typically a very slow process—making neighborhoods more susceptible to short-term changes, such as crime, becoming entrenched and hard to combat. Further, "crime will become a primary change agent that amplifies and accelerates the decline" of hard-hit neighborhoods (Wilson & Paulsen, 2010, p. 1).

These theoretical postulates form the foundation for the current work, and for most work that has been completed to date on the topic. The next section reviews some key research on foreclosures and crime, and examines the varied methods and parameters employed, along with some inconsistent findings on the relationship between the two phenomena.

The spatial clustering of foreclosures

During the late 2000s, most research focused on causes of the foreclosure crisis and took an economic or financial approach to the topic, leaving stories about the negative consequences of foreclosures to the popular media. Early research on the causes of foreclosure and the foreclosure crisis identified spatial patterns of foreclosure, relevant for this work. Part of the impact of foreclosures was not simply the sheer number that were happening every day, but the fact that many foreclosures were clustered spatially—creating neighborhoods that were 'hard-hit' or experienced proportionally more foreclosures than would otherwise be expected given homeownership rates. But the housing bubble and resulting crisis combined to create a situation where the most vulnerable homeowners also tended to cluster together in similar neighborhoods, exacerbating the problem.

Most prior research documenting the spatial distribution of foreclosures found that foreclosures were concentrated mainly in low income, minority neighborhoods (Aalbers, 2009; Avery, Brevoort, & Canner, 2007; Kaplan & Sommers, 2009; Newman & Wyly, 2004; Schloemer et al., 2006; Smith, 2008). This pattern was closely tied to the spatial pattern of subprime mortgages, those lent "at higher fees and interest rates whether or not the borrower actually has bad credit"(Aalbers, 2009). Because of these attributes, subprime mortgages are disproportionately held by low income and minority individuals.

THE EFFECTS OF SUBPRIME MORTGAGES

The practice of predatory lending, often associated with subprime mortgages, has also been found to be spatially clustered (Crossney, 2010). Newman and Wyly (Newman & Wyly, 2004) document trends that led to further spatial concentration of subprime mortgages and foreclosures in low income, minority neighborhoods beginning in the late 1990s. A focus on increasing opportunity for racial/ethnic minorities and low income families in late 1990s stressed extending homeownership to populations traditionally excluded from the housing market. Alongside a housing policy environment that promoted homeownership, major changes in the mortgage markets (relaxed lending regulations, the emergence of non-banks as major mortgage providers, and the development of a secondary market for non-prime mortgages) laid the groundwork for the boom in subprime lending. Compounding the problem is the fact that many residents of these areas carry higher levels of debt and are therefore more susceptible to major and unexpected costs (e.g., home or car repair costs, medical bills) (Newman & Wyly, 2004).

A subprime borrower's increased risk of default combined with growth in popularity of subprime mortgages since the late 1990s and predatory lending practices led to a spatial concentration of foreclosures in low income, minority neighborhoods at the time of the foreclosure crisis. A disproportionate number of subprime mortgages end in foreclosure: while subprime mortgages represented only 13 percent of loans in 2006, 60 percent of foreclosures were on subprime loans (Nassar, 2007). Such mortgages also go into foreclosure more often and faster, with an estimated 20 percent of the subprime mortgages between 2004 and 2006 in some state of foreclosure (Schloemer et al., 2006). Immergluck and Smith (Immergluck & Smith, 2005) agree that subprime mortgages were more susceptible to foreclosure and that where rates of foreclosure were high, subprime mortgages accounted for large portions of the foreclosures. We know of no systematic review of the spatial pattern of prime versus subprime loan foreclosures, but the same minority, low-income neighborhoods with higher rates of subprime lending also have more precarious employment situations and lower education levels. The presence of increase foreclosures then, may add an additional criminogenic risk factor to a neighborhood that already has significant risks.

COLLAPSING HOUSING MARKETS AND VACANCIES

While research has consistently documented the concentration of foreclosures in areas with economically vulnerable populations, recent developments in housing markets have led to an expansion of the foreclosure crisis to areas traditionally shielded from economic hardship. Immergluck (2008) demonstrates that an increase in subprime mortgages had a small effect on foreclosures when housing prices were rising dramatically but as prices began to level off or fall, areas with a large proportion of subprime mortgages experienced quickly-rising foreclosure rates. In particular, areas that experienced rapidly-appreciating housing values are particularly vulnerable as housing prices drop and borrowers owe more on their mortgages than their houses are worth.

Aalbers (2009) presents evidence that during the booming housing markets of the early 2000s, other types of non-traditional mortgages like interest-only loans were aimed at middle class buyers. These buyers typically resided in areas of rapid growth, like Washington, DC, New York, and California (Schloemer et al., 2006). Two to three years into the foreclosure crisis, defaults and foreclosures increased at faster rates in these areas than in areas traditionally plagued with foreclosure problems, with the Sunbelt states seeing the highest increases in foreclosure rates (Aalbers, 2009).

Investigating the crime-foreclosure link

As scholarship on the effect of foreclosure expanded, more work focused on the negative outcomes and consequences of concentrated foreclosures, including their relationship with crime. Only one systematic study completed prior to 2010 attempted to quantify the effects of foreclosures on crime. Using data from Chicago and controlling for relevant neighborhood factors, Immergluck and Smith (Immergluck & Smith, 2006) found that a 1 percent increase in foreclosures led to a 2.3 percent increase in violent crime. Property crime and foreclosure did not have a statistically significant relationship. The authors suggest that the null finding for property crimes may have been due to underreporting, either because the crimes occur in or to houses that are vacant, or because they are more common in disadvantaged areas, where crime reporting rates tend to be lower. The authors tested for simultaneity in their model—the idea that foreclosures and crime may be part of a feedback loop, influencing each other—but found no evidence of such an effect.

Immergluck and Smith's (2006) comprehensive look at foreclosures and crime was published before the rise in foreclosures escalated. Since 2010, more research has been undertaken in an effort to understand the links between foreclosures and their impacts on neighborhoods and communities. Table 1 below summarizes 16 recent studies on the topic. The table identifies key features about each article, including the foreclosure and crime measure(s) used in the analysis, the geographic unit of analysis employed, and the study area. The last column in the table indicates briefly what each analysis found regarding the foreclosure-crime relationship; articles highlighted in gray found positive relationships between foreclosures and crime (i.e., rising foreclosures are related to rising crime rates).

FORECLOSURE MEASURES

Foreclosure is a process consisting of multiple events, and determining what point in the process should be investigated to best capture its effects has been an ongoing challenge for researchers. Generally, the foreclosure process is prompted by loan payment delinquency, and can take anywhere from several months to years to complete. Research on the relationship between foreclosures and crime has recognized that foreclosure is a process in addition to an event, or several events (e.g., filing, mediation, sale). Criminological theory suggests that the effects of foreclosures operate through vacancies, which are an end-result of the foreclosure process. But disinvestment in a home may occur while a foreclosure is in process (before it has completed), if homeowners are unable to maintain repair of their homes—a plausible proposition given that those in foreclosures have been unable to pay their mortgages. Broken windows theory suggests that such homes that are allowed to fall into disrepair can contribute to higher levels of crime in a neighborhood.

Prior research on the effect of foreclosures on crime has tested different measures of foreclosures. Typically, the measures include foreclosure filings (starts or *lis pendens*), active foreclosures (inventory), or real estate-owned (REO) foreclosures (sales) (Arnio & Baumer, 2012; Cui, 2010; Ellen, Lacoe, & Sharygin, 2013; Kirk & Hyra, 2012). Because foreclosure sales data are sometimes hard to acquire, many studies focus on foreclosure starts. Such studies generally employ lagged regression models to allow for the foreclosure to mature before effects become manifest in neighborhoods. Depending on the jurisdiction, access to information beyond foreclosure filings/starts may require data from additional sources. In analyzing the relationship between both foreclosure filings and real estate owned foreclosures and crime, for example, Cui (Cui, 2010) linked city court data on foreclosure filings with county deeds data through a common identifier.

Findings on the relationship between filings and crime are mixed. Half of the studies reviewed in Table 1 identified positive relationships between the two measures. Of those studies that tested *only* foreclosure filings, and no other foreclosure measures, Teasdale and colleagues (2012) are the only authors who found a positive relationship. That work tested the impact of subprime lending foreclosure filings between 2001 and 2003 on public order crimes between 2003 and 2004. The findings suggested that foreclosures on subprime loans increased crime by 2-3 percent.

TABLE 1. SUMMARY OF PRIOR RESEARCH ON FORECLOSURES AND CRIME

	Study	Foreclosure Measure			Crime Investigated			Unit of Analysis	Study Area	Positive effect of foreclosures on crime?
		Start	Active	REO	Violent	Property	Disorder			
1	Immergluck & Smith, 2006			X*	X	X		Census tract	Chicago	Yes violent crime only
2	Cui, 2010	X		X	X	X		250' buffers around foreclosed properties	Pittsburgh	Yes, b/t foreclosure-caused ***vacancy*** and crime
3	Goodstein & Lee, 2010			X	X	X		County	National	Yes
4	Madensen, Hart, & Miethe, 2011	X			X	X	X	Residential subdivision	Las Vegas	No
5	Pandit, 2011	X	X	X	X	X		MSA	National	Yes but weak, property crime only
6 7	Katz, Wallace, & Hedberg, 2011; Wallace, Hedberg, & Katz, 2012	X			X	X	X (drug)	Census tract	Glendale, AZ	No
8	Arnio & Baumer, 2012			X	X	X		Census Tract	Chicago	Yes but varies by place
9	Arnio, Baumer, & Wolff, 2012			X	X	X		County	National	Yes
10	Baumer, Wolff, & Arnio, 2012			X				Census tract	50 large US cities	Yes
11	Jones & Pridemore, 2012	Housing Mortgage Stress Index			X	X		MSA	National	No
12	Kirk & Hyra, 2012	X			X	X		Chicago Comm'ty Area (grps. of census tracts)	Chicago	No
13	Stucky, Ottensmann, & Payton, 2012			X	X	X		1,000 sq. ft. grids	Indianapolis, IN	Yes
14	Teasdale, Clark, & Hinkle, 2012	X					X	Census tract	Akron, OH	Yes
15	Ellen, Lacoe, & Sharygin, 2013	X	X	X	X	X	X	Block face	New York City	Yes
16	Wolff, Cochran, & Baumer, 2013			X				County	National	No

*Not specified; assumed to be completed foreclosures

Madensen and colleagues (Madensen et al., 2011), on the other hand, tested the impact of foreclosure filings on crime for three time periods. While most results were null, one result indicated that foreclosure filings for one time period (2006–2007) had a significant, negative effect on crime rates for the second time period (2008–2009). That is, an increase in foreclosures was associated with a decrease in crime. This finding not only suggests a relationship unobserved by other studies, but it also identifies and underscores a temporally-sensitive relationship between foreclosures and crime.

Only two of the studies included measured the effects of the foreclosure inventory, an intermediary stage in the foreclosure process, on crime. Active foreclosures, or foreclosure inventory, are the number of foreclosures at any point in the foreclosure process at a given point in time. Results from Ellen and colleagues (Ellen et al., 2013) indicate that active foreclosures are more strongly associated with crime rate than foreclosure filings. That work also found that the relationship between foreclosures and crime is most robust when foreclosure is measured as a REO (bank-owned) property.

Nine of the ten studies that employed measures of completed foreclosures, or REO properties, found some level of positive relationships between foreclosures and crime, although most with some caveats. Foreclosure sales include properties that are most likely to be vacant, if not sold at auction. These properties may have also been involved in the foreclosure process for some time by the point of completion, giving any lagged effects time to manifest. Where investigation of the effects of foreclosure filings on crime may not result in a significant relationship between the two phenomena, the use of REO properties may: Cui (Cui, 2010) found a positive relationship between vacancies caused by foreclosure sales and crime, and the same findings did not hold for foreclosure filings and crime.

The positive findings are not without caveat, however. Baumer, Wolff, and Arnio (Baumer et al., 2012) found that positive results were not consistent across places; once demographic and socioeconomic context were accounted for, foreclosures were only related to increased crime where foreclosure rates were low and disadvantage was high. Similarly, Arnio, Baumer and Wolff's (2012) analysis of foreclosures at the county level found that the effect of foreclosure sales on crime was highest after the foreclosure rate reached "historically high levels" (p. 1598). Stucky, Ottensmann, and Payton (Stucky et al., 2012) studied the effects of foreclosure sales on crime, and found a positive relationship between the two, although the effects they identified were stronger in areas with high levels of existing residential stability. The relationship between foreclosure sales and crime, then, varies with context and prior levels of foreclosure. This crime-foreclosure relationship is also sensitive to the unit of spatial analysis being tested.

UNITS OF SPATIAL ANALYSIS

To the extent that crime, foreclosures, and demographic characteristics vary significantly within a given space, observable relationships may surface depending on the spatial unit of analysis. Arnio and Baumer (2012) underscore how the unit of analysis can affect research findings. The researchers first analyzed the impact of foreclosures and other neighborhood variables on homicide, robbery, and burglary in Chicago using a “global” approach that assumes spatial invariance within the designated unit of analysis (census tract). Results from maximum likelihood spatial regression indicated that the change in foreclosure rates between 2007 and 2009 was positively and significantly related to the number of neighborhood robberies.

Second, the researchers use geographically weighted regression (GWR) to test whether these relationships vary locally. Results indicated that the impact of foreclosures on robbery and burglary varied across localities and were “not uniformly statistically significant.” This finding again suggests that the relationship between foreclosures and crime may be contextual. Additionally, the traits of nearby neighborhoods may affect the foreclosure-crime relationship. Generally, of the studies included in this review, those that used smaller geographic units (census tracts or smaller) were more likely to find positive effects of foreclosures on crime levels.

SPILLOVER OR CONTAGION EFFECTS

Several studies have shown negative spillover effects of foreclosures on housing prices in nearby areas (Immergluck & Smith, 2006; Schuetz, Been, & Ellen, 2008; Shlay & Whitman, 2006), and spillover effects of crime have also been observed. Munroe and Wilse-Sampson’s (Munroe & Wilse-Samson, 2013) look at the effects of foreclosures in one neighborhood on subsequent foreclosures in neighboring areas identified a contagion effect; nearby areas experienced higher levels of foreclosure than those that were not nearby areas with other foreclosures. The findings also suggest that the contagion effect is durable, lasting for several years beyond the initial foreclosure event.

Likewise, levels of crime in one place may be affected by structural characteristics of adjacent neighborhoods. Cohen and Felson (1979) first formalized the idea that all else being equal, targets who live in closer proximity to areas with high rates of offending will have a greater risk of victimization than targets that live farther away. Thus if one area is adjacent to another with high levels of violence, spillover effects of offenders into nearby areas can increase the risk of crime in those nearby areas. Likewise, characteristics of one area may serve to attract offenders who look for opportunity not only in the “attracting” area but also in adjacent areas. Therefore, high levels of crime, foreclosures, or both can affect the occurrence of crime and foreclosure in nearby areas, signifying the importance of spatial considerations in modeling the relationship between foreclosures and crime.

AS THE DUST FROM THE CRISIS SETTLES

At the height of the current foreclosure crisis, in the late 2000s, it was hard to predict how long the crisis would last, how far it would reach, and what the extent of the negative consequences would be. Initial research efforts at a variety of geographic and temporal scales, and with sophisticated modeling techniques, have found modest but positive relationships between foreclosures and crime. With additional time, perspective, and an increased ability to observe both short and long-term effects in various neighborhoods—both those hard-hit and those relatively "immune" from the crisis—researchers have begun to question the causality of the observed increases in crime in areas where foreclosures were particularly bad (Kirk & Hyra, 2012; Wolff et al., 2013).

Kirk and Hyra (2012) were the first to suggest that a crime-foreclosure relationship might be spurious. The authors employed random effects models to investigate the foreclosure-crime link and found that once "time invariant" characteristics were taken into account the foreclosure-crime relationship disappeared. Instead, the authors suggest that both foreclosures and crime are related to similar characteristics of neighborhoods; they found the most important covariates of crime to be "residential instability, community disadvantage, and the relative political influence of a community."

Kirk and Hyra (2012) also suggested that their results did not negate the possibility that foreclosures may affect crime levels at a micro-level, such as at the block level, because local dynamics between foreclosures and crime may vary from the globally-observed results. This supports the findings of Arnio and Baumer (2012), who used geographically-weighted regression to investigate foreclosures and crime. They found that the relationship between the two phenomena varied across their study area, and was not always significant. Kirk and Hyra's concession also supports the findings from two investigations of crime and foreclosures in micro-places, which both found positive relationships between the two phenomena (Ellen et al., 2013; Stucky et al., 2012).

Wolff and colleagues (2013) also addressed the possibility of the spurious relationship between foreclosures and crime, through the use of propensity score matching to identify matching pairs of U.S. counties based on an extensive set of socio-demographic characteristics. The matched pairs allowed the authors to identify "treatment" (high foreclosure) and "control" (low foreclosure) counties similar on socio-demographic characteristics, and compare these two groups on their selected outcomes: burglary and robbery rates. The results indicated that when socio-demographic characteristics are included in modeling efforts, foreclosures and crime are not significantly related.

GAPS IN RESEARCH

The findings presented above represent some of the most rigorous work to date on foreclosures and crime. On balance, the evidence, previously supporting a positive relationship, now appears quite mixed, with recent work calling into question earlier findings that demonstrated a relationship between crime and foreclosure. The question of whether a relationship exists between foreclosures and crime, then, is far from settled, and because recent work used relatively large geographic units of analysis, additional research into micro-level effects of foreclosures is needed.

In addition to providing mixed results on foreclosure and crime, prior research has left a number of gaps that should be explored in order to more fully understand the neighborhood-level processes that occur in areas hard-hit by foreclosures. The research discussion identified temporal elements as being important to the foreclosure crime link, indicating that negative outcomes of foreclosure may be slow to manifest, depending on the foreclosure process and time to completion, or foreclosure sale. Additionally, spillover or contagion effects of foreclosures have also been observed, indicating the possibility of a spatial dependency between neighborhoods. In other words, foreclosures observed in one neighborhood may contribute to crime in a nearby neighborhood. Finally, a circular relationship between foreclosures and crime may exist indirectly through property values; it is important to control for a possible spurious relationship between the two measures.

Most of the recent research identified above has modeled *either* temporal or spatial effects. Temporal effects have been incorporated through either the use of time series data (Katz et al., 2011; Wallace et al., 2012) or, more commonly, lagged measures of crime following foreclosures (e.g., Goodstein & Lee, 2010; Stucky et al., 2012). Possible spatial dependency in the foreclosure and crime measures have been taken into account by including a spatial lag term in models (Ellen et al., 2013) or employing a spatial regression model (Arnio et al., 2012). Finally, we are aware of only one study—Immergluck and Smith (2006)—that considered the possibility of simultaneity of effects between foreclosures and crime. That study was conducted prior to the current foreclosure crisis, and did not find indications that simultaneity between foreclosures and crime existed.

The main gap in research, then, is the development of a model that incorporates both spatial and temporal elements into the model, and controls for a possible bi-directional relationship (between foreclosures and crime and vice versa) that could mask the true relationship between the two phenomena. Using dynamic equilibrium modeling techniques, the present research seeks to address this gap in the research, considering the effects of both foreclosures and crime on each other, and considering these effects over time and in nearby areas.

The next chapters provide descriptive information on the two sites employed for this research—DC and Miami.

Washington, DC

The authors selected DC and Miami for the present study on the localized foreclosure-crime relationship for several reasons. First, the levels of both foreclosures and crime were sufficiently high in each site to make statistical analysis of both feasible for small geographic units. Foreclosure rates in DC, however, are much lower than those in Miami, creating an opportunity to compare impacts in two cities with different foreclosure experiences and responses. Crime rates for each city are high relative to national levels: According to FBI statistics for 2008, the City of Miami had a violent crime rate of 1,334 crimes per 100,000 persons while DC had a violent crime rate of 1,375 crimes per 100,000 persons. In comparison, the national rate was 454.5 crimes per 100,000 persons (FBI, 2009). Both cities also had the detailed data on foreclosures and crime that were required for the planned statistical analyses readily available.

This chapter describes the context of the foreclosure crisis in DC, the data collection and processing effort, and descriptive analyses of both crime and foreclosure data.

Demographics of Washington, DC

After having fallen from just over 800,000 residents in 1950 to about 570,000 in 2000, a decrease of nearly 30 percent, DC's population grew during the 2000s.[6] This was the first time the city's population had grown in five decades. The 2000s—the decade of the modern housing boom and foreclosure crisis—also heralded a period of significant change in the city's population and racial make-up. Since 1950, the majority of the city's population has been Black or African-American. This remained true through the 2000s—although just barely, with the proportion of Black or African-American residents in the city shrinking from about 60 percent in 2000 to just over half of the population (51%) in 2010. Over that same period, the proportion of White and Latino residents grew considerably, with the percentage of White residents increasing from 31 to 39 percent and Latino residents from 8 to 9 percent.

These population trends have had a distinct geographic pattern as well, as demonstrated in Figure 3. As has historically been the case, White residents in DC are clustered in the city's Northwest quadrant while Black residents tend to be clustered in the Southeast and Northeast quadrants. The smaller Latino population clusters in the central and north-central parts of the city. These racial and ethnic patterns mirror

[6] All figures referenced in this section are from the U.S. Census Bureau's various data products presenting historical data and data from the 2000 and 2010 censuses, unless otherwise noted. For more information on DC's changing population patterns, see Our Changing City presented by the Urban Institute, at http://datatools.urban.org/features/changingcities/#index.

those of poverty and housing values in DC, as well, shown in Figure 4 and Figure 5. As with the racial and ethnic maps, these spatial patterns of poverty have persisted for decades.

When the foreclosure crisis hit, it disproportionately affected minority populations nationwide, and this was true in DC as well. Minority homeowners were more likely to have used subprime loans to purchase homes and to have smaller financial safety nets in case of economic hardship than White residents. Thus, the foreclosure crisis, like housing values and race in DC, had a distinct geographic pattern, presented below. While historic racial/ethnic and poverty stories in DC are certainly much more nuanced than is presented here, this demographic information provides sufficient context to understand the patterns of foreclosure and crime that occurred in the 2000s.

The foreclosure crisis in Washington, DC

The late 2000s foreclosure crisis in the United States came on the heels of an unprecedented housing bubble. In DC, average housing sales prices for single family homes during the bubble years rose 77 percent, from just over $300,000 in 2002 to $531,000 in 2007, when the foreclosure crisis was still developing. After the foreclosure crisis began in 2008, prices dropped slightly, to an average of $512,000 in 2012 (NeighborhoodInfo DC, 2012). Average housing prices, then, still remained significantly higher at the end of the 2000s than at the beginning. In short, the foreclosure crisis decreased housing prices only slightly in DC in the second half of the 2000s, and the price drop experienced in the city was not nearly as extreme as it was in other areas of the country.

With an economy buoyed by the federal government's relatively stable employment levels and spending, DC fared better than other cities when the country's economic recession and foreclosure crisis hit (Lowrey, 2013). The city was not wholly immune, however. Many residents did experience financial hardship, and the city's average housing values were also significantly higher than prices in many metropolitan areas, making attaining affordable housing a struggle.

Figure 6 provides median housing values for Washington, DC, Miami-Dade County, and the United States overall during the 2000-2011 period. Comparable data for the years 2001-2004 were not available: the line between 2000 and 2005 is an estimate of the trend. The post-2005 low and high values for each area are identified on the graph, as well as the starting median values for each, in 2000. The graph demonstrates how both the housing bubble and subsequent economic crisis affected DC and Miami differently. The characteristics of the crisis in Miami are discussed in detail in the following chapter.

FIGURE 3: WHITE AND AFRICAN AMERICAN RESIDENTS IN WASHINGTON, DC, 2010

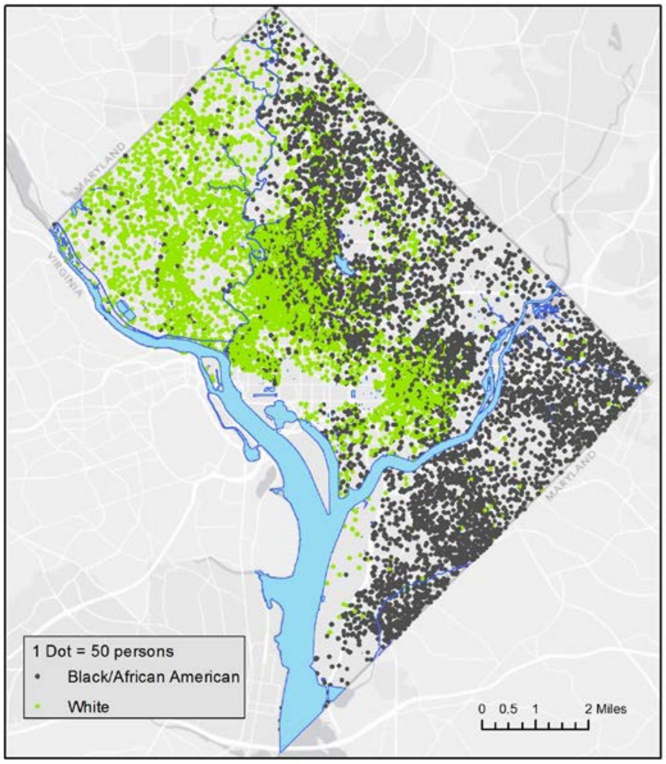


FIGURE 4: PERCENT BELOW THE POVERTY LEVEL BY CENSUS TRACT, WASHINGTON, DC, (AVG. 2008-2012)

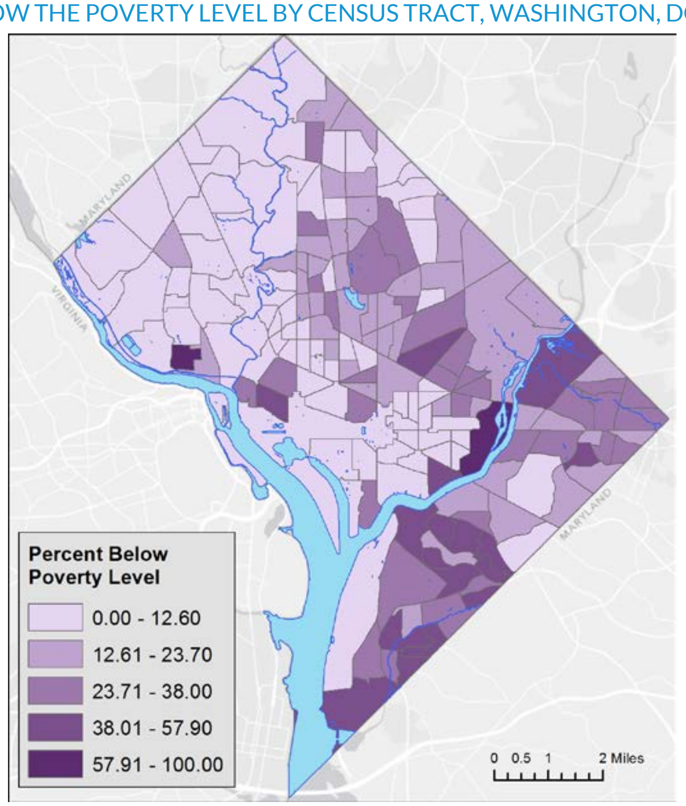
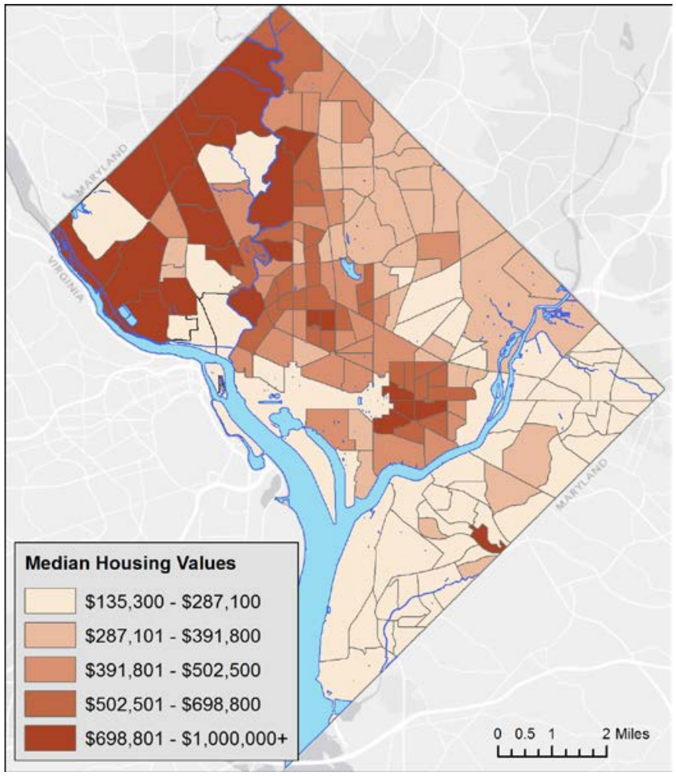


FIGURE 5: MEDIAN HOUSING VALUES BY CENSUS TRACT IN WASHINGTON, DC, (AVG. 2008-2012)



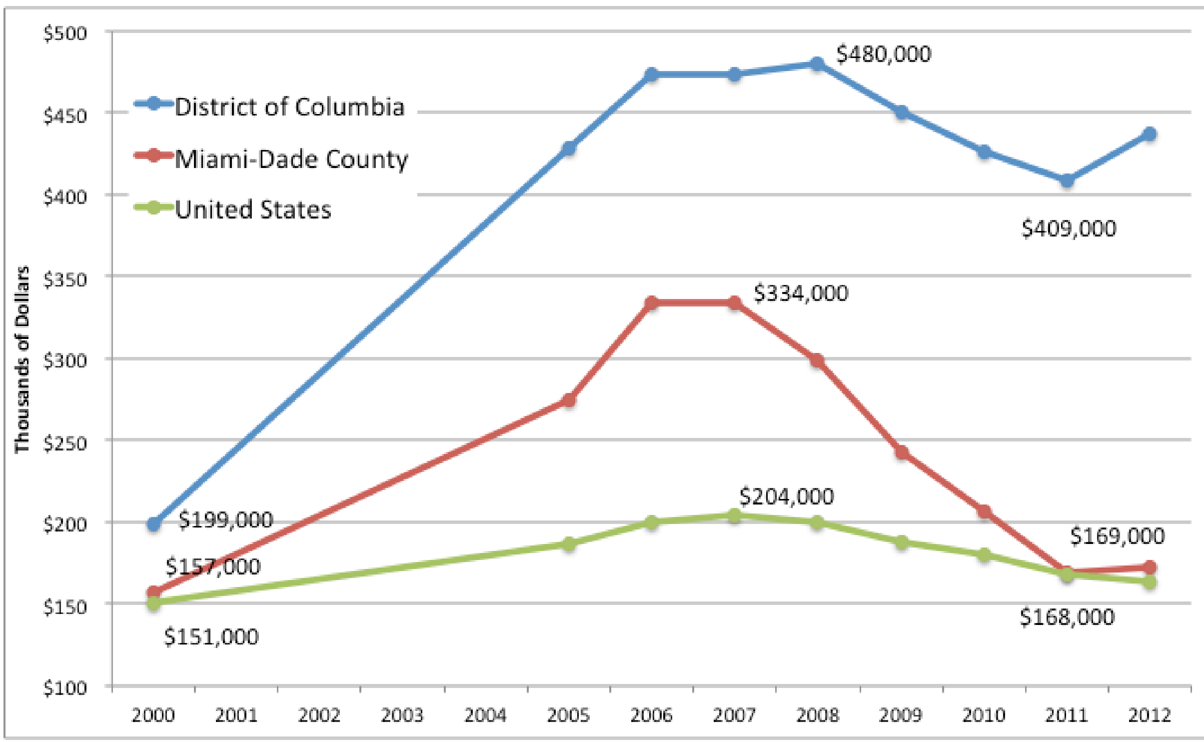
In 2000, the median housing value in the United States was approximately $151,000;[7] in DC it was $199,00, putting it in the top five percent of county housing values nationwide (U.S. Census Bureau, 2000). Median housing values in the U.S. peaked at $204,000 in 2007, at the tail end of the housing bubble and the start of the foreclosure crisis, and dropped nearly 20 percent by 2011, to $168,000—barely more than the median housing value a decade earlier. In DC, median housing values peaked at $480,000 in 2008—135 percent higher than peak median values nationwide. The city's housing value increase had pushed DC into the top two percent of counties based on housing values. Values in the city dropped over the next three years by about ten percent, to $409,000 in 2011, but rebounded by seven percent in 2012. This trend suggests that the housing market in DC was likely difficult to enter for many residents because of extremely high housing values, and that the city did not see as dire drops in housing values as occurred elsewhere, including in Miami.

As housing prices rose during the 2000s, so did the total number of foreclosure filings, particularly in the few years before the peak of the nationwide foreclosure crisis. By December 2009, one year into the foreclosure crisis, the DC foreclosure inventory for single-family and condominium homes had climbed to

[7] All housing values adjusted to 2010 dollars to facilitate comparison.

about 2,900 properties, about 1.6 times the foreclosure inventory from early 2007 (NeighborhoodInfo DC, 2010). This translates to about 20.6 housing units per 1,000 at various stages of foreclosure. In response to the crisis, DC's City Council enacted legislation that created a foreclosure mediation program in November, 2010. Mediation is typically available in states with judicial foreclosure processes, but DC is a non-judicial jurisdiction. Adding mediation was intended to help homeowners slow down or avoid altogether a foreclosure sale, providing them the opportunity to negotiate with their lenders, for example, for different terms of a mortgage or to approve a short sale (District of Columbia Department of Insurance Securities and Banking, 2010).

FIGURE 6: MEDIAN HOUSING VALUES, 2000-2011, IN THOUSANDS OF DOLLARS, IN UNITED STATES AND STUDY AREAS



Source: Census 2000 and American Community Survey 1-year estimates for each year between 2005 and 2011. Note that no data were available for the years 2001-2004; the trend line is estimated for those years. All dollar figures have been adjusted to 2010 dollars.

While mediation is not mandatory, servicers/lenders are required to file a notice of default prior to the notice of foreclosure sale and inform borrowers of the mediation option and send them a loss mitigation application. If a borrower does not opt-in to mediation in the specified time period, the Mediation Administrator issues a mediation certificate and the lender can proceed with the foreclosure as they normally would have. If the borrower elects to participate in mediation, the process must be completed according to the rules established by the DC Department of Insurance, Securities and Banking before the mediation certificate is issued and the foreclosure proceedings can begin.[8]

When the law was passed, the city had neither the ability to mediate negotiations between homeowners and lenders nor the capacity to administer the requirements of the new law. While these were being implemented, the law effectively halted foreclosures in DC. Since passage of the law in November 2010, the flow of foreclosures was slow in the city, even after mediation was fully implemented; DC had a lower number of foreclosures than any state in the country in 2013 (CoreLogic, 2014). Despite this slowdown, some question the success of the law in helping homeowners avoid foreclosure (Kass, n.d.), but discussion of its merits and drawbacks are beyond the scope of this work. Note, however, that the mediation law was passed in the last two months of our study period, limiting its effect on the statistical analyses of DC foreclosures.

Data collection and processing

FORECLOSURE DATA

The source for foreclosure indicators in DC is the D.C. Recorder of Deeds (ROD) and the D.C. Office of Tax and Revenue (OTR). NeighborhoodInfo DC, a local data intermediary operated by the Urban Institute, processed the raw data from these agencies to produce the indicators used in this report. NeighborhoodInfo DC's methodology for creating the indicators is described in the following paragraphs.

DC has a non-judicial foreclosure process and until 2011, the foreclosure process for a property began when the lender or servicer filed a "notice of foreclosure sale" with ROD.[9] This notice includes, among other pieces of information, a parcel id, the borrower, the lender (or lender's representative) and a scheduled date for the property to be auctioned off if the default is not cured, typically around 35 days after the notice is recorded. If a property is sold at a foreclosure auction either to a third party or the back to the lender (if there are no acceptable bids), a notice of trustee's deed is recorded with ROD. Additionally the property sale is registered with OTR as a sale of real property.

In order to create the indicators used in this study the ROD and OTR data were merged together by parcel id and date. Merging these two sources allowed us to obtain the property characteristics (e.g. single-family home or condominium) and geographic information (e.g. address, census tract) found in the OTR data and attach them to the foreclosure records. It also allowed us to see the ownership, sales, and foreclosure

[8] See http://disb.dc.gov/page/foreclosure-mediation-program-fmp for more information on the program.
[9] A non-judicial foreclosure process means that the judicial system is not involved; a power of sale clause in the deed of trust for a mortgage gives the lender the right to sell the property in the event the borrower defaults on the mortgage.

history on a particular property in one place. One can learn who bought the property, how long they held it, whether they ever entered foreclosure, and to whom and how the property was sold.

This study uses three indicators created from the ROD and OTR data. The first is the number of properties with a foreclosure start, which was created by combining all the notices of foreclosure sale from ROD and de-duplicating them by parcel id. We also examined the length of time between notices of foreclosure sale to decide which of two scenarios is more likely: 1) the subsequent notices are part of the original financial crisis that led to the initial notice of foreclosure or 2) the subsequent notices represent a new episode and the previous crisis had been cured. Our assumption was that notices issued within two years of each other were part of the same foreclosure episode. Therefore the measure of foreclosure starts captured the beginning of the entire foreclosure episode and did not count a separate foreclosure start for each notice of foreclosure sale issued.

The second indicator we developed was the number of properties in the foreclosure inventory. Properties are considered to be in the foreclosure inventory from the date of the foreclosure start to when the property is sold or ownership is transferred (whether or not the sale is a trustee's sale) or 18 months after the start of the foreclosure episode if there is no sale.[10] If a property had multiple notices of foreclosure sale within a two-year period and was not sold, the assumption was that the property was in the foreclosure inventory until 18 months after the most recent notice was recorded.

The final indicator developed was the number of properties with completed foreclosures. This indicator counts only those properties with a trustee's sale, whether or not the property becomes part of the REO inventory or is bought by a private individual or company at auction. Other possible exits to foreclosure such as a deed in-lieu of foreclosure or short sale are not counted in the measure of completed foreclosures because they represent methods that homeowners have avoided foreclosure specifically, even while the method of avoidance may not have resulted in the original owner retaining the home.

While our goal was to analyze foreclosures at the smallest geographic and temporal levels possible, we found that the relatively low frequency of foreclosures in DC limited statistical power. Therefore we made the decision to aggregate data at the census tract level and by quarter instead of month, in order to have sufficient variation in the foreclosure measures across geographic and temporal units, as well as to avoid creating an extremely high number of observations with no foreclosures.

To create foreclosure measures for each quarter and geographic unit, we created flags based on the assumptions described above and added them to the data to signal foreclosure starts and completed foreclosures during the quarter in which they occurred. Flags for a property in the foreclosure inventory were created for each quarter that the property was in the inventory. The data were thus summarized by

[10] We chose 18 months as the maximum length of time allowed for activity related to foreclosure of a property based on knowledge of the process and how long each step in the process typically takes.

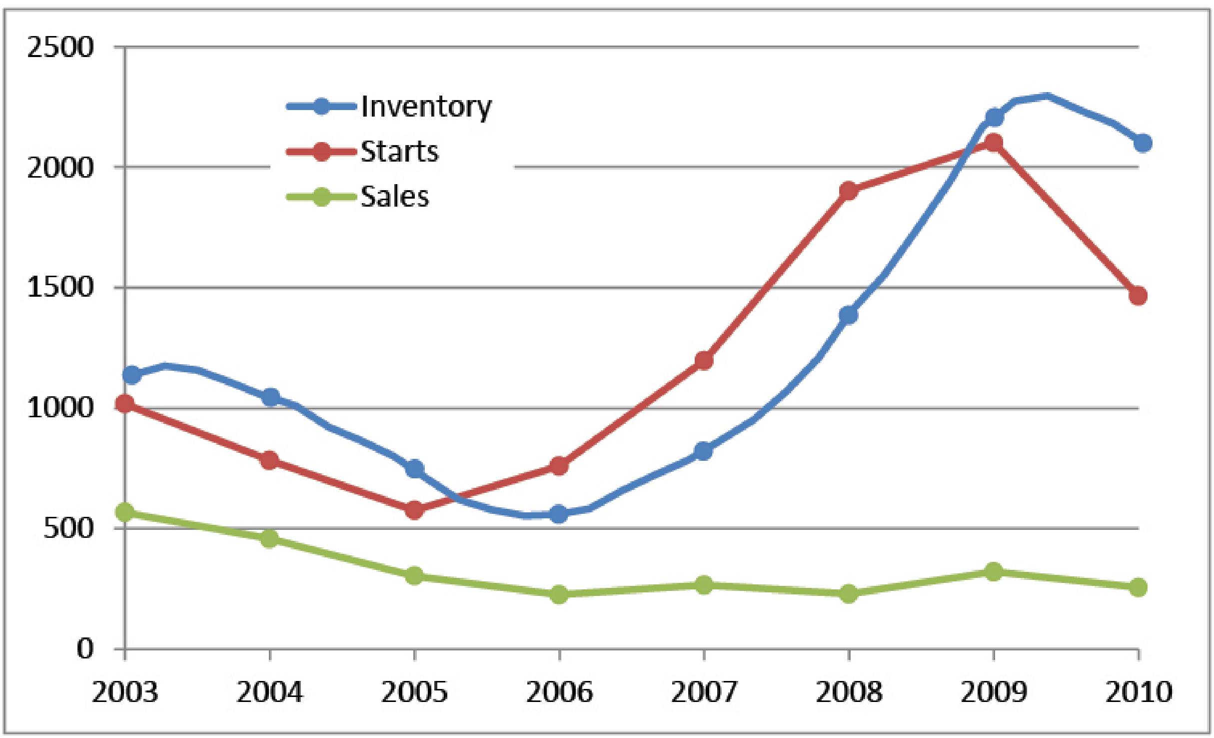
quarter and census tract to create a census tract-level file with data from 32 quarters, January 2003 through December 2010, for each of 188 census tracts in DC.

CRIME DATA

The research team obtained address-level incident data for DC from the Metropolitan Police Department (MPD) for the period covering January 2003 through December 2010. Incident data included all Part I offenses as classified under the Uniform Crime Report system run by the Federal Bureau of Investigation. MPD provided the research team with the geographic coordinates of all incident locations, so no geocoding was necessary. The offenses were classified by researchers into personal (violent) and property offenses. Personal offenses included homicide, sexual offenses, assault, and robbery. Property offenses included burglary, theft, motor vehicle theft, and theft from a motor vehicle.

As with foreclosures, offenses were aggregated into quarterly counts by census tract, giving project staff 32 quarters of data for each of 188 census tracts with which to conduct statistical analyses.

FIGURE 7: TRENDS IN THREE FORECLOSURE MEASURES, WASHINGTON, DC



Source: D.C. Recorder of Deeds and Office of Tax and Revenue.

Patterns of foreclosure and crime

The first step in exploring the relationship between foreclosures and crime in DC was to conduct exploratory analyses on the geographic and temporal patterns of those phenomena in the city.

FORECLOSURE PATTERNS

Figure 7 provides yearly trends over time of three foreclosure measures in DC: inventory, starts (filings), and sales.[11] The trend lines demonstrate the typically lagged relationship of the inventory measure to starts/filings and sales. Starts and sales are both discrete events while the inventory measure includes all properties at any stage in the foreclosure process at that point in time. Any changes in the length of time to foreclosure, such as processing taking longer due to volume of case filings, will increase the inventory measure in future months, as more housing units slowly move through the process.

The graph indicates that foreclosures in DC actually dropped leading into the peak of the housing bubble in the city; starts bottomed out in 2005 while inventory and sales reached their lowest points in 2006. However, after 2006, all three foreclosure measures increased—starts and inventory more dramatically than sales. Nationwide and in DC, foreclosure starts peaked in 2009. The inventory measure hit its highest point in the study period in 2009 and stayed relatively high even as starts dropped dramatically with the halting of foreclosures in 2010. Sales remained relatively low and stable after 2006 with no significant peak through the end of the study period. This indicates that many homeowners who may be at risk of foreclosure are able to avoid a foreclosure sale through one of a number of methods of exiting the foreclosure process.

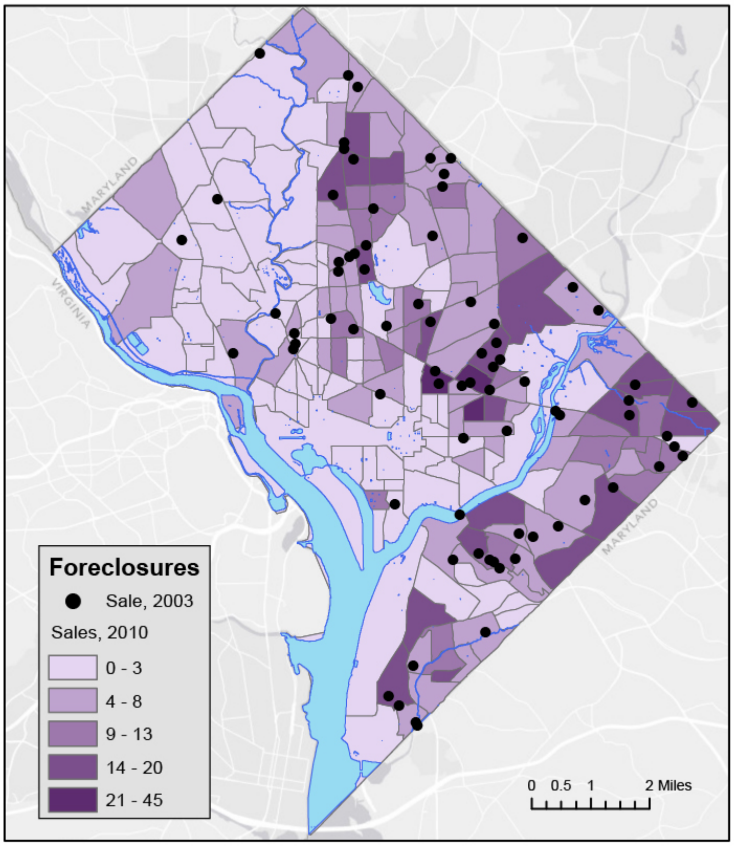
Figure 8 displays foreclosure sales in DC for 2 years: 2003 and 2010. Because they were so sparse, foreclosure sales from 2003 are shown on the map as single dots, with each dot representing one sale. Foreclosure sale volume had increased enough by 2010 to allow mapping the yearly total sales by census tract. This overlay reveals that while the volume of foreclosure sales increased over time, the spatial patterns of foreclosure remained relatively stable. The pattern of foreclosures in DC closely follows racial and poverty lines, with many foreclosures, even before the start of the most recent crisis, clustering in the city's Northeast and Southeast quadrants. While some foreclosures did occur in the Northwest quadrant of the city, those were very low in volume compared to other parts of the city. The maps also reveal that foreclosures increased most in areas where they were already occurring prior to the current crisis.

The yearly Moran's I values—a measure of spatial autocorrelation, or spatial clustering of similar values—for foreclosure sales in DC were examined. Values for most years were significant and all were very

[11] The graph displays counts of these measures because a yearly estimate of housing units by census tract—which would be used as the basis for calculating rates—is not available.

low, ranging from I=0.02 (2010) to I=0.19 (2008). These figures indicate that while census tracts with higher numbers of foreclosures were more tightly clustered than if they had been distributed at random, the clustering was still relatively weak. This finding is not surprising given the low number of foreclosures in the city, but also indicates that spatial models of foreclosures in DC may not add significant explanatory power, as originally hypothesized.

FIGURE 8: FORECLOSURE SALES, WASHINGTON, DC, 2003 AND 2010

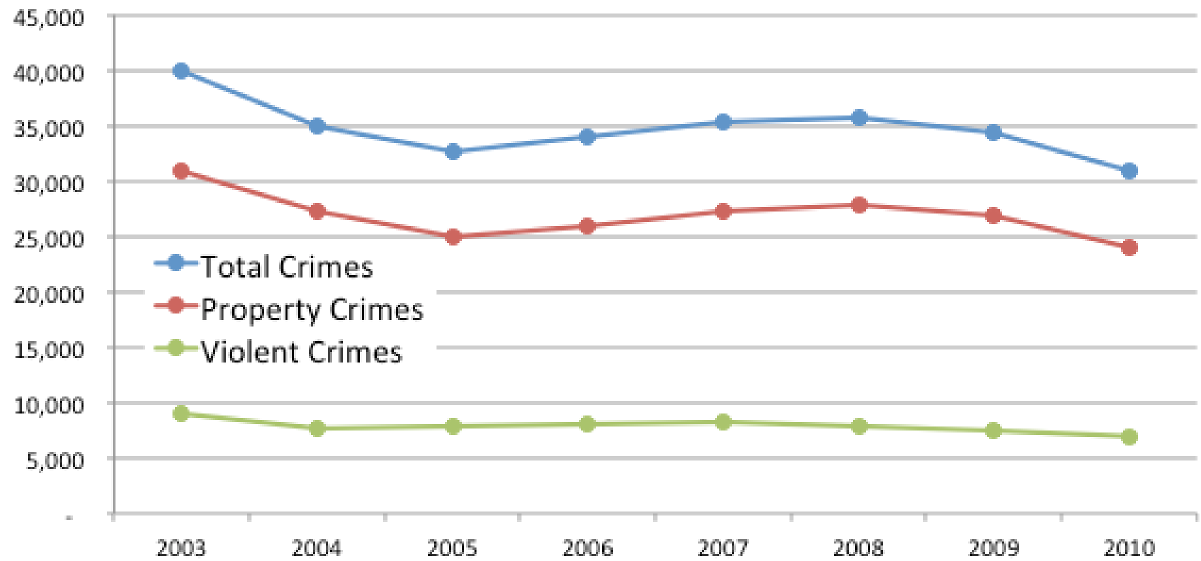


Source: Authors' map of data from D.C. Recorder of Deeds and Office of Tax and Revenue.

CRIME PATTERNS

Figure 9 provides the trends in total crime, violent crime and property crime in the city over the period from 2003-2010. The trends in all three measures in DC echo nationwide crime levels over the same period. While property crime measures saw a slight bump upwards in 2008 (near the peak of foreclosure inventory in the city), the trend over the entire study period was downward, and all three measures decreased by nearly 25 percent over the study period. Thus while foreclosures in the city were peaking, crime was heading towards its lowest level in decades. Figure 10 and Figure 11 below map violent crimes and total

FIGURE 9: TRENDS IN THREE CRIME MEASURES, WASHINGTON, DC



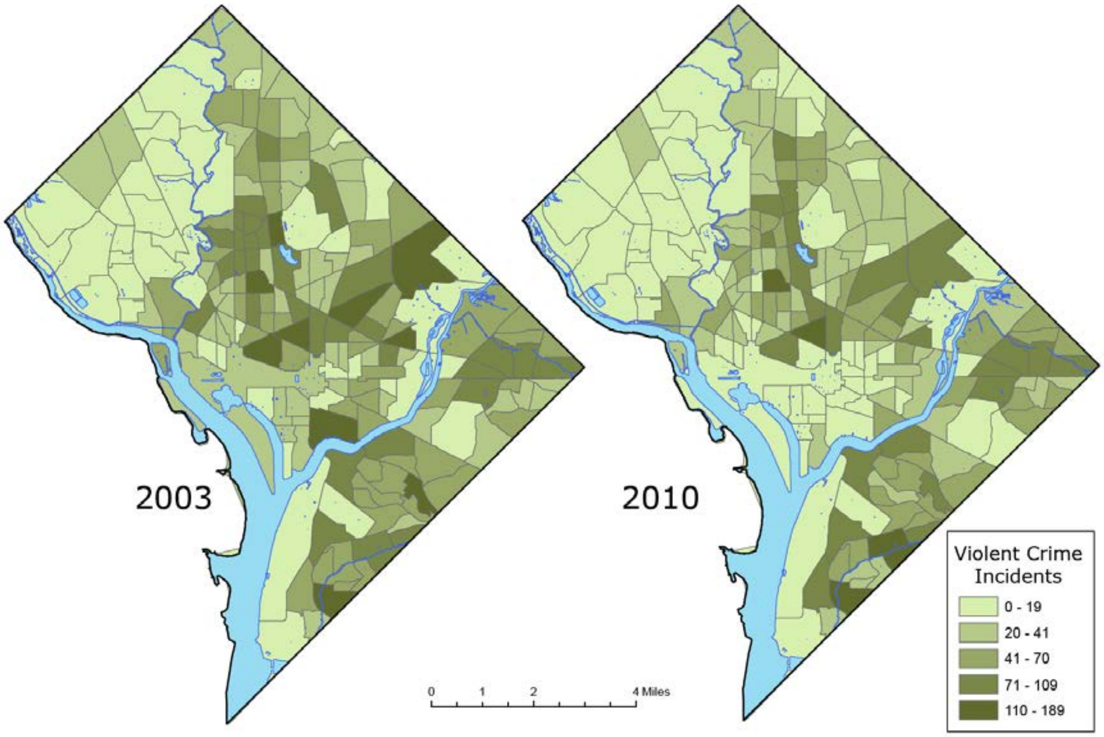
Source: District of Columbia Metropolitan Police Department.

crimes (violent and property), respectively, in the same years used in the foreclosure maps above—2003 and 2010. These maps show a trend nearly opposite that of foreclosures: Crimes dropped significantly over the study period, with much of the decrease concentrated in the center and northern parts of the city. Like foreclosures, crime was higher in the eastern half of the city, although property crime occurred with higher frequency in some areas of the Northwest quadrant of the city—mostly in well-populated and high-opportunity business districts.

We also examined the level of clustering of census tracts based on crime levels; as with foreclosures, clustering was significant but very weak. The Moran's I values ranged from I=0.05 (2009) to I=0.10 (2006), very similar to values observed for foreclosure starts.

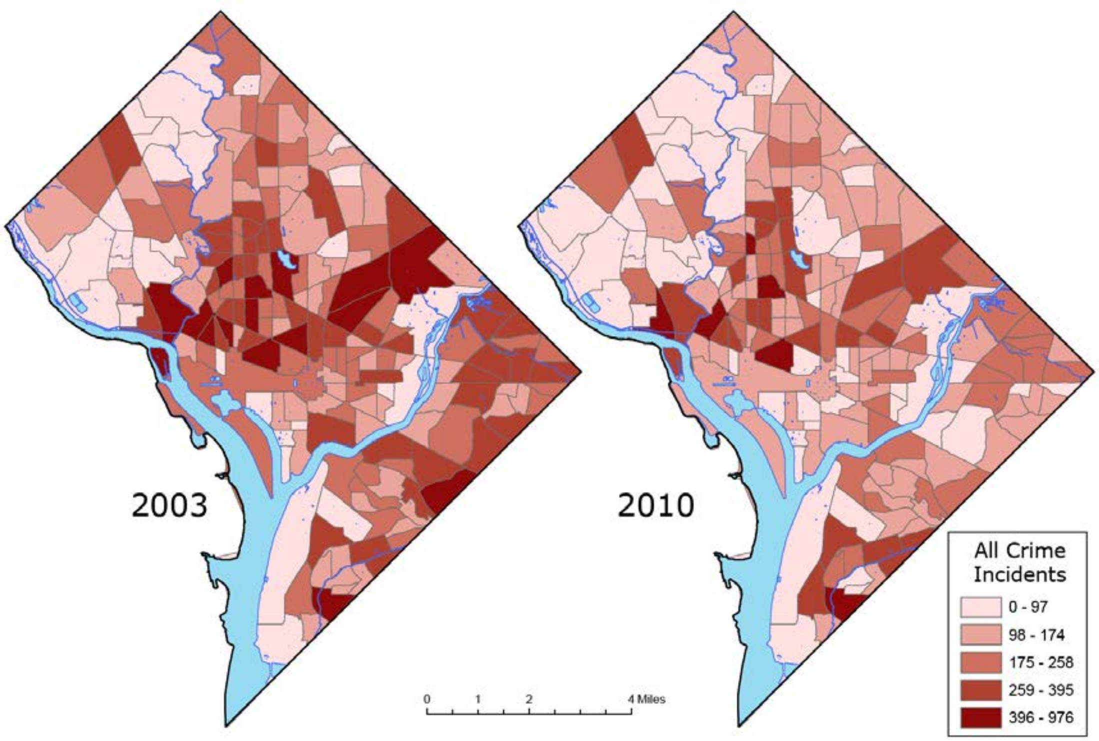
Even though the two phenomena, foreclosures and crime, trend in opposite directions over the study period, the geographic comparison of crime and foreclosure demonstrates the persistent similarity in the spatial patterns of these phenomena. In addition, this pattern predates the current foreclosure crisis and continues through the end of the study period. Geographically, a modest relationship between foreclosures and crime does appear to exist. That relationship, however, was present prior to the onset of the foreclosure crisis, and could reflect either common neighborhood risk of both crime and foreclosure or an effect of foreclosure on crime. The fact that common patterns existed before the foreclosure crisis suggests that underlying factors may have more influence on both crime and foreclosure rates than these crime and foreclosure have on each other.

FIGURE 10: VIOLENT CRIME BY CENSUS TRACT, WASHINGTON, DC, 2003 AND 2010



Source: Authors' map of data from District of Columbia Metropolitan Police Department.

FIGURE 11: TOTAL CRIME BY CENSUS TRACT, WASHINGTON, DC, 2003 AND 2010



Source: Authors' map of data from District of Columbia Metropolitan Police Department.

The following chapter reviews the analysis of Miami, describing the data collection and processing efforts and then providing a brief overview of the county's demographic, foreclosure, and crime patterns and trends over the study period.

Miami, FL

Miami is the second study area employed in this research.[12] We conducted analysis in Miami-Dade County rather than the city exclusively because the county government oversees foreclosures in any jurisdiction within the county boundaries. Also, while the county as a whole was significantly impacted by the foreclosure crisis, the City of Miami proper had relatively low foreclosure rates. If analysis were restricted to only the city many of the high foreclosure neighborhoods would be excluded, making it more difficult to determine the relationship between crime and foreclosures.

Demographics of Miami-Dade County

Kochar, Gonzalez-Barrera, and Dockterman's (Kochhar, Gonzalez-Barrera, & Dockterman, 2009) analysis found that foreclosure rates were especially high in United States counties that were both traditional and new destinations for immigrants, including Florida. They further suggested that demographic factors were among the most important among factors that contributed to foreclosure in immigrant destination counties; economic factors were relatively more important than demographic ones in non-destination counties. In Miami-Dade County, on average more than half of householders—51 percent—were foreign born from 2008-2012, while just over 13 percent of the U.S. population was foreign born and in the entire state of Florida, just under 20 percent were.[13] In terms of race/ethnic background only about 23 percent of the Miami area householders were white, non-Hispanic while nearly two-thirds (62 percent) were Hispanic. Recent work has suggested that minority homeownership rates are higher in more ethnically diverse metropolitan areas (Painter & Yu, 2010). Miami certainly qualifies as such.

Figure 12 is based on data from the 2008–2012 American Community Survey. The map displays the percent of foreign-born residents by census tract, revealing the high percentage of foreign-born within the City of Miami and also to the northwest and southwest of the city. Fewer foreign-born residents live to the immediate north or south of the city. Figure 13 compares the spatial patterns of Cuban and black, non-Hispanic residents, revealing high levels of residential segregation in the county. The light blue dots represent 100 Cuban residents each, while light gray dots represent 100 black/African American residents

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[12] This report alternatively refers to Miami-Dade County as simply Miami for convenience; all references specifically to the City of Miami as distinct from the County are noted as such.
[13] From the 2008-2012 5-year American Community Survey Data, US Census Bureau.

FIGURE 12: PERCENT FOREIGN-BORN RESIDENTS BY CENSUS TRACT, MIAMI-DADE COUNTY (AVG. 2008-2012)

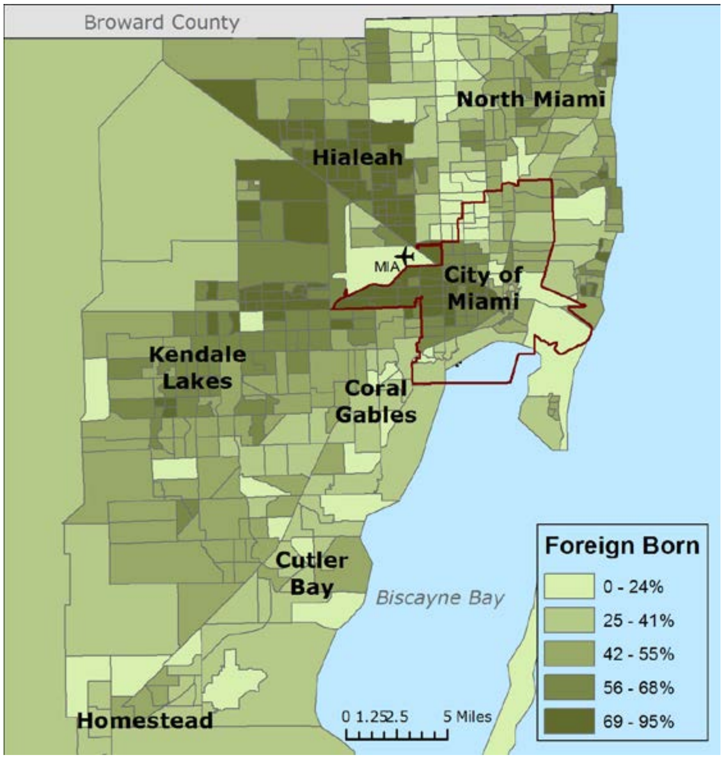
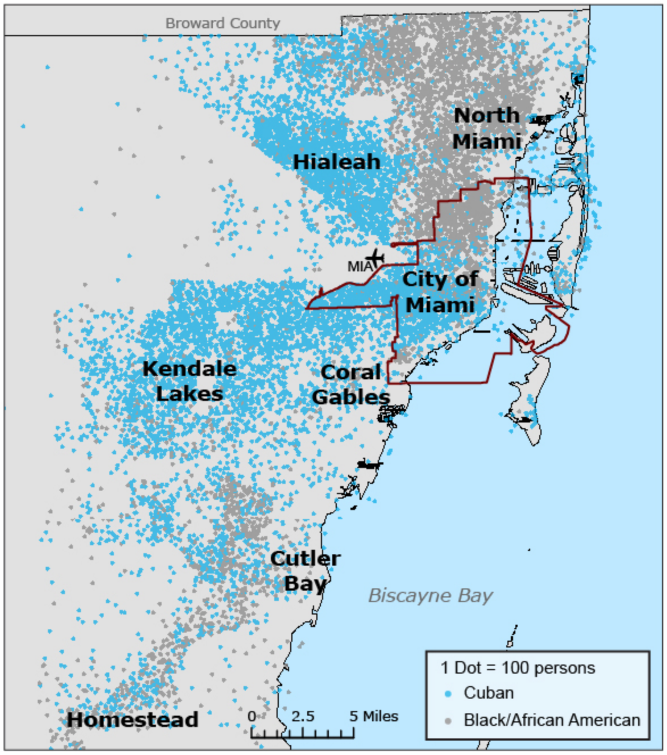
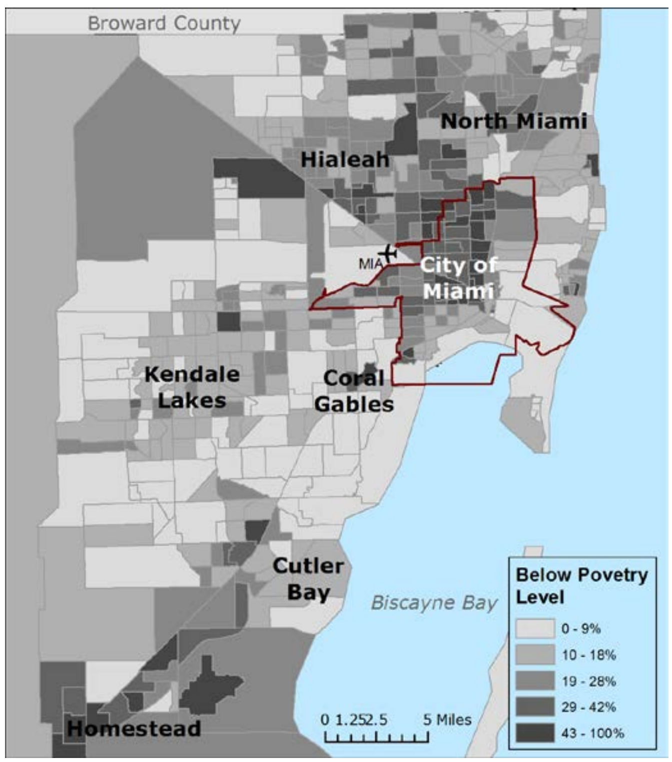


FIGURE 13: CUBAN AND BLACK, NON-HISPANIC RESIDENTS, MIAMI-DADE COUNTY (AVG. 2008-2012)



each. The patterns for each group are nearly opposite one another, with the county's Cuban residents (and Hispanic residents in general, though not shown) concentrated in the southern half of the City of Miami proper, and spreading outward in two directions, to the northwest and southwest. Black, non-Hispanic residents, on the other hand, tend to cluster in the northern half of the City of Miami and spread northward. Directly to the south of the City of Miami, towards Homestead, is a mix of Cuban and black, non-Hispanic residents. This clear segregation of race and ethnicity in Miami-Dade County may contribute to higher levels of foreclosures among certain minority groups (Rugh & Massey, 2010).

FIGURE 14: PERCENT RESIDENTS BELOW POVERTY LEVEL BY CENSUS TRACT, MIAMI-DADE COUNTY (AVG. 2008-2012)



The patterns of poverty in the county follow a fan-like pattern that spreads outward from the City of Miami as shown in Figure 14. The strongest concentration of poverty appears to be in the northwestern part of the city and to move outward towards Hialeah and North Miami. Another strong pocket of poverty exists in the southern part of the county, near Homestead. Wealthier parts of the county are closer to the coast, south of the city.

The foreclosure crisis in Miami

Miami, along with many other fast-growing markets across the country, was disproportionately impacted by the housing crisis of the 2000s. Figure 15 displays the same chart as seen in Figure 6 above—median housing values for the two study sites and DC. As in DC, Miami experienced a housing boom early in the decade. However, while median housing values in DC were well above median figures for the United States at the start of the decade and remained high, median housing values in Miami were very close to nationwide figures in 2000, at $157,000. Housing values in Miami-Dade County more than doubled through 2006-2007, stabilizing at a peak of $334,000, an increase of 113 percent over 2000 figures. At their peak, housing values in Miami-Dade County were nearly two-thirds higher than nationwide median values, which increased only about 35 percent over the same period. Median housing values in Miami-Dade County, however, dropped even faster than they rose: in the four-year period between 2008 and 2011, median values were cut almost in half, to just over what the median value had been in 2000. Moreover, this occurred in half the time it took for prices to peak in the middle of the decade.

Median housing values across the county, shown in Figure 16, reflect a similar pattern as seen in the poverty map; lower value homes are clustered north of the city, northwest towards Hialeah, and South towards Homestead. Areas with the highest housing values are clustered along the coast throughout the county.

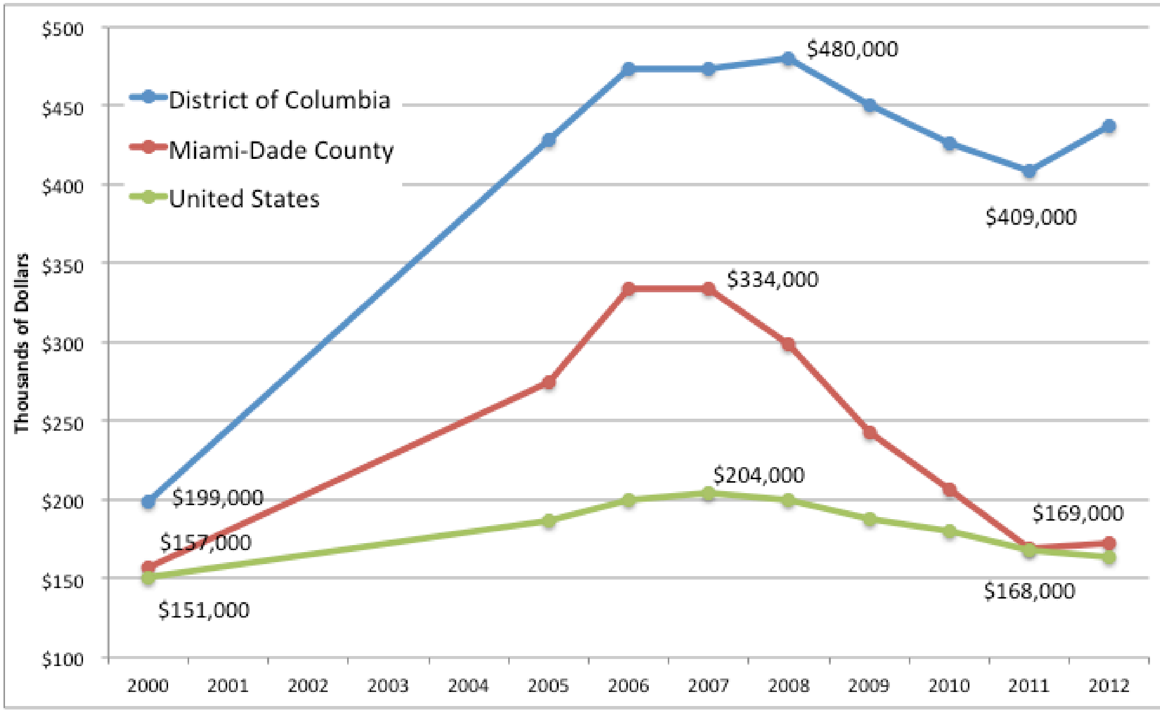
The foreclosure crisis in Florida broadly, and more specifically in Miami-Dade County, was caused by the confluence of a number of factors. Some of these factors affected cities nationwide, like loose lending regulations, low mortgage interest rates, and buyers over-reaching to purchase homes they couldn't afford. Other factors were unique to a few states including Florida, like a boom in new home construction—especially in exurban areas (areas even farther from the central urban areas than suburban areas) (Wilson & Paulsen, 2010); speculation by investors (Van Sickler, Sokol, & Martin, 2009); and a large number of second-home buyers (Olefson, 2009). A boom in the condo market also contributed to the extremely high number of units on the market (Wolf, 2009). These last two factors were a major feature in Florida's foreclosure crisis but did not play nearly as large a role in DC's crisis.

When the economic downturn began in the mid-2000s, many of the new construction homes had never been occupied, builders stopped construction halfway through new developments, and the supply of homes for sale far exceeded the demand for housing. In 2008, there was about a seven-month[14] supply of single family housing that was vacant in Miami-Dade County (Olefson, 2009). Housing values began to drop, and the foreclosure crisis set in. In Miami-Dade County, there were 64,000 foreclosure filings in 2009, 2.4 times the number of filings in 2007 and 6.5 times the number of filings in 2006 (MDCFOS, 2010). The Miami-Dade

[14] A 2-3 month supply is considered healthy.

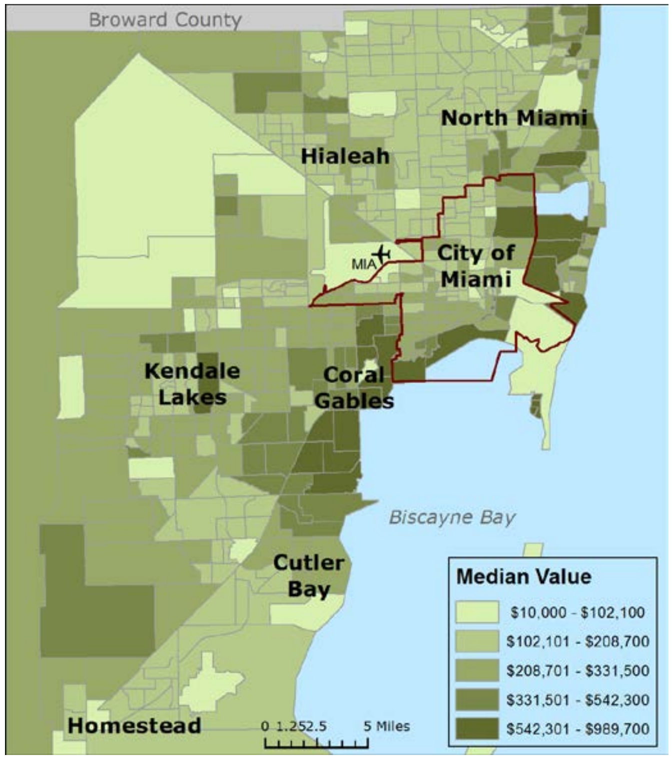
metropolitan area ranked 10th out of all metropolitan areas in the United States in foreclosure filings at the end of 2009, with 1 in 14 households experiencing foreclosure (RealtyTrac, 2010). Contributing to the large volume of homes in the foreclosure inventory is the fact that Florida is a judicial foreclosure state, where the foreclosure process happens through the courts. The judicial foreclosure process can be extremely slow, especially with so many foreclosures happening at once, increasing the foreclosure inventory through backlogs (CoreLogic, 2014).

FIGURE 15: MEDIAN HOUSING VALUES, 2000-2011 IN THOUSANDS OF DOLLARS, U.S. AND STUDY AREAS



Source: Census 2000 and American Community Survey 1-year estimates for each year between 2005 and 2011. No data were available for the years 2001-2004; the trend line is estimated for those years. All dollar figures have been adjusted to 2010 dollars.

FIGURE 16: MEDIAN HOUSING VALUE BY CENSUS TRACT, MIAMI-DADE COUNTY, 2008-2012 AVERAGE



Because of the large volume of foreclosures in Florida and the slow pace at which they proceed, Florida homeowners experienced a 'robo-signing' scandal, where banks pushed mortgages through the foreclosure process as fast as possible without checking ownership, verifying who had the right to foreclose, and in some cases fabricating missing paperwork in order to push foreclosure forward. When these practices were exposed in 2010, foreclosures slowed, and involved banks and mortgage lenders eventually settled litigation with Florida and other states in 2012. Shortly afterwards, foreclosure filings re-started with additional efforts to ensure the process was legal for each homeowner. Florida also signed a 'foreclosure fast track' law in 2013 to speed up the process and address the backlog issues that had plagued the state since 2008. These events mainly affected foreclosure filings, not foreclosure sales that were already in progress. Therefore, the events have minimal effect on our statistical analyses.

Anecdotally, many communities in the Miami metropolitan region reported that crime was an issue in the area of foreclosed properties (Dellagloria, 2009). Local areas tried to take a pro-active stance on addressing the negative effects of vacancies left in the wake of foreclosures. In response to the crisis, cities like Doral and Miami Lakes passed ordinances to allow enforcement officers to clean and secure foreclosed properties that have been abandoned. Other communities allowed contractors to clean up properties (Dellagloria, 2009). Yet while many states have experienced recoveries, Florida remains in the grips of a foreclosure crisis: its volume of foreclosures is still high relative to other states. During 2013, Florida had the highest number of completed foreclosures of any state, and 11.2 percent of mortgages there were considered seriously delinquent, the highest percent of any state (CoreLogic, 2014). While small drops in foreclosures have begun to occur, the state still has a long way to go before the crisis can be considered resolved.

Data collection and processing

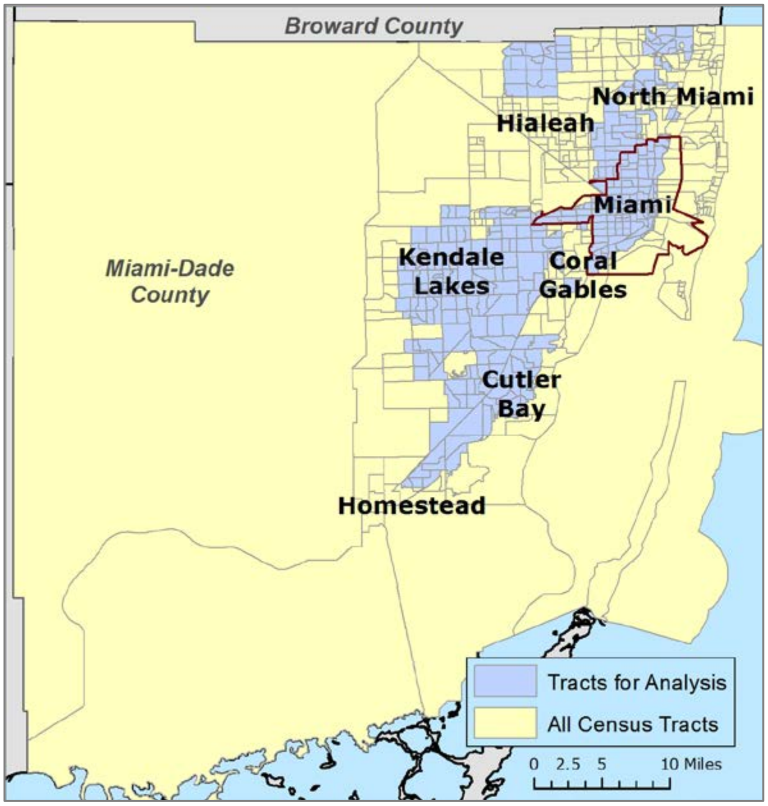
One issue that affected both foreclosure and crime data processing in Miami was the selection of the geographic unit of analysis. While we had hoped to conduct analyses at a very small geographic level, that was not feasible in either site, and we chose census tracts as the unit of analysis in both places. In DC, the relatively small number of block groups that had any foreclosures during the study period required us to use larger geographic units, while in Miami, there were too many geographic units. The selected method of analysis required a computationally intense simulation process and could not handle the number of blocks or block groups over the selected time period of analysis.

A large part of western Miami-Dade County is industrial or rural farmland (see Figure 17); very large tracts in the western part of the county are rural). The census tracts in this part of the county significantly larger than those near the coast, and many have no or very few housing units. These census tracts were dropped from the analysis because, with little to no housing, they had almost no risk for foreclosure *or* crime and therefore represented outliers in the analysis that could have significantly skewed the analytic results.

Finally, we obtained police data for the two largest police departments in Miami-Dade County: The Miami-Dade County Police Department and the City of Miami Police Department. However, there are a number of small jurisdictions in the county that provide their own police services; the Miami-Dade County Police Department does not provide police services there nor do they collect data from those jurisdictions. While our data collection strategy included a large proportion of the crime that occurred in the county, we did not have full, county-wide geographic coverage of crime incidents. We therefore also had to drop those census tracts for which we had no crime data.

This process resulted in a total of 329 census tracts in Miami-Dade County that were included in the analysis—there are 519 census tracts in the county altogether. Figure 17 provides a map of all census tracts in the county and the census tracts that were included. In the study.

FIGURE 17: CENSUS TRACTS INCLUDED IN ANALYSIS, MIAMI



FORECLOSURE DATA

Foreclosure data were obtained from the Clerk of Courts for Miami-Dade County. The data included property case data, all civil case data, and the docket file from raw recorder files. From the case and docket files, the research team extracted foreclosure filing and sales information. These data included the date of all foreclosure starts (first *lis pendens* notice sent) and completions (foreclosure sales) for the county beginning in 2000. Foreclosure filings constituted about ¾ of the data, while sales made up the remaining ¼ of data. Those properties that ended in a foreclosure sale also had a *lis pendens* record in the dataset, allowing the research team to identify when the foreclosure process for that property began, and whether there were multiple cycles into and out of the foreclosure process for that property. The data also included a recording book/page number and, in some cases, a folio number. These fields were used to match the court records to standard parcel ids used by the County Property Appraiser and to sales data.

Urban Institute purchased complete current parcel data and property sales data for the period August 2003 through April 2011 for Miami-Dade County from the Miami-Dade County Property Appraiser. These data were matched to the foreclosure filing and sales data to add property information and property address to the County Clerk's data. Property characteristics and sale information, including original price paid for the home, the sale price of the foreclosed home, square footage of the lot for the foreclosed home, and limited information about the owner(s) were extracted from the sales database. Property address and location (x, y coordinates) were determined using the parcel file. The parcel data were provided in a mapping file format, so once foreclosures were matched to parcels, they could be mapped. Parcels were then matched to census tracts in order to create a count of foreclosure sales by census tract. In addition, we used parcel information to restrict our analysis to only those foreclosures that occurred to residential units.

In the course of data processing, we discovered that only foreclosure *sales* records included a folio id; none of the foreclosure *filings (lis pendens)* that did not end in a sale had this variable, which was necessary to match a foreclosure record to a parcel. Despite extensive exploration of all fields provided, no other information was included that would enable us to determine the address or another, less specific type of location, such as subdivision, of a foreclosure filing that did not end in a sale. Therefore, we were unable to calculate start or inventory measures at the census tract level. The analysis in Miami is thus limited to foreclosure sales data. While not ideal, foreclosure sales have been shown in prior research to have the strongest relationship of the three main foreclosure measures with crime. Also, while detailed analysis at the census tract level cannot be conducted using measures other than sales, discussion of countywide foreclosure levels can make use of foreclosure filing and sales measures.

Foreclosure sales were restricted to residential units only and then aggregated into quarterly counts by census tract for the period October 2003–March 2011,[13] providing 30 quarters of data and 329 census tracts with which to conduct statistical analyses.

CRIME DATA

The Urban Institute obtained incident data from the Miami-Dade County (FL) Police Department for August 2003 through June 2011 and from the City of Miami Police Department for the same period. To make these data comparable, Urban Institute staff coded the incidents from each department using the offense categories and definitions established for the National Incident-Based Reporting System (NIBRS). The offenses were classified by researchers into personal (violent) and property offenses. Personal offenses included homicide, assaults, and robbery. No sexual assault cases were provided from Miami-Dade County Police, so those were dropped from the city data as well and not included in the county-level analyses. Property offenses included burglary, theft, motor vehicle theft, and theft from a motor vehicle. Records from both departments included x and y values of the incident location, so geocoding was not required. Offenses were aggregated into quarterly counts by census tract for the period October 2003-March 2011,[15] giving project staff 30 quarters of data and 329 census tracts with which to conduct statistical analyses.

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[15] Data were truncated at the beginning and end of the time series to include only full quarters.

One limitation of these data is that that they are collected from two different police departments. Although we used NIBRS categories to aggregate incidents into uniformly defined categories, it is possible that the incidents are recorded differently in the two jurisdictions, introducing some bias into the measurement.

Patterns of foreclosure and crime

The first step in exploring the relationship between foreclosures and crime in Miami was to conduct exploratory analyses on the geographic and temporal patterns of those phenomena in the city.

FORECLOSURE PATTERNS

Figure 18 provides yearly trends over time for foreclosure sales in Miami-Dade County for the period 2004-2010 (the first and last years for which we have complete data).[16] The two measures follow broadly similar trends from 2004 to 2007, when the number of *lis pendens* filings skyrocketed. *Lis pendens* filings reached their peak in 2009, at more than 60,000 filings for the year. Over that same period, foreclosure sales were also increasing, but at a slower rate, given the amount of time required for the foreclosure cases to move through the court system to completion—judicial states, including Florida, have some of the longest foreclosure processes in the nation and the number of *lis pendens* being filed created an enormous backlog in the state's courts, slowing the process even further. In 2010, *lis pendens* filings drop noticeably, due to the uncovering of the robo-signing scandal in the state. While filings were reduced, the number of sales continued to increase, reaching their highest levels in the study period in 2010 at nearly 25,000 sales.

Table 2 provides a yearly summary of the measures associated with the foreclosure data and shows that the foreclosure crisis was worst in Miami-Dade County in 2010, with foreclosures that year more than double the number in 2009. The table also demonstrates that foreclosures in the condo market steadily constituted a larger portion of all foreclosures throughout the study period, with more than half of the foreclosure sales occurring on condo units by 2010. Finally, average purchase price of foreclosed units more than tripled, reflecting the effects of the housing bubble before the foreclosure crisis. The average time to first foreclosure notice (*lis pendens*) dropped slightly over the period, reaching a low in 2007, when filings were occurring at a rapid pace. The average time to first filing then grew as foreclosures slowed as result of the robo-signing scandal in 2010. The average time to foreclosure sale changed accordingly, reaching a low in 2007 and peaking in 2010.

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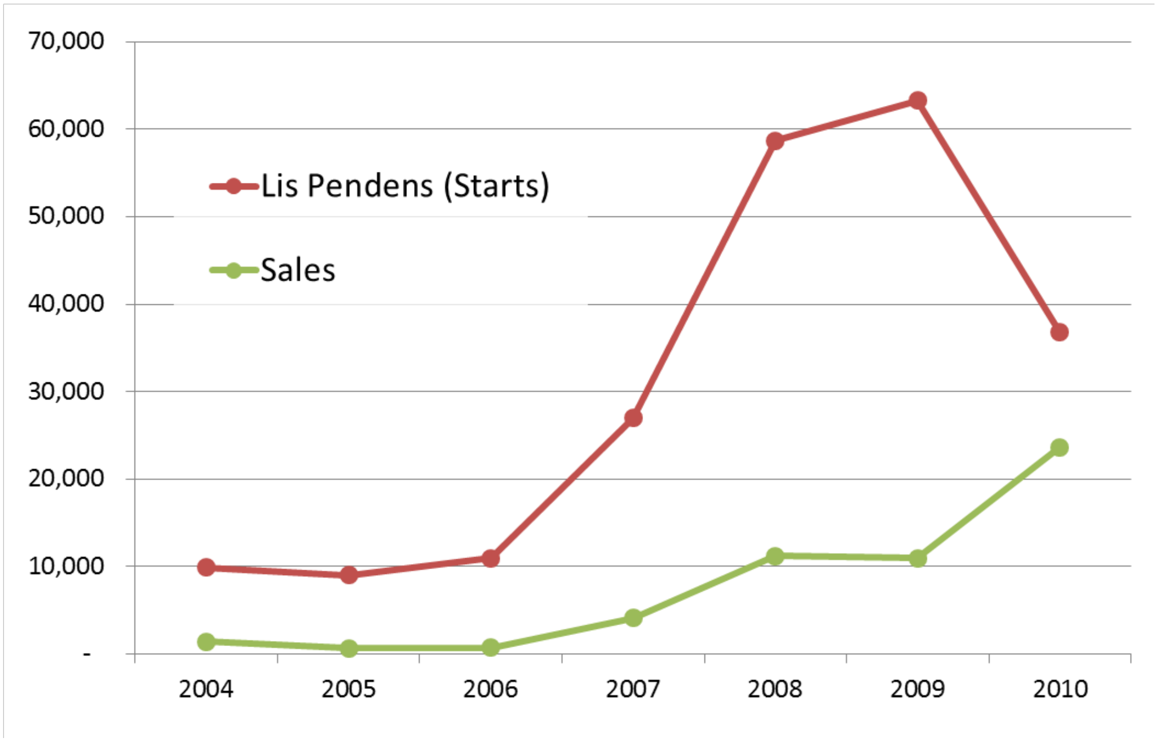
[16] These data cover the entire county; not just the area used in the analysis (see Figure 17). Because we don't have location data for the *lis pendens* filings, we can only report those yearly figures at the county level.

FIGURE 18: FORECLOSURE SALES, MIAMI-DADE COUNTY, FL



Source: Miami-Dade County Clerk of Courts foreclosure data. These data are reported for the entire county and are not restricted to those census tracts shown in Figure 17.

Figure 19 provides a map of foreclosure sales by census tract for 2004 and 2010 (the first and last full years of data in our study period). The maps highlight the extreme increases experienced throughout the county in foreclosure rates over the period, and also reveal that high foreclosure rates are spatially clustered. The City of Miami proper has relatively low foreclosure rates compared to surrounding areas. In addition, areas to the south appear to have higher foreclosure rates in 2010 than areas to the north of the city.

In addition, the map of foreclosures (Figure 19) shows that sales are high in both Cuban and black neighborhoods, indicating that the relationship between demographics and foreclosures may have more to do with minority and low income status than with nativity itself. A similar pattern was observed in DC. These overlapping spatial patterns are the subject of our statistical analysis below, as we investigate the strongest factors influencing neighborhood foreclosure rates in the county.

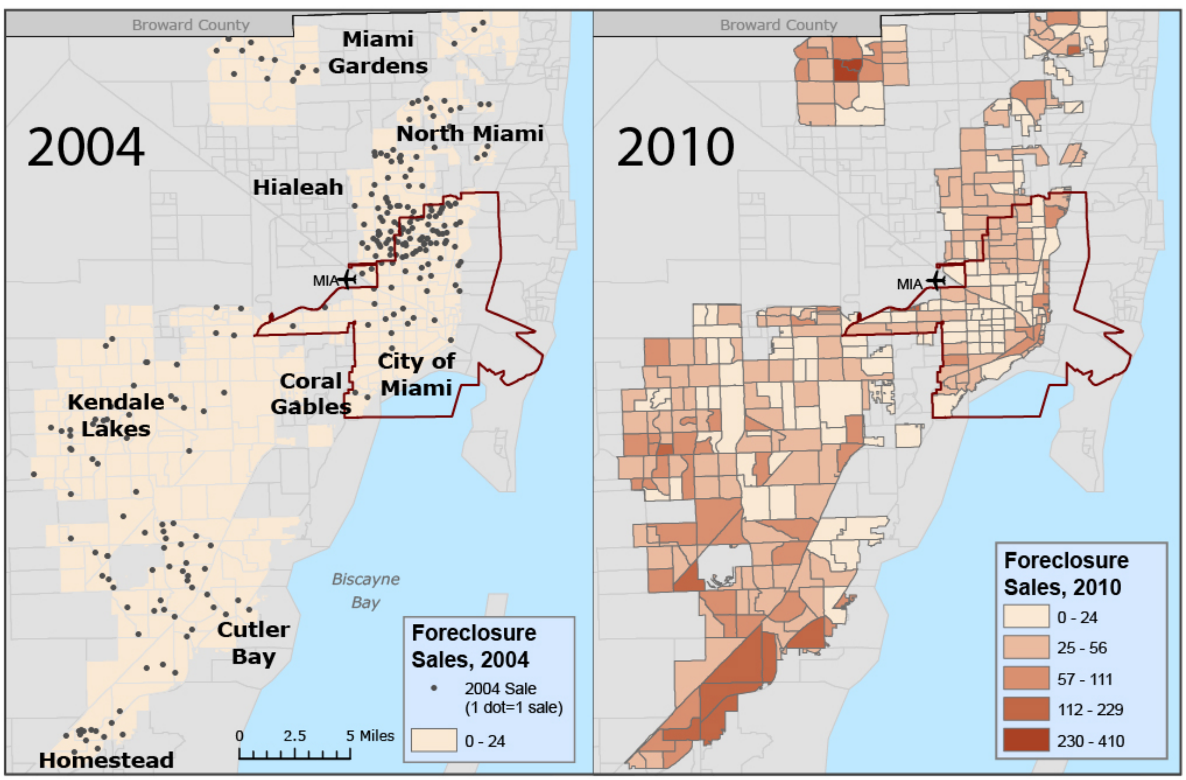
Spatial clustering of similar sales levels was also examined. The Moran's I value in Miami for foreclosure sales was much higher than in DC. In Miami, the values ranged from a low of I=0.17 (2009) to a high of 0.65 (2008). Significant levels of spatial clustering were found in every year, indicating that census tracts with higher levels of foreclosures tend to be located close to each other. Incorporating spatial elements into the model of foreclosures for Miami, then, may be more fruitful than in the DC model.

TABLE 2: YEARLY FORECLOSURE SALES CHARACTERISTICS, MIAMI-DADE COUNTY

Year	Number of Foreclosure Sales	Condo Foreclosures (as % of all forecl.)	SFH/Duplex Foreclosures (as % of all forecl.)	Average Purchase Price ($)*	Average months to first *lis pendens*	Average months to forecl. sale
2004	1,355	22%	76%	99,889	41.2	52.4
2005	617	23%	75%	118,833	34.8	48.1
2006	710	24%	73%	187,839	30.1	40.5
2007	4,073	34%	65%	300,340	20.8	27.6
2008	11,159	37%	62%	323,038	27.1	36.0
2009	10,907	47%	52%	301,875	33.1	47.2
2010	23,604	52%	47%	343,491	38.8	58.5

*Source: Miami-Dade County Clerk of Courts foreclosure data. Reported for foreclosure sales only. *Reflects purchase price at time of purchase, but it is displayed by year of foreclosure. For example, on average, homes that went through foreclosure sale in 2009were purchased nearly 4 years (47 months) earlier in 2006 for $343,491.*

FIGURE 19: FORECLOSURE SALES BY CENSUS TRACT, MIAMI, 2004 AND 2010



CRIME PATTERNS

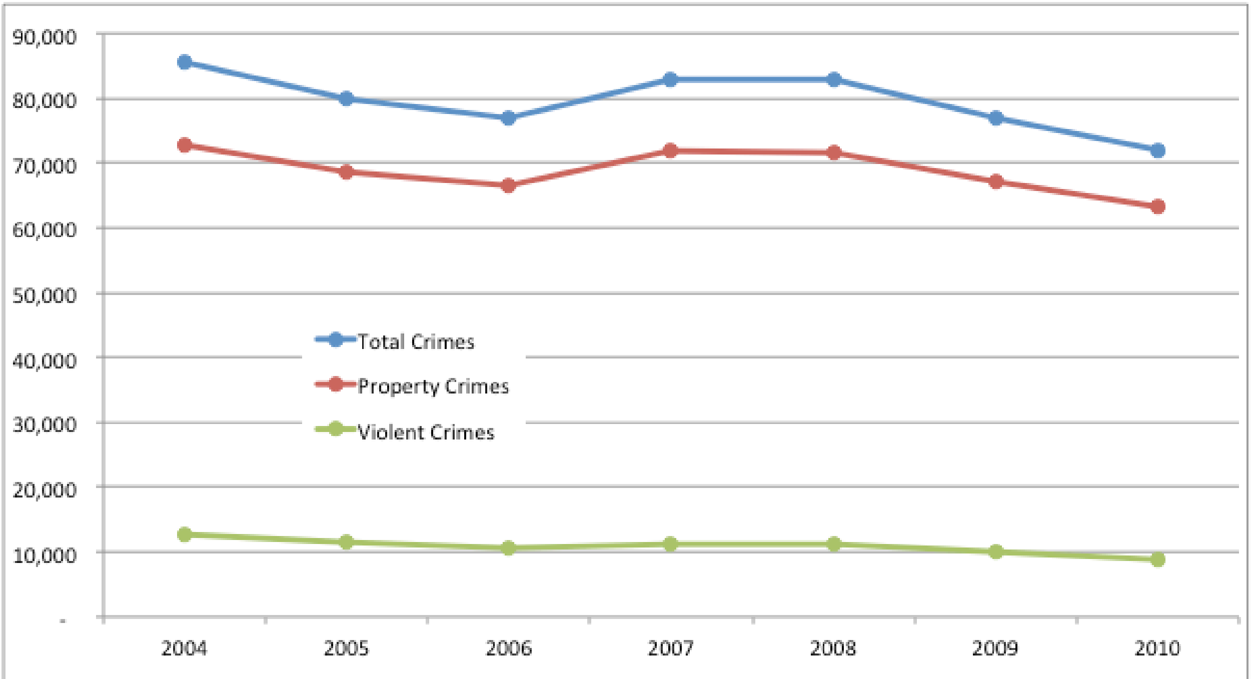
Miami's pattern of crime volume over time was very similar to that observed in DC, with an overall downward slope over the study period. A slight increase in the middle of the period occurred in 2007. This mid-decade increase occurred later in Miami than in DC but the size of increase relative to the overall volume of crime was very similar in both study areas. The 2007 increase in all three measures was followed by stabilization and then decrease through 2010. Over the study period, property crime decreased approximately 14 percent and violent crime decreased more than 30 percent. Total crime decreased about 15 percent over the same period. These trends in both study areas follow nationwide trends of overall decreasing crime levels during the 2000s.

Figure 21 and Figure 22 provide maps of violent and total crime patterns in the Miami study areas. Both violent and total crime measures are highest in the northern part of the City of Miami and north of the city, towards Hialeah and North Miami. To the south, crime is relatively low for a relatively large section of the county which is also the more affluent area of the county. Another cluster of higher crime levels is noticeable from Cutler Bay south to the Homestead area. These patterns generally do follow the patterns of foreclosure in the county, again suggesting that models for Miami may have relatively stronger results than those of DC.

We also examined spatial clustering of crime levels and found that while not quite as strongly clustered as foreclosure sales, the Moran's I values for crime indicated significant and moderate clustering, with an average of I=0.32. This indicates that areas with similar crime levels are located near each other, and that explicitly modeling the spatial relationships between units of analysis is supported in Miami.

Chapter 5 discusses the results of the modeling of foreclosures and crime and the findings of the qualitative data collection efforts.

FIGURE 20: TRENDS IN THREE CRIME MEASURES, MIAMI



Source: Miami-Dade County Police and City of Miami Police crime incident records.

FIGURE 21: VIOLENT CRIME BY CENSUS TRACT, MIAMI, 2004 AND 2010

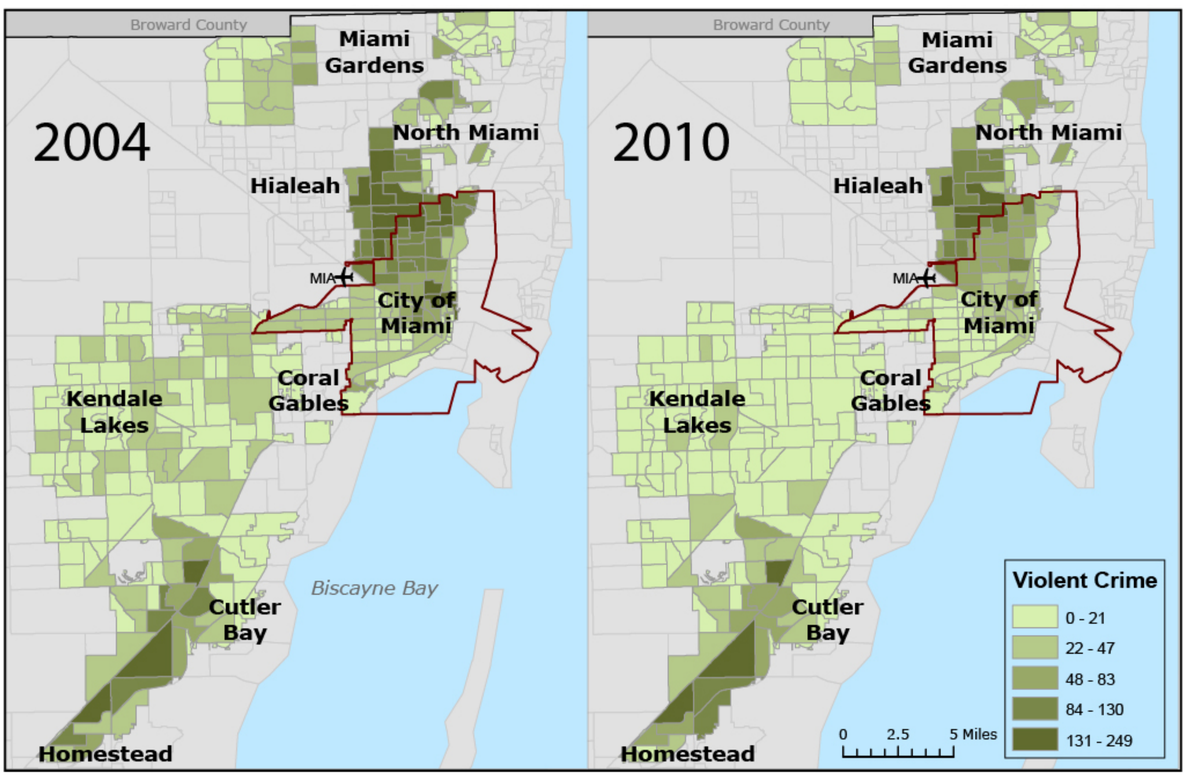
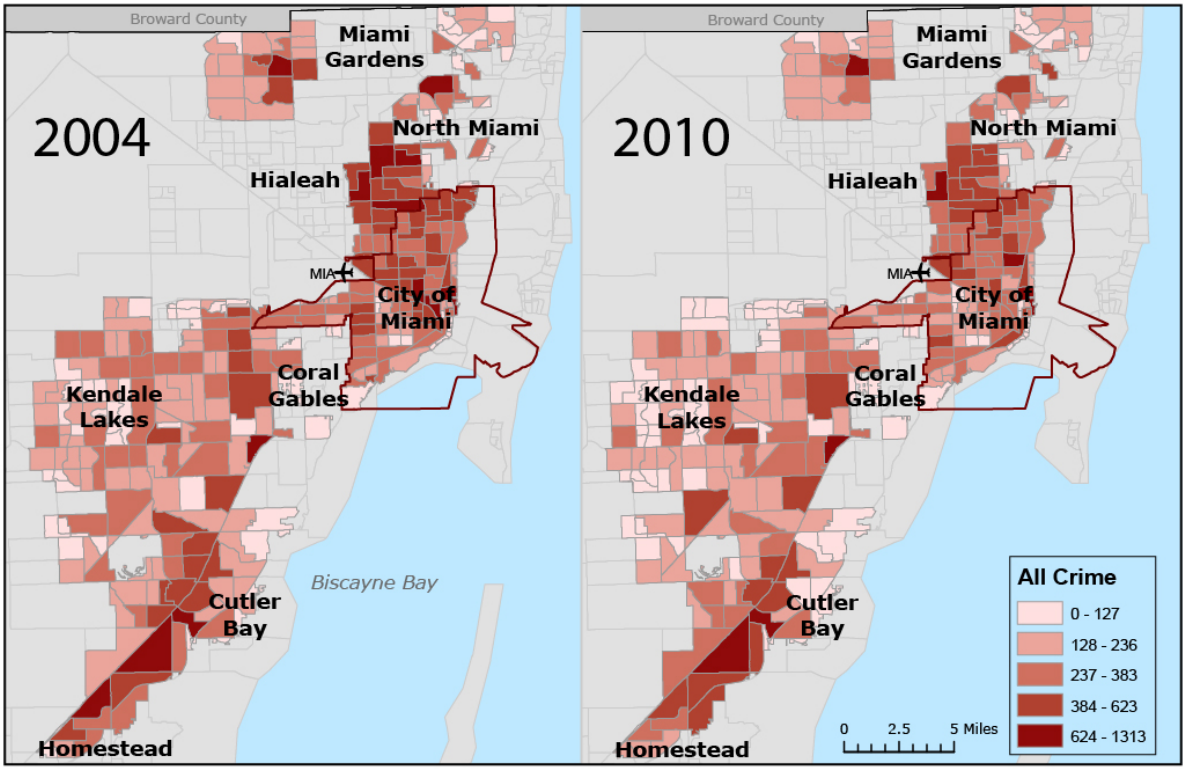


FIGURE 22: TOTAL CRIME BY CENSUS TRACT, MIAMI, 2004 AND 2010



Modeling the Foreclosure-Crime Link

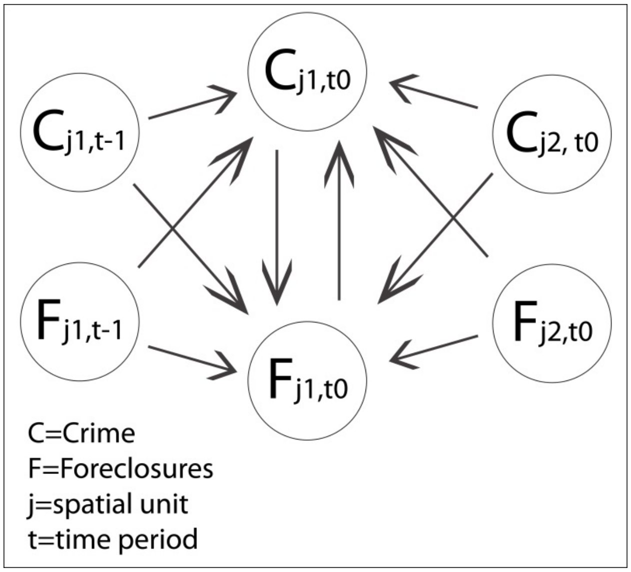
This chapter describes in more detail the methods used to model the relationship between foreclosures and crime, and presents the results of those models. The chapter also presents the results of qualitative data collection efforts—in the form of stakeholder interviews and resident focus groups—that were used to deepen the understanding of conditions on the ground in the most affected areas, and the best approaches to addressing crime-related problems.

Methods

The current research seeks to understand the complex links between foreclosures and crime both over time and over space. These models were developed for geographic units—census tracts— that were used to approximate neighborhoods. This approach allowed us to determine how one neighborhood's (census tract's) levels of foreclosures and crime may affect those of a nearby neighborhood. Our analyses were framed under a dynamic systems approach that modeled both temporal and spatial aspects of the foreclosures and crime relationship simultaneously.

We hypothesized that the relationship between the two phenomena would represent a feedback loop, so that an initial shock of foreclosures in a neighborhood (census tract) may lead to increased crime, but increased levels of crime in turn lead to decreased property values and waning desirability of the area, leading to additional foreclosures. Those additional foreclosures contribute to even more crime and the cycle continues, escalating as the ability of remaining residents to stem the tide of neighborhood deterioration decreases. We further hypothesize that areas with high levels of foreclosure and crime may have negative effects on nearby areas, spreading neighborhood deterioration to adjacent (or further) neighborhoods. The relationships between foreclosures and crime rapidly become very complex when the feedback loop and temporal and spatial aspects are added. This is demonstrated in Figure 23, which depicts the directionality of relationships for one spatial unit at one point in time, including relationships with prior measures (temporal lags) and nearby measures (spatially lags).

FIGURE 23: CONCEPTUAL MODEL DEMONSTRATING THE RELATIONSHIP BETWEEN FORECLOSURES AND CRIME OVER SPACE AND TIME



Note: this model represents one spatial unit, j1, at one point in time, t0.

SPATIAL AND TEMPORAL EFFECTS

The modeling effort that we undertook for the current work was informed by two main assumptions about the relationships between foreclosures and crime. The primary theorized relationship between these two phenomena is that, at a local level, an increase in foreclosures will cause an increase in crime. The mechanisms through which a tract's *crime levels are affected by foreclosures* include the impacts of:

- Current foreclosures in that tract (independent variable)
- Recent foreclosures in that tract (**temporal** lag in independent variable)
- Foreclosures in a neighboring tract (**spatial** lag in independent variable);
- Recent foreclosures in a neighboring tract (**temporal** and **spatial** lag in independent variable)
- Recent crime in that tract (**temporal** lag in dependent variable); and
- Recent crime in a neighboring tract (**temporal** and **spatial** lag in dependent variable)

The hypothesized feedback loop addresses the idea or assumption that crime may have an impact on foreclosures as well—even though it will likely be indirectly through property values—either contemporaneously or after an impact on crime from foreclosures occurs. While this effect is not central to the theoretical underpinnings of the study, we control for these possible effects in the model. Thus, a tract's *foreclosures may be affected by crime* via:

- Current crime in that tract (independent variable)
- Recent crime in that tract (**temporal** lag in independent variable)
- Crime in a neighboring tract (**spatial** lag in independent variable);
- Recent crime in a neighboring tract (**temporal** and **spatial** lag in independent variable)
- Recent foreclosures in that tract (**temporal** lag in dependent variable); and
- Recent foreclosures in a neighboring tract (**temporal** and **spatial** lag in dependent variable)

Because the measures are computed at the census tract, the outcomes are relatively rare. As such, counts were used in the analytic models presented below. The combination of the discrete nature of the outcomes (in counts rather than rates), simultaneous nature of crime and foreclosures (the feedback loops), and panel nature of the data (with temporal and spatial dependence incorporated), the estimation problem was unique and nontrivial—which was suggested by the complex model of relationships shown in Figure 23. An information-theoretic framework was thus developed to address these issues. The framework used here is an extension of the standard Poisson count model, which builds on earlier applications to the problem of studying rare events (Bhati, 2005, 2008).

FIXED EFFECTS

Fixed effect models allow one to control for all time-stable differences among a set of units for which we have repeated measures. For example, if we have a set of neighborhoods with a time series of observations for each neighborhood, then estimating the effects of a time-varying variable on an outcome of interest is well identified if all time stable differences (fixed neighborhood effects) can be accounted for. Unfortunately, the estimation of fixed effects is not trivial—especially when there are a large number of cross-sectional units. The problem becomes more intractable when we wish to measure fixed effects in non-linear models like count outcomes.

An approximate solution to this problem is to estimate the fixed effects first and then introduce them as a variable (with its own parameter) in the next stage. The full process for estimating the fixed effects in the models presented is provided in Appendix A. The coefficients on these variables are not of interest to the analysis but their inclusion in the model helps control for all time-stable differences among the cross-sectional units.

MODEL ESTIMATION

The estimated models included spatial lags, temporal lags, cross-spatial and cross-temporal lag terms, unobserved heterogeneity, simultaneous system modeling, and fixed effects. Because the resulting models are very complex, the objective functions often fail to converge (i.e., no solution is found). Therefore, a two-step process was used to simply the estimation problem.[17] The full explication of the development of the model form ultimately used is provided in Appendix A.

Data

The relationship between crime data and foreclosures was modeled at the census-tract level for DC and Miami. Crime counts and foreclosures were aggregated at the census tract level by quarter. This allowed the creation of panel datasets with measures of crime and foreclosures varying with time and cross-sectional unit. Data from DC spanned the periods Q1 2003 through Q4 2010 while data for Miami spanned the period Q4 2003 through Q1 2011. There were 188 census tracts in DC and 329 census tracts in Miami, FL. This resulted in a total of 6,016 data points in the DC data and a total of 9,870 data points in the Miami, FL data.

In each city, available measures of crime and foreclosures were aggregated and used as the key measures of interest. Crime was measured either as the number of violent crimes, property crime, or a measure of both combined (total crime). Similarly, foreclosures were measured as the total number of foreclosure sales (in both study areas) or the foreclosure inventory (housing units in the foreclosure process) (only in DC). Each measure of crime (violent, property, total crime) was modeled with each measure of foreclosures (starts, inventories, sales) to assess if results were sensitive to the measure used.

Finally, in order to model spatial lags—or the neighbors for each census tract in the dataset—we created spatial weights matrices, one for each study site. The row-standardized spatial weight matrices were constructed using queen contiguity criteria.[18] Despite the large number of data points in each set, the size of the weight matrices was dependent on the units of spatial units; the matrix was 188 X 188 for DC and 329 X 329 for Miami. In addition, year and quarter dummy variables were included in each model.

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[17] EM (expectation-maximization) algorithm, which simplifies the estimation problem and provides results for the parameters of interest, was used to simply estimation. This process is described in more detail in Appendix A.

[18] The queen contiguity matrix counts a location's neighbors as those that share a border or a vertex. These were calculated for first-order neighbors only (direct neighbors, not including neighbors-of-neighbors).

Descriptive comparisons of the foreclosure and crime patterns

Our initial exploration of the relationship between foreclosures and crime included inspection of correlations between foreclosure inventory (at the census tract level) and three crime measures (total crime, violent crime, and property crime) for each year (see Figure 5). Table 3 provides summary statistics on all of the foreclosures and crime series used. The table shows that the two study areas are comparable in terms of crime levels by census tract but that Miami has a much higher level of foreclosure activity than DC. Table 3 also reveals that both crime and foreclosures, as measured, are relatively rare. In each case, several census tracts record 0 events (no crime or foreclosure activity).

TABLE 3: DESCRIPTIVE STATISTICS ON CRIME AND FORECLOSURES SERIES USED IN THE ANALYSIS

Washington, DC	N	Mean	Std. Dev.	Min	Max
Crime					
Violent	6,016	10.49	8.44	0	64
Property	6,016	35.67	25.72	0	273
Total	6,016	46.17	31.07	0	306
Foreclosures					
Sales	6,016	0.44	0.86	0	7
Inventory	6,016	6.63	8.51	0	60
Miami	N	Mean	Std. Dev.	Min	Max
Crime					
Violent	9,870	8.26	10.48	0	83
Property	9,870	52.31	37.78	0	403
Total	9,870	60.57	44.33	0	415
Foreclosures					
Sales	9,870	3.16	7.20	0	288
Inventory	-	-	-	-	-

TABLE 4: UNCONDITIONAL CORRELATION STATISTICS FOR CRIME, FORECLOSURES MEASURES USED IN ANALYSES

Foreclosures	Crime		
	Violent	Property	Total
Washington, DC			
Sales	0.186	0.070	0.108
Inventory	0.235	0.048	0.103
Miami			
Sales	0.049	0.084	0.083

Table 4 provides unconditional correlations between each pair of crime and foreclosure series—correlations in DC are based on 6,016 observations and in Miami, on 9,870 observations. The unconditional correlational analysis suggests that the links between crime and foreclosures are weak. In DC, the correlation between measures of foreclosures and violent crimes was stronger than between measures of foreclosures and property crime. The correlation between the inventory measure and violent crimes is the strongest, but is still relatively weak at only r=0.235. In Miami the relationship between property crimes and foreclosures was stronger. However, the correlations in Florida were very weak, with r values indicating that the two measures explain only between one-quarter and one-half of a percent of the variance in the each other. This relationship is even weaker than the relationship observed in DC, where the two measures explained between one and 6 percent of the variance in each other. The unconditional correlation analysis suggests weak association between foreclosures and crime even before including additional controls—the spatial and temporal lags—into the models.

To further explore the possible relationships between the multiple foreclosure and crime measures that were included in our analyses, we calculated additional correlation coefficients by year. This allowed us to examine whether the relationship between the measures changed over time, as the foreclosure crisis developed and then deepened through the end of the study period. Observations used in the correlations were yearly totals of crime and the foreclosure sales in each tract. Each yearly correlation was based on 188 observations in DC (one for each of the 188 tracts in DC) and on 329 observations in Miami.

Table 5 reveals that in DC, foreclosures were related to each measure of crime at a modest level, and, as with the unconditional correlations shown in Table 4 above, violent crime was more highly correlated with foreclosures than was property crime. This is also clear in Figure 24, which shows that the relationship between foreclosure and all three crime measures over time. The correlation between violent crime and foreclosure sales is highest in every year of the study period. Figure 24 also demonstrates that while different in strength, correlations between the foreclosure and crime series actually tracked very closely over time; the patterns of change are nearly identical for all three sets of correlations. The correlations between the foreclosures and crime series experienced two nearly equal peaks, one just before the foreclosure crisis began, in 2005, and one when the crisis was fully underway, in 2009. If the foreclosure crisis initially hit hardest in vulnerable areas that were also experiencing high levels of crime, it would have contributed to an initial strengthening of the foreclosure-crime relationship. These vulnerable places were the ones most susceptible to predatory lending practices and in turn, higher foreclosures early in the foreclosure crisis. Therefore, as the crisis began, the relationship between foreclosures and crime strengthened. But when the crisis spread to places not traditionally susceptible to foreclosures—and with lower crime levels—the relationship between the two measures weakened. However, as the number of foreclosures grew during the crisis, and the likelihood that foreclosures were concentrated in specific neighborhoods, their impact on crime may have also become stronger.

TABLE 5: YEARLY CORRELATIONS BETWEEN FORECLOSURE SALES AND CRIME, WASHINGTON, DC

	Crime		
	Violent	Property	Total
2003	0.285**	0.067	0.134
2004	0.262**	0.082	0.135
2005	0.353**	0.143*	0.216**
2006	0.273**	0.022	0.088
2007	0.288**	0.085	0.144*
2008	0.320**	0.084	0.150*
2009	0.366**	0.163**	0.227**
2010[a]	0.242**	0.096	0.143*

[a] Note that correlation for 2010 is only for the first quarter of the year.
**Correlation is significant at the p<0.05 level.*
***Correlation is significant at the p<0.01 level.*

FIGURE 24: CORRELATION COEFFICIENTS BY YEAR, FORECLOSURE SALES AND CRIME, WASHINGTON, DC

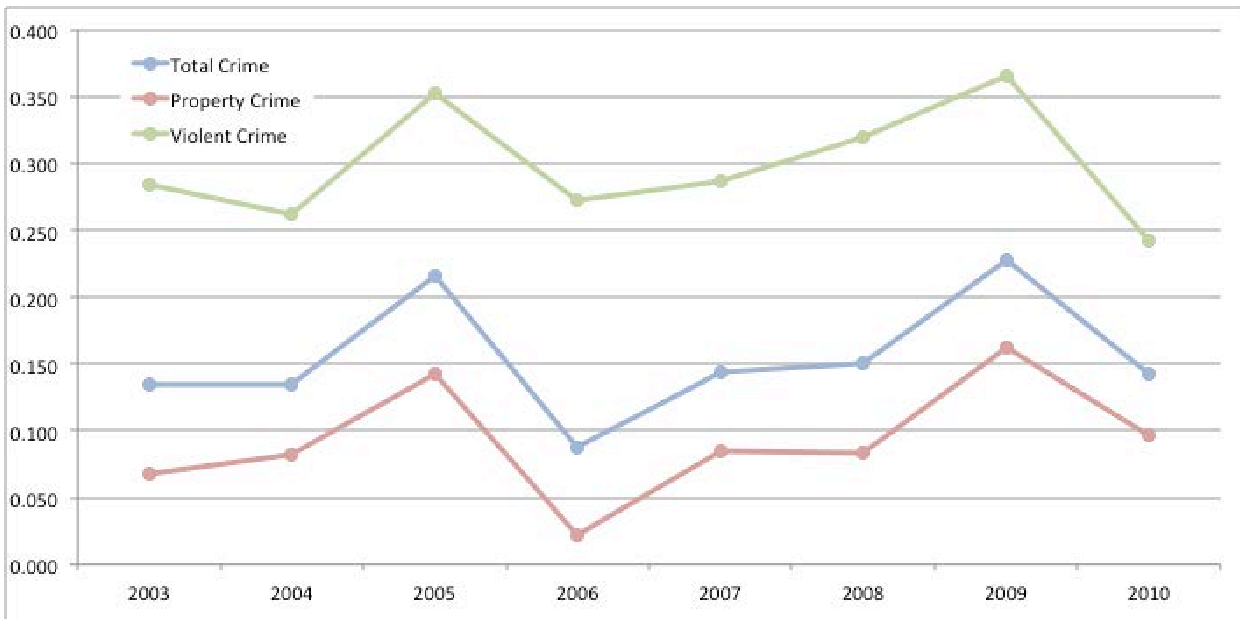


Table 6 provides the same information for Miami. Even though the raw foreclosures and crime series in the two study areas display similar trends over the study period, the correlations over time are very different in the two study areas. Of particular note are the much higher correlations between violent crime and foreclosure sales early in the study period; in 2004, violent crime and foreclosure sales had a correlation coefficient of 0.65. In both the prior and following years (2003, 2005), the correlation coefficients between violence and foreclosure sales were nearly 0.5—much higher than what was observed in DC or between foreclosures and the other crime measures. The correlation coefficients in Miami, though stronger than those in DC, echo the observation that violence appears to have the strongest relationship with foreclosures. The correlation between property crime and foreclosure sales was relatively low, similar to those observed in DC.

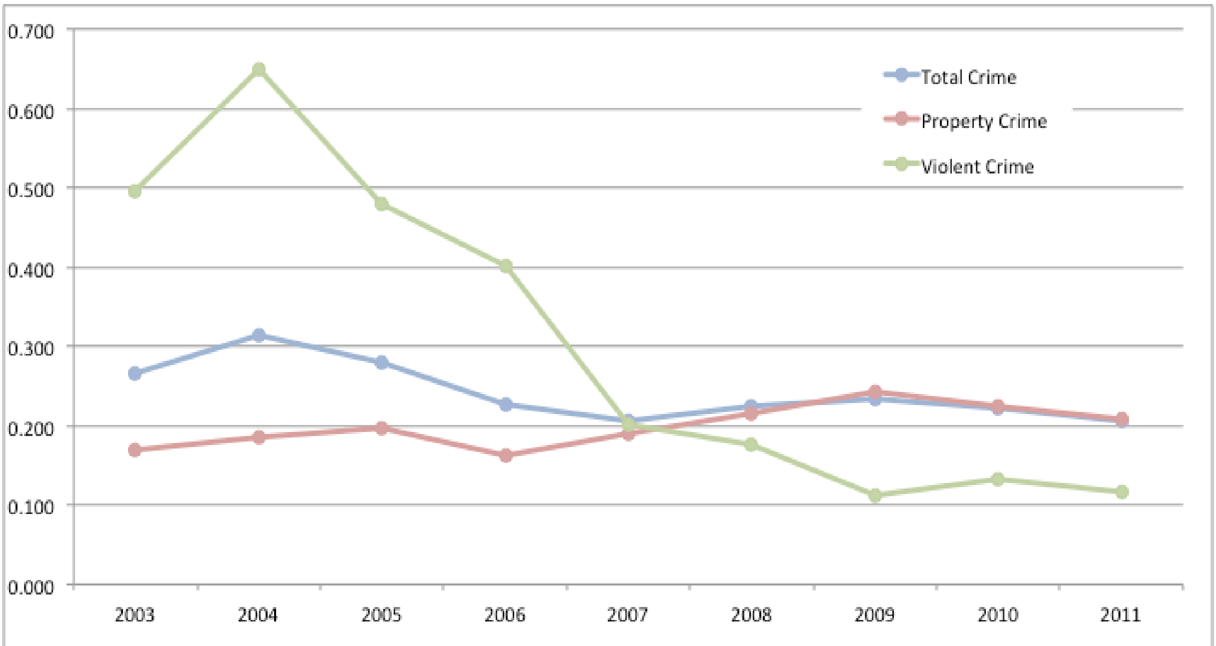
After the onset of the crisis in Miami, correlations between foreclosure sales and all three crime measures was low, and the coefficients for the violence measure were closer to those for property and all crime. Figure 25 provides trends over time in the correlations coefficients for foreclosure sales and the three crime measures. The graph highlights the strong correlations between sales and the violence measure early in the study period. By 2007, however, the correlation dropped to the level of, and below, the coefficients for property and total crime. The fact that the highest correlations were observed prior to the onset of the foreclosure crisis provide further support for the possibility that foreclosures and crime, while they may be related, are more likely both functions of other mechanisms and thus both occur in the same areas together. The models presented below will provide more insight into that possibility.

TABLE 6: YEARLY CORRELATIONS BETWEEN FORECLOSURE SALES AND CRIME, MIAMI

	Crime		
	Violent	Property	Total
2003[a]	0.495	0.168	0.266
2004	0.650	0.186	0.313
2005	0.479	0.198	0.281
2006	0.402	0.161	0.228
2007	0.202	0.189	0.206
2008	0.177	0.216	0.223
2009	0.112	0.244	0.234
2010	0.132	0.224	0.223
2011[a]	0.206	0.208	0.116

[a] *Note that correlation for 2003 is only for the last quarter of the year and for 2011 is only for the first quarter of the year.*
All correlations are significant at the p<0.01 level

FIGURE 25: CORRELATION COEFFICIENTS BY YEAR, FORECLOSURE SALES AND CRIME, MIAMI



To complete our exploratory work prior to developing the dynamic models, we also tested several basic spatial lag regression models with data from both sites. We did this to guide our expectations for the more complex dynamic modeling that was the main goal of this work. While the extensive results of these test models are not provided here, they suggested a number of findings prior to examining the dynamic model results.

Using crime as the dependent variable, we examined the impact of spatially lagged measures of foreclosures and crime. Using spatial lag models in both sites, we found crime in one tract to be significantly affected by crime in nearby tracts (all measured for the same time period). This was an unsurprising result that nonetheless supported our use of spatially lagged crime measures. In DC, crime in one tract was not significantly impacted by nearby foreclosures. In Miami, however, crime was significantly affected by nearby crime and nearby foreclosures in the same time period, supporting inclusion of spatially lagged foreclosure measures in addition to spatially lagged crime measures.

These descriptive findings support our inclusion of spatially lagged terms in the dynamic models for both crime and foreclosures, which are presented in the next section.

Results

MODEL IMPLEMENTATION

The correlation analysis presented above suggested that the relationship between foreclosures and crime was very weak and typically not statistically distinct from the null effect (no relationship), except in the case of violent crime. Even the statistically significant coefficients, however, were small in most cases.

The models presented below included dummy variable controls for year and quarter as well as controls for temporal and spatial lags of the series. The key coefficients of interest were the effects of foreclosures and the spatial lag of foreclosures on crime. For system identification, the effects of crime on foreclosures were not included. The estimated system of equations is:

$$\begin{aligned} c^*_{it} &= \alpha_c + \gamma_c \delta^c_i + \boldsymbol{\beta}'_c \mathbf{y}_{it} + \boldsymbol{\phi}'_c \mathbf{q}_{it} + \tau_c L^T_1(c^*)_{it} + \rho_c L^S_1(c^*)_{it} + \theta_1 f^*_{it} + \theta_2 L^S_1(f^*)_{it} \\ f^*_{it} &= \alpha_f + \gamma_f \delta^f_i + \boldsymbol{\beta}'_f \mathbf{y}_{it} + \boldsymbol{\phi}'_f \mathbf{q}_{it} + \tau_f L^T_1(f^*)_{it} + \rho_f L^S_1(f^*)_{it} \end{aligned}$$

where, for each equation (*c* denoting crime, *f* denoting foreclosures, and a * denoting a log transformation), α are the overall intercept terms; δ^i are the fixed effect variables from stage one and Y are the corresponding coefficients on these measures; $\mathbf{y}_{it}$ and $\mathbf{q}_{it}$ are a series of year and quarter dummy variables with β and ϕ the corresponding coefficients; $L^t_1(\cdot)$ and $L^s_1(\cdot)$ are the temporal and spatial lag terms (of order 1) with τ and ρ the corresponding coefficients.

The key coefficients of interest in this system are Θ_1 and Θ_2, which measure the contemporaneous and spatially-lagged effects of foreclosures on crime. The three tables below summarize these two coefficients for all the models estimated and the coefficients for the impacts of temporal and spatial lags in the dependent variables. Coefficients for all other terms in the model are provided in the full model results in Appendix A.

RESULTS

The research team estimated a large number of models to explore the various combinations of crime and foreclosure models that may impact each other, including testing multiple lags in the models. The use of multiple lags would help to discern whether longer lags (2, 3, or 4 prior quarters) or neighborhoods farther away (neighbors of neighbors) might have a greater effect on the current neighborhood in the current quarter. However, we found very little of significance in any of the models. We therefore selected three sets of models to present here: foreclosure inventory and each crime measure (violent, property, total) in DC (Table 7); foreclosure sales and each crime measure (violent, property, total) in DC (Table 8); and foreclosure sales and each crime measure (violent, property, total) in Miami (Table 9). The tables provide the direct and spatially lagged effects of foreclosures on crime, and the spatially and temporally lagged effects of crime on crime. Tables with the full set of results from each model are provided in Appendix A.

Because the models are in log-log form (i.e., the outcome measure is a logged count and the foreclosures measures are also logged) the coefficients are interpreted as elasticities. Elasticities reflect a percent change in the outcome measure (dependent variable) for a percent change in the predictor (independent variable).

Main effects. The first main effect of interest was the direct effect of foreclosures on crime; this effect was statistically significant in only one of the models (Table 9, Miami sales-violent crime). The coefficient for current foreclosures is equal to 0.0157 in the Miami violence model, suggesting that a one percent increase in foreclosures results in a 0.0157 percent increase in violent crimes. Despite its significance, the effect size is small enough to be considered non-existent. In other models, this coefficient, in addition to being non-significant, was also extremely small.

The second main effect of interest was the spatially lagged foreclosure measure. None of the coefficients on the spatially lagged foreclosure measures were significant in any of the models, and similarly, the effect sizes were extremely small. The results suggest a weak or non-existent effect of foreclosures on crime.

Additional model parameters. The research team examined other model parameters for insight into the data and the relationship between foreclosures and crime. In all of the models the fixed effect terms were statistically significant, suggesting that there were sufficient time-stable effects in the census tracts. If these effects are ignored, then time-stable differences may be mistaken for substantive effects. These time-stable effects indicate that there are elements other than foreclosures and crime—neighborhood disadvantage or demographic characteristics, for example—that have a significant effect on both crime and foreclosure levels. Without accounting for these unmeasured but significant effects (through the inclusion of fixed effects), the model results may have led the research team to believe that the direct effects of foreclosures and crime on each other was significant and greater than their true relationship.

The temporally and spatially lagged effects of crime on current crime were expected to be significant because areas that are high in crime tend to cluster together, and crime levels are relatively stable over a period as short as a quarter within one neighborhood. In DC (Tables 7 and 8), the coefficients on both of the lagged crime measures were significant only in the violence models but again, with very small effect sizes. In Miami, the temporal lag of crime was significant across all three models but small, suggesting that crime in Miami neighborhoods is relatively stable, as expected. The effect of crime in nearby areas in Miami, however, was non-significant.

TABLE 7: WASHINGTON, DC FORECLOSURE INVENTORY MODELS

	Dependent Variable		
	Violent Crime	Property Crime	Total Crime
Intercept	-0.4454**	-0.0992**	-0.0863**
Foreclosures (current/direct)	0.0035	0.0011	0.0007
Foreclosures nearby (spatial lag)	-0.0011	0.0007	0.0005
Crime, prior Q (temporal lag)	-0.0179*	-0.0007	-0.0020
Crime nearby (spatial lag)	0.0239*	0.0012	0.001

**Significant at the $p<0.05$ level.*
***Significant at the $p<0.01$ level.*

TABLE 8: WASHINGTON, DC FORECLOSURE SALES MODELS

	Dependent Variable		
	Violent Crime	Property Crime	Total Crime
Intercept	-0.4371	-0.0932**	-0.0823**
Foreclosures (current/direct)	0.0011	0.0006	0.0008
Foreclosures nearby (spatial lag)	0.0042	0.0020	0.0002
Crime, prior Q (temporal lag)	-0.0181*	-0.0010	-0.0018
Crime nearby (spatial lag)	0.0223*	0.0004	0.0006

**Significant at the $p<0.05$ level.*
***Significant at the $p<0.01$ level.*

TABLE 9: MIAMI FORECLOSURE SALES MODELS

	Dependent Variable		
	Violent Crime	Property Crime	Total Crime
Intercept	-0.0868*	0.0470	0.1075**
Foreclosures (current/direct)	0.0157*	0.0021	0.0023
Foreclosures nearby (spatial lag)	-0.0165	0.0005	0.0014
Crime, prior Q (temporal lag)	0.0596**	0.0214**	0.0306**
Crime nearby (spatial lag)	-0.0045	0.0025	0.0009

**Significant at the $p<0.05$ level.*
***Significant at the $p<0.01$ level*

In all of the models, the crime series (violent, property, and all crime) showed strong trending (across years) and seasonal variation (across quarters). Typically, quarters 2, 3 and 4 had more crime than quarter 1 (the omitted category). For the foreclosures series, the temporal trends were evident. However, the seasonal variation was evident in only the inventory series and not the sales series (for DC). Miami sales series displayed seasonal variation.

Finally, as expected, when the temporal and spatial lag terms were statistically significant, they tended to be positive but small. This suggests that the spatial and temporal dynamics are stable (i.e., a small increase in crime or foreclosures spills over to the next period and to the surrounding areas).

Understanding the local context

To gain a local perspective on the foreclosure crisis in both cities, investigate the nature of the neighborhoods that might have been most affected by the foreclosure crisis, and to understand foreclosures' potential effects on crime locally, we interviewed individuals in each city who had intimate knowledge of housing, mortgage, and foreclosure markets and of the neighborhoods most affected by the foreclosure crisis in each city. We also conducted a focus group of residents in DC to collect more on-the-ground perspective in that city. This information provides a complement to the results of the statistical analysis above. The insight from participants in the interviews and focus groups paints a richer picture of the issues facing residents, service providers, and policy makers in each city with regards to the current housing and foreclosure crisis. The insight also helps to shed light on the unexpected lack of relationship between foreclosures and crime observed through the statistical modeling just presented.

WASHINGTON, DC: INPUT FROM LOCAL EXPERTS

We interviewed nine people with intimate local knowledge of DC and of the relationship of the city's foreclosure crisis to changing crime patterns. The individuals represented a variety of local groups, most of which provided community-based housing assistance or focused on community development efforts. The interviews were all conducted in-person or on the phone in mid-2011. The interviewees gave relatively consistent opinions on the housing context in DC.

The main takeaway from the interviews with locals knowledgeable about the housing market and context of foreclosures suggest that foreclosures have typically not been associated with increases in crime in DC. Respondents agreed that the foreclosure crisis was much less severe in DC than in other major cities, because of the federal government presence and employment. However, one respondent cautioned that federal budget uncertainty could cause financial hardship for individuals who otherwise would not be at risk for foreclosure; these are likely to be individuals who stretched too much in their mortgage as opposed to those who received subprime loans.

Respondents agreed that the foreclosures that have occurred in DC have not been strongly concentrated in local areas, but that minorities in the city, as in other areas, were more likely to face foreclosure than other residents. Respondents consistently identified several neighborhoods as suffering from housing problems, of which foreclosures were just one issue. Other issues plaguing neighborhoods like

Deanwood, Ivy City, and Trinidad (all in the city's northeast quadrant) that were mentioned by respondents included absentee landlords, high vacancy rates (that pre-dated the foreclosure crisis), vacant lots, and lack of economic opportunity. These factors have contributed to an overall dilapidated housing stock that has developed over decades, and the city itself has reportedly not been successful in rehabilitating the housing with its efforts to date in these neighborhoods.

FIGURE 26: EXAMPLE OF DILAPIDATED HOUSING IN DEANWOOD NEIGHBORHOOD, WASHINGTON, DC

Source: Google Street View Imagery, taken August 2014.

Many respondents reported that more of the problems of residents in these disadvantaged areas have economic roots, like joblessness, than anything to do with houses themselves (e.g., foreclosure). Respondents were careful to mention that many of the current issues existed in these areas before the foreclosure crisis began. Many disadvantaged areas are home to rentals, so foreclosure was not as prominent of an issue there; other areas had a significant number of vacant lots or dilapidated housing well before the housing boom and bust occurred in DC.

Two main issues stemming from foreclosure that respondents did mention included vandalism and squatters. One respondent suggested that squatters are not typically involved in illegal activities beyond the squatting itself, and some may have even been former residents of the foreclosed homes where they were illegally staying. Others suggested that squatters may in some cases be involved with drug use. Vandalism was the most serious criminal behavior that respondents associated with foreclosures, or more specifically, with vacancies. However, most respondents downplayed this as a serious issue, instead suggesting that the foreclosure activity itself was not associated with crime in local areas.

While respondents did not identify any serious issues with foreclosure-related crime in DC, they did offer solutions to addressing the foreclosure crisis. These solutions are mentioned here because they echo solutions that are supported by the theoretical underpinnings of this research—especially collective efficacy and social disorganization. Respondents suggested that educating residents about how to keep their homes (prevent foreclosure), create stricter budgets, and avoid foreclosure scams, and providing timely assistance in handling foreclosures could help. Community building, however, was most consistently mentioned as the key to improving neighborhoods that have experienced foreclosures and crime (whether or not the two are related in those places). One respondent also suggested that community policing could play a key role in improving communities. The respondents agreed that bringing residents together and empowering them through education and guidance would be the best way to ensure that the neighborhood creates lasting change.

WASHINGTON, DC: INPUT FROM RESIDENTS

In order to more fully understand the impact of foreclosure on residents in DC, we conducted one focus group with residents from both hard hit and relatively unscathed neighborhoods. We conducted the focus group at a community organization in the neighborhood where participants lived, which was located in the north central part of DC. Fourteen residents spoke with the research team about what they saw as the main challenges in their neighborhood that were related to foreclosure. Residents received a small incentive to thank them for their participation in the discussion.

Participants had generally lived in the area for long periods of time, with some having lived in the neighborhood for 5-10 years, and others for 40-50 years. Residents reported that the neighborhood had its "ups and downs" but were content with living in the neighborhood, citing its convenience and superiority compared to other parts of the city, such as Southeast.

Participants began by identifying the issues with foreclosures in their neighborhood, and quickly pointed out that foreclosures were surely occurring—they saw "obvious" indicators of foreclosure, like a 'for sale' sign and overgrown grass, or having heard about it from the owner who used to live there. The bigger issue, however, was with vacant houses, and participants indicated a high volume of vacancies existed in the neighborhood. Respondents added that houses may have become vacant as a result of processes other than foreclosure, such as nonpayment of taxes.

Reports on the impact of vacancies on the neighborhood, however, were equivocal. Respondents noted while vacancies may attract or generate crime by providing offending opportunities, they also recognized investment in the vacant property could increase their (residents') ability to transform the neighborhood through gentrification. While vacancies left unattended may drive housing prices down, vacancies that are renovated may increase property values. These reports suggest awareness of the types of processes identified by broken windows theory—that vacant or dilapidated housing can negatively affect neighborhoods if left too long.

The discussion also indicated that vacancies were altering the social fabric of the neighborhood. According to participants, vacancies that were renovated attracted individuals with higher incomes, but forced low-income families out of the neighborhood. As a result, neighborhood institutions were changing—for instance, new grocery stores moved in and the common activities in parks changed (e.g., a new organic market was perceived to be too expensive for most residents' budgets, and a park was converted to a dog park for residents' use). Further, social ties were weakened with the influx of new folks in the neighborhood and the departure of old residents that had been established in the neighborhood. Because of the gentrification process that was underway, the neighborhood social bonds were becoming weakened. Residents reported that they used to know their neighbors, but now they don't, and that senior citizens, many who were long-time residents, seemed to be more likely victims of foreclosure. One participant said that people were buying homes to renovate and resell, creating an economic investment in the neighborhood, but not investing time in the community or contributing to its social well-being.

While social bonds were reportedly weakened as a result of gentrification, some residents noted that there had been less crime in the neighborhood, and that individuals were able to walk around with less fear of victimization than they had historically felt. One respondent shared that there used to a drug-addicted person in their neighborhood but when his home was foreclosed upon, it was a "sign of relief" for the neighborhood. Some mentioned that they noticed criminal activity that was associated with vacant properties, such as children squatting and drug activity. Others suggested that new residents, with higher incomes and more attractive property (e.g., luxury items, electronics) were more likely to be the targets of crimes like robberies and burglaries. Residents discussing their interactions with neighbors, whether positive or not, iterated themes raised by Jacobs (1961) with regards to friendly acquaintances and the network of weak ties that help to create security in the area; residents were not friendly with the 'problem' neighbor but seemed more welcoming of new residents, even if only on a superficial basis. According to Jacobs, as long as residents have a shared idea about maintaining safety in the area, they need not be close friends. At least in this one neighborhood in DC, newer residents seem to be helping existing homeowners to better secure the community.

Residents at the focus group reported that their ward[19] was not as proactive in coming together as a community to resolve issues as they presumed other wards' residents were. Residents also felt that the neighborhood itself lacked the political will to solve the problems they identified. This sentiment echoed the reports from local housing experts who suggested that residents needed guidance but also needed to be

[19] Washington, D.C. is divided into eight wards for local political and organizational purposes.

empowered to solve problems themselves. Discussions on the role and importance of social connections and resident's ability (or lack thereof) to solve neighborhood problems points to the importance of collective efficacy of residents, as suggested by social disorganization theorists, and suggests that one avenue for improving neighborhoods is to, as experts suggested, work with residents to help them create grass roots solutions to their issues, instead of imposing policy solutions from the top down.

While the expert interviews and resident focus group provided useful insight into the foreclosure and crime relationships in DC, they also suggested that the link between these two phenomena was weak at best—a finding that supports the results of the statistical modeling. Most conversations with both local housing experts and residents centered around improvement of disadvantaged neighborhoods that had struggled for years, sometimes decades, to overcome economic and other challenges. While foreclosures may have been one small part of the recent story of the neighborhood situations, they certainly were not identified as the cause of or even a major factor in the quality of the neighborhoods where they occurred.

MIAMI: INPUT FROM LOCAL EXPERTS

As in DC, the research team interviewed local experts on housing issues in Miami. The five individuals with whom we spoke provided a local perspective on the foreclosure crisis and helped us to identify those neighborhoods that might have been most affected by the foreclosure crisis. The individuals had extensive local knowledge of the county and the local foreclosure crisis' relationship to crime. Interviewees provided historical knowledge to inform their suggestions on approaches to addressing the foreclosure crisis. The individuals represented a variety of local groups, including Florida International University, a community-based housing assistance organization, a local grass-roots organizer, and an organization doing a wide array of social service provision and policy work in South Florida, with special interest in housing issues. The interviews were all conducted in-person in late 2011. The interviewees gave relatively consistent opinions on the housing context in Miami.

Most interviewees discussed the foreclosure problem in South Florida with significant detail, providing historical context to the current crisis. Several respondents described a push in the early part of the 2000s to "drive till you qualify" for housing. In other words, potential homebuyers were often encouraged to look for housing in far reaching suburbs or exurbs—until they were far enough out that they could afford the housing prices, as houses on the fringes of the metropolitan area are significantly cheaper than more close-in housing. This outward push both spawned and spurred on a significant amount of new home construction on the fringes of Miami, in places like Florida City and Homestead, which are on the southern fringes of the county. One respondent described Homestead as "Ground Zero" for the Miami foreclosure crisis.

However, soon after these affordable homes lured purchasers with less means from more conveniently-located housing to areas much farther out, gas prices began to skyrocket. The costs of commuting to and from jobs in other parts of the metro area became increasingly untenable for many residents in these areas, contributing to financial stress on new homeowners. In addition, the new home developments were built in areas with limited existing infrastructure or services. When the foreclosure crisis began, these were the first areas to succumb. Many homes were never even occupied, and respondents described virtual "ghost towns" where few to no residents occupied the homes. These areas, from the start, lacked the "eyes on the street" that Jacobs (1961) suggested were so important for maintaining security in an area. In addition, with few residents occupying homes, it would be hard for existing occupants to establish an element of collective efficacy to address issues in the neighborhood.

FIGURE 27: PARTIALLY COMPLETED HOUSING DEVELOPMENT IN HOMESTEAD, FL

Source: Google Street View Imagery, taken March 2011.

Another area that was particularly hard hit was the coastal part of the county, where many homes were purchased as vacation/ second homes or investment properties. Housing in these categories were also early victims of the foreclosure crisis, as homeowners were more willing to lose vacation homes than their primary residences.

These areas contributed significantly to the foreclosure crisis in South Florida, but had an unclear relationship with crime, according to respondents. While the extreme southern and northern parts of Miami generally had higher levels of crime (see Figure 22 below), neighborhoods inhabited by few to no residents and that are far away from centers of population do not tend to attract a significant amount of crime. Thus, these areas of extremely high foreclosures levels were not associated with correspondingly high crime rates.

Respondents suggested that urban planning policies could address the foreclosure crisis itself, such as encouraging infill development closer to the central parts of the county, focusing on improving transportation options in the county, and using property taxes to support resident owners and discourage concentrations of investment properties in vulnerable communities. These, however, do not address crime problems *per se*. In fact, we spoke with few interviewees who connected crime and foreclosures, despite the popular media's reports on the topic.

Another area that was particularly susceptible to the foreclosure crisis in Miami was the closer-in suburbs, including areas like North Miami, Brownsville, and Hialeah Gardens. In these areas, vacancies due to foreclosures were a more significant problem, and because they are more accessible than exurban parts of the county, the vacancies have a greater potential to be associated with increased crime. The areas are also home to a significant number of vacant lots. These communities, however, were also areas with relatively low-income populations and less expensive housing prior to the foreclosure crisis. And, as with the exurban areas that interviewees identified, these areas did not appear to suffer from a worsening of crime that wouldn't have happened had the foreclosure crisis not occurred. Respondents reported that the county did step up enforcement of housing codes in order to improve neglected properties and prevent further dilapidation. This code enforcement was handled mainly by local police officers. But the enforcement was not necessarily related to an increase in crime, rather to a crime prevention effort and neighborhood maintenance effort.

In other words, local individuals well-informed on housing issues and the local policy context did not connect the foreclosure crisis with an increase in crime in hard hit (or other) areas. The situations reported in the local and national media on the connection between crime and foreclosures appeared to be isolated or outliers.

FIGURE 28: BOARDED-UP HOME IN BROWNSVILLE, FL

Source: Author's photo, taken November 2011.

Discussion and Conclusions

The foreclosure crisis exploded in many areas in the late 2000s, including in Florida and Miami more specifically. The most prominent theories on communities and crime provided support for the idea that an increase in foreclosures could negatively impact a neighborhood's social cohesion and collective efficacy, disrupting normal patterns of informal social control that previously had prevented or controlled crime, and these changes would lead to neighborhood decline. Once decline began and social control ebbed in a neighborhood, according to these same theories, crime would begin to rise.

As researchers began to turn their attention to the impacts of foreclosures at a neighborhood or community level—beyond the financial impacts to families who experienced foreclosure, the theory supporting the relationship between foreclosures and crime was more fully explicated (Wilson & Paulsen, 2010). Anecdotal reports in the media suggested that crime was running rampant in many neighborhoods where foreclosures were occurring. Thus, at the outset of this research, we expected to find a significant relationship between foreclosures and crime, with concentrated foreclosures causing crime to rise, and rising crime indirectly causing an increase in foreclosures. We expected these relationships to be strongest in neighborhoods where foreclosures were heavily concentrated.

The relationship between foreclosures and crime is complex, and indeed, in many ways, the two are related. However, evidence from a number of sources—maps of the two phenomena in both study areas before and after the foreclosure crisis hit, insight from local experts and residents in both study areas, descriptive analysis of foreclosures and crime data, and complex statistical models—suggests that the relationship is not direct, and is instead built on each phenomenon's mutual relationships with other factors, like pre-existing and relatively stable neighborhood characteristics.

Maps of foreclosures and crime both prior to and after the foreclosure crisis in DC and Miami indicated that both phenomena were clustered spatially, and that they were occurring in similar locations prior to the foreclosure crisis' start. In both study areas, foreclosures and crime tended to occur in areas that were more disadvantaged before the crisis, and with the onset of the crisis, foreclosures spread to neighborhoods that would not traditionally have experienced many foreclosures. This pattern was especially strong in Miami but less noticeable in DC, where the volume of foreclosures was lower.

Local experts and residents in both cities did not connect crime to foreclosures. We spoke with individuals who gave insightful information on the foreclosure crisis but most interviewees in both cities felt that the two phenomena were weakly related, if at all. The impact of foreclosures on crime, then, was not cause for significant concern among housing market experts and community housing assistance providers during the crisis. Residents in DC discussed negative aspects of foreclosures but were more concerned about the effects of gentrification that was occurring in previously disadvantaged neighborhoods in the wake of the housing boom.

Finally, the results of the statistical modeling confirmed the qualitative findings and descriptive analysis, suggesting that there is either a very weak or nonexistent effect of foreclosures on crime. In the absence of fixed effects (which account for unobserved but time-stable differences between different tracts), they appear to be closely related, with coefficients both statistically significant and positive. When fixed effects are added to the model, however, the effects of foreclosures on crime are no longer significant. This would suggest that the observed relationship between foreclosures and crime exists primarily because both phenomena happen in disadvantaged neighborhoods. Given this evidence, there is no reason to conclude that concentrated foreclosures, at least to the extent experienced in DC or Miami in the late 2000s, led to significant increases in crime on their own.

Policy Implications

Because we essentially found no connection between foreclosures and crime, there is little expectation that policy changes that address foreclosures would impact levels of crime in any significant way. However, some interviewees suggested responses to the foreclosure crisis itself that, while not directly intended to address crime levels in a neighborhood, have the potential do so as a secondary or side benefit. These solutions are supported by ideas from collective efficacy and social disorganization theories and include educating residents about how to keep their homes (prevent foreclosure) and providing timely assistance in handling foreclosures could help. In addition, neighborhoods, and larger civic or municipal associations can also enact policies that foster community building. This approach may help improve conditions in neighborhoods that have experienced foreclosure and crime (whether or not the two are statistically related in those places). Along with community building efforts, community policing, where police focus individual officers on specific neighborhoods in order to develop proactive and positive relationships with residents there, could also help to improve these communities. Bringing residents together and empowering them—through education and guidance—is the best way to ensure that the neighborhood creates lasting change.

However, these are very broad and generalized policy suggestions, and could be identified as appropriate responses to a variety of neighborhood-level factors of disadvantage. While they may address crime in areas where foreclosures also occur, they are not designed to specifically address areas where foreclosures and crime co-locate.

CONCLUSION

This report presented the findings from an in-depth examination of the role of foreclosures in increasing levels of crime in neighborhoods. While the expectation, based largely on ecological theories of crime, was that a significant relationship existed between these two phenomena, we did not find any indication that such a relationship exists. The research team developed complex, dynamic models that simultaneously modeled the effects of foreclosures and crime on each other over space and time. The results suggest that at the neighborhood level, increased foreclosures are not expected to lead to higher levels of crime, but that preexisting neighborhood conditions are likely to lead to both higher levels of foreclosures and higher levels of crime concurrently.

While there remains the possibility on a micro-scale, such as by property or by block, that such a genuine relationship exists between crime and foreclosure, given the results of the current study, we do not expect that such a relationship is widespread, nor that medium- or large-scale policies can be designed to address these two phenomena alone. Instead, policies should be designed to address wider community problems or disadvantage that is likely leading to higher incidences of both foreclosures and crime.

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Appendix A. Technical Appendix

This technical appendix describes an information-theoretic approach for estimating models of rare crimes (foreclosures and crime) in a simultaneous system of equations. The models permit inclusion of temporal, spatial, and cross-spatial lag effects in the system. In addition, the models control for all stable unit-specific effects by employing a two-step fixed-effects modeling strategy. The methods are applied to a model of foreclosures and crime in two cities—Washington, DC and Miami-Dade County, FL.

The appendix first describes the generic information theoretic framework and then expands it to include several features including spatial lags, temporal lags, cross-spatial and cross-temporal lag terms, unobserved heterogeneity, simultaneous system modeling, and fixed effects. Findings are then discussed. Detailed tables are provided in the following appendix.

THE GENERIC PROBLEM

Let a set of $i = 1....; N$ signals (denoted $s = s_1, ..., s_N$) be emitted from a hidden source. We only observe imperfect manifestations of these signals in the form of outcomes (denoted $y = y_1, ..., y_N$). Theory or past experience suggests that the intensity of each signal varies with a set of K exogenous attributes (denoted by $\boldsymbol{x}_i = xi_1; ...., x_{iK}$). How can we recover the signals in the most conservative manner?

We start by noting that the outcomes are only imperfect manifestations of the signals (i.e., $y_i \approx s_i \ \forall i \in N$). Since the signal intensities vary with the attributes x_{ik}, if we assume that, in the aggregate, the covariance between the attributes and the signals are preserved perfectly in the covariance between the attributes and the outcomes, then we may claim:

$$\sum_i y_y x_{ik} = \sum_i s_i x_{ki} \quad \forall k \in K \tag{1}$$

We still need some way of recovering the signals from this information. The nature of the problem at hand will also provide us guidance on what values the signal can take. I.e., the support space for the signal will usually be known. For example count outcomes may have the natural support defined as $\mathbf{z} = (0, 1, 2, ..., Z)$. If we define $p_m = \Pr(s = z_m)$ then we can write the signal as an expectation over a support space as $s_i = \sum_m Z_m P_{im} \ \forall i \in N$. Moreover, if we assume that the signal support space is mutually exclusive and exhaustive then it is natural to assume:

$$\sum_m p_{im} = 1 \quad \forall i \in N \tag{2}$$

Equations 1 and 2 provide us the basic structure to recover information from. Since there are more unknowns than equations linking the, we face an ill-posed inversion problem—there are an infinite number of probability distributions (p_{im}) that can satisfy these basic set of conditions. How do we solve this problem?

Suppose we have some prior beliefs about the probabilities p_{im} denoted by p^0_{im}. The information theoretic solution to recovering information from the conditions (1) and (2) is to minimize the directed divergence between the priors and the posteriors (i.e., to be conservative) while ensuring that the recovered probabilities satisfy the conditions imposed by (1) and (2) (i.e., be consistent with the evidence). One way to measure the directed divergence between the priors and the posteriors is via the Kullback-Leibler information measure (also known as cross-entropy).[20] This measure is defined as:

$$\mathscr{K} = \sum_{im} p_{im} \ln\left(\frac{p_{im}}{p^0_{im}}\right) \tag{3}$$

The philosophical problem of recovering information from the conditions is now converted into a mathematical problem of minimizing (3) subject to (1) and (2). This is a standard non-linear constrained optimization problem that can be solved with the method of Lagrange.

The primal Lagrangian function is set up as:

$$\begin{aligned}\mathscr{L} \;&=\; \sum_{im} p_{im} \ln\left(\frac{p_{im}}{p^0_{im}}\right) + \sum_i \phi_i\left(1 - \sum_m p_{im}\right)\\ &\quad + \sum_k \lambda_k\left(\sum_i y_y x_{ik} - \sum_i \sum_m z_m p_{im} x_{ki}\right)\end{aligned} \tag{4}$$

where the φ_i and λ_k are Lagrange multipliers corresponding to the set of constraints (2) and (1), respectively. The first order conditions for this problem are:

$$\frac{\partial \mathscr{L}}{\partial p_{im}} = 0 \quad \Longrightarrow \quad \ln\left(\frac{p_{im}}{p^0_{im}}\right) - z_m \sum_k x_{ik}\lambda_k - 1 - \phi_i = 0 \tag{5}$$

$$\frac{\partial \mathscr{L}}{\partial \phi_i} = 0 \quad \Longrightarrow \quad \sum_m p_{im} = 1 \tag{6}$$

Solving these conditions simultaneously yields the optimum solution:

$$p_{im} = \frac{p^0_{im} \exp\left(z_m \sum_k x_{ik}\lambda_k\right)}{\sum_m p^0_{im} \exp\left(z_m \sum_k x_{ik}\lambda_k\right)} = \Omega_i^{-1} p^0_{im} \exp\left(z_m \sum_k x_{ik}\lambda_k\right) \tag{7}$$

where $\Omega_i = \sum_m P^0_{im} \exp(z_m \sum_k x_{im}\lambda_k)$ is termed the partition function that ensures that the probabilities sum to 1.

[20] The Kullback-Leibler measure is only one in a larger class of divergence measures.

Finally, plugging this solution back into the primal (4) and solving out, we obtain the concentrated dual version of the optimization problem as:

$$\mathscr{F} = \sum_i y_i \sum_k x_{ik}\lambda_k - \sum_i \ln \Omega_i \tag{8}$$

which is an unconstrained optimization problem in just the K Lagrange multipliers λ_k. This can be solved using iterative non-linear optimization routines such as the Newton-Rhaphson method. The gradient of this function (with respect to each of the λ_k) are

$$\mathscr{G} = \frac{\partial \mathscr{F}}{\partial \lambda_k} = \sum_i y_i x_{ik} - \sum_i \sum_m z_m p_{im} x_{ik} \quad \forall k \in K \tag{9}$$

which are the just the original moment constraints of (1).

In matrix notation, the dual would be defined as

$$\mathscr{F} = \mathbf{y}'\mathbf{X}\lambda - \mathbf{1}_n' \ln \mathbf{\Omega} \tag{10}$$

where $\mathbf{\Omega} = (\mathbf{I}_N \otimes \mathbf{p}^0)' \exp((\mathbf{I} \otimes \mathbf{z})\mathbf{X}\lambda)$ and the gradient vector as

$$\frac{\partial \mathscr{F}}{\partial \lambda} = \mathbf{X}'\mathbf{y} - \mathbf{X}'\mathbf{s} \tag{11}$$

This is the basic set up of the problem. Different choices of $\mathbf{z}$ and $\mathbf{p}^0$ can yield a variety of solutions. Additional constraints on higher moments can also be introduced into the problem. The next section extends the generic problem to the specific case of the foreclosures/crime models we are considering.

THE CRIME/FORECLOSURES PROBLEM

Let the incidents of crime recorded in any period t and any spatial unit $i = 1, \ldots, N$ be denoted by $\mathbf{c}_t = \mathbf{c}_{1t}, \ldots, c_{Nt}$. Let the foreclosures in these neighborhoods for these time periods be denoted by f_{it} $\forall i \in N$ and $t \in T$. Let us define the vector $\mathbf{y}$ as a stacked vector of crime and foreclosures in all neighborhoods over all time periods. I.e., let

$$\mathbf{c} = \begin{pmatrix} c_{11} \\ \vdots \\ c_{N1} \\ c_{12} \\ \vdots \\ c_{N2} \\ \cdots \\ c_{1T} \\ \vdots \\ c_{NT} \end{pmatrix} \quad ; \quad \mathbf{f} = \begin{pmatrix} f_{11} \\ \vdots \\ f_{N1} \\ f_{12} \\ \vdots \\ f_{N2} \\ \cdots \\ f_{1T} \\ \vdots \\ f_{NT} \end{pmatrix} \quad \text{and} \quad \mathbf{y} = \begin{pmatrix} \mathbf{c} \\ \mathbf{f} \end{pmatrix} \tag{12}$$

Also let $\mathbf{X}_c$ and $\mathbf{X}_f$ denote the set of exogenous variables that explain variations in crimes and foreclosure series respectively. Each of them may vary over time and neighborhood. They may be constant over locations (for any given time) but may not be constant for any given location over time. Let a composite exogenous matrix be defined as

$$\mathbf{X} = \begin{pmatrix} \mathbf{X}_c & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_f \end{pmatrix} \tag{13}$$

Next, consider a set of weight matrices (to be defined later) that capture mutual dependence between the observations. This may include, for example, spatial lags, temporal lags, or cross temporal lags between the two endogenous variables (c and f). Let there be $l \in L$ such terms so that we may write a generic rate process as:

$$\ln \boldsymbol{\eta} = \mathbf{X}\boldsymbol{\beta} + \sum_l \rho_l \mathbf{W}_l \ln \boldsymbol{\eta} \tag{14}$$

or, in reduced form, as

$$\ln \boldsymbol{\eta} = (\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1} \mathbf{X}\boldsymbol{\beta} \tag{15}$$

This suggests using constraints of the form:

$$((\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1} \mathbf{X})' \mathbf{y} = ((\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1} \mathbf{X})' \mathbf{B}\mathbf{p} \tag{16}$$

in addition to the adding up constraints

$$(\mathbf{I}_2 \otimes \mathbf{I}_N \otimes \mathbf{I}_T \otimes \mathbf{1}_M)\mathbf{p} = \mathbf{1} \tag{17}$$

while minimizing the Kullback-Leibler directed divergence measure. The primal problem is set up as:

$$\begin{aligned} \mathscr{L} \;=\; & \mathbf{p}' \ln \mathbf{p} - \mathbf{p}' \ln \mathbf{p}^0 \\ & + \boldsymbol{\phi}'(\mathbf{1} - (\mathbf{I}_2 \otimes \mathbf{I}_N \otimes \mathbf{I}_T \otimes \mathbf{1}_M)\mathbf{p}) \\ & + \boldsymbol{\lambda}'((\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1} \mathbf{X})'(\mathbf{y} - \mathbf{B}\mathbf{p}) \end{aligned} \tag{18}$$

Here $\mathbf{B}_p = \mathbf{s}$ are the recovered signals of which $\mathbf{y}$ is an imperfect manifestation. $\mathbf{B} = \mathbf{I}_2 \otimes \mathbf{I}_N \otimes \mathbf{I}_T \otimes \mathbf{z}$ is a matrix of support points.

Solving the primal problem yields the solution

$$\mathbf{p} = \frac{\mathbf{p}^0 \exp\left(\mathbf{B}(\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1} \mathbf{X}\boldsymbol{\lambda}\right)}{\boldsymbol{\Omega} \otimes \mathbf{1}_m} \tag{19}$$

and the corresponding dual problem

$$\mathscr{G} = \left((\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1}\mathbf{X}\lambda\right)'\mathbf{y} - \left(\mathbf{1}_2 \otimes \mathbf{1}_N \otimes \mathbf{1}_T\right)' \ln \mathbf{\Omega} \tag{20}$$

where

$$\mathbf{\Omega} = (\mathbf{1}_2 \otimes \mathbf{1}_N \otimes \mathbf{1}_T \otimes \mathbf{p}^0)' \exp\left(\mathbf{B}(\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1}\mathbf{X}\lambda\right) \tag{21}$$

with gradient components

$$\frac{\partial \mathscr{G}}{\partial \lambda} = \left((\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1}\mathbf{X}\right)'(\mathbf{y} - \mathbf{s}) \tag{22}$$

$$\frac{\partial \mathscr{G}}{\partial \rho_l} = \left[(\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1}\mathbf{W}_l(\mathbf{I} - \sum_l \rho_l \mathbf{W}_l)^{-1}\mathbf{X}\lambda\right]'(\mathbf{y} - \mathbf{s}) \quad \forall l \in L \tag{23}$$

The last derivation coming from the following generic derivative:

$$\frac{\partial}{\partial \rho}(\mathbf{I} - \rho\mathbf{W})^{-1} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{W}(\mathbf{I} - \rho\mathbf{W})^{-1} \tag{24}$$

which is just the matrix version of the standard derivation

$$\frac{\partial}{\partial \rho} g(\rho)^{-1} = g(\rho)^{-2}\frac{\partial g(\rho)}{\partial \rho} \tag{25}$$

So far the weight matrices have been left generically defined. Next, we specify them explicitly. Consider, first a pure spatial lag term. That is, let each neighborhood crime in each time period be a function of the crimes in surrounding neighborhoods. Let the row-standardized spatial contiguity matrix among the neighborhoods be defined as **C**. Then, a simple spatial lag process between crimes would be captured by a **W** matrix defined as

$$W = \begin{pmatrix} \mathbf{I}_T \otimes \mathbf{C} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{26}$$

and the spatial lag of foreclosures would be captured as

$$W = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_T \otimes \mathbf{C} \end{pmatrix} \tag{27}$$

whereas the cross-process spatial lag would be captured by

$$W = \begin{pmatrix} \mathbf{0} & \mathbf{I}_T \otimes \mathbf{C} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{28}$$

In a similar manner, a within crime process temporal lag can be captured by defining

$$W = \begin{pmatrix} \mathbf{L1}_T \otimes \mathbf{I}_N & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{29}$$

where

$$\mathbf{L1}_T = \begin{pmatrix} 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 \end{pmatrix} \tag{30}$$

is an identity matrix with the diagonal ones shifted to the first off-diagonal cells. Because the ones are shifted to the first off-diagonal, the last row in this matrix is composed entirely of zeros. The within-foreclosures temporal lag is similarly captured by

$$W = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{L1}_T \otimes \mathbf{I}_N \end{pmatrix} \tag{31}$$

whereas the link between current crime and the temporal lag of foreclosures (the cross-temporal lag terms) are captured by

$$W = \begin{pmatrix} \mathbf{0} & \mathbf{L1}_T \otimes \mathbf{I}_N \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{32}$$

Implementation

The above derivation was done for general problems. However, because of the highly non-linear nature of the derived dual objective function (and the corresponding gradient and hessian functions), there is no guarantee that a feasible solution will be found. Indeed, as the complexity of the problem is increased, the ability of a Newton-Raphson type algorithm to converge to a solution diminishes considerably. As a result, to implement the information theoretic approach two simplifications were introduced. These involve a two-step process for estimating the fixed effects and an EM type iterative algorithm for estimating the lagged terms (spatial and temporal) and the endogenous cross-effects of interest. Each of these is described below.

FIXED EFFECT MODELS

Fixed effect models allow one to control for all time stable differences among a set of units for which we have repeated measures. For example, if we have a set of neighborhoods with a time series of observations for each neighborhood, then estimating the effects of a time-varying variable on an outcome of interest is well identified if all time stable differences (fixed neighborhood effects) can be accounted for. In a linear model context, this can be represented as:

$$y_{it} = \alpha_i + \sum_k \beta_k x_{it} + e_{it} \tag{33}$$

where the estimates of β are more robust if we can estimate each of the fixed effects α_i. Unfortunately, the estimation of fixed effects is not trivial—especially when there are a large number of cross-sectional units. The problem becomes more intractable when we wish to measure fixed effects in non-linear models like count outcomes.

An approximate solution to this problem is to estimate the fixed effects first and then introduce them as a variable (with its own parameter) in the next stage. In the above example, this would mean first estimating a regression model

$$y_{it} = \alpha_i + e_{it} \tag{34}$$

and using the $\hat{a}_i$ to predict $\hat{y}_{it}$. In the second stage we would then estimate the regression

$$y_{it} = \alpha + \beta_0 \hat{y}_{it} + \sum_k \beta_k x_{it} + e_{it} \tag{35}$$

to get unbiased estimates of β_k (the coefficients of interest). Note that although the prediction is indexed by i and t, it is really a constant within a unit ($\forall t$). In fact, it is defined as $\hat{y}_{it} = \hat{a}_i$ $\forall i, t$.

It is well known from linear regression theory that a model with only categorical terms need not be estimated but can be computed directly as the mean of outcomes within the unit. In other words, $\hat{a}_i = T^{-1} \sum_t y_{it}$ $\forall i$. Therefore, we can simply create a new variable that is the mean of the outcome y within each of the neighborhoods and use that as a variable in the second stage regression. This procedure accounts for most of the fixed time-stable differences within the units and yields robust estimates for the β parameters of interest.

In the current setting, the models are not linear but log-linear. As a result, we first created auxiliary variables

$$c^*_{it} = \log\left(T^{-1} \sum_t c_{it}\right) \tag{36}$$

$$f^*_{it} = \log\left(T^{-1} \sum_t f_{it}\right) \tag{37}$$

and included them in the data matrices $\mathbf{X}_c$ and $\mathbf{X}_f$. The coefficients on these variables are not of interest to the analysis but their inclusion in the model helps control for all time-stable differences among the cross-sectional units.

ITERATIVE PROCEDURE FOR ESTIMATING ENDOGENOUS TERMS

A second complication in the implementation of the information-theoretic model is the complexity of the dual objective function (20) and its gradient/hessian. This is because the problem is non-linear in parameters.

The problem stems from the need to estimate reduced form equation (15) rather than in its structural form (14). We need to ensure that the $\boldsymbol{\eta}$ on both sides of the structural form are the same value. For convenience, the structural form is reproduces below.

$$\ln \boldsymbol{\eta} = \mathbf{X}\boldsymbol{\beta} + \sum_l \rho_l \mathbf{W}_l \ln \boldsymbol{\eta} \tag{38}$$

As can be seen, the term ln $\boldsymbol{\eta}$ appears on left and right hand sides of this equation. We need to ensure that in the final estimates of the parameters of interest $\boldsymbol{\beta}$ and ρ_l are such that they produce the same ln $\boldsymbol{\eta}$ terms on both sides of the equation. The typical strategy is to derive the reduced form by taking all ln $\boldsymbol{\eta}$ terms to the LHS and all unknown parameters to the RHS. The reduced form solution (15) is reproduced below for convenience.

$$\ln \boldsymbol{\eta} = \left(\mathbf{I} - \sum_l \rho_l \mathbf{W}_l\right)^{-1} \mathbf{X}\boldsymbol{\beta} \tag{39}$$

Note that this form creates two complexities. First, it involves the inversion of full N X N matrix. Second, the parameters to be estimated $\boldsymbol{\beta}$ and ρ_l are no longer linearly separable. These two issues make this a particularly difficult problem to solve.

The EM solution to this problem is to successively re-estimate the parameters using predictions of $\boldsymbol{\eta}$ from the previous iteration in the current set of predictors. That is, first estimate the equation setting $\rho_l = 0$ $\forall l$. Use the estimated $\boldsymbol{\beta}$ to predict $\hat{\eta}$ and then re-estimate all parameters by replace $\boldsymbol{\eta}$ by its prediction on the RHS. This procedure can be repeated till convergence. The iterative procedure can be defined as

$$\ln \boldsymbol{\eta} = \mathbf{X}\boldsymbol{\beta}^{(j)} + \sum_l \rho_l^{(j)} \mathbf{W}_l \ln \hat{\boldsymbol{\eta}}^{(j-1)} \tag{40}$$

and convergence is achieved when $\hat{\eta}^{(j)} = \hat{\eta}^{(j-1)}$ which happens when $\hat{\beta}^{(j)} = \hat{\beta}^{(j-1)}$ and $\hat{\rho}_l^{(j)} = \hat{\rho}_l^{(j-1)}$ $\forall l$. Now the final solution is such that the $\boldsymbol{\eta}$ is the same on both sides of the structural equation.

This iterative procedure was employed to estimate the spatial, temporal, and cross effects in the simultaneous system of equations linking foreclosures and crime.

Results and Discussion

The tables in Appendix B are organized in three panels each—the first panel (labeled CE-Static) presents results form the traditional Poisson model, the second panel (labeled GCE-Static) presents results from allowing over-dispersion in the static model, and the third panel (labeled GCE-dynamic) presents findings from the full dynamic model with all temporal and spatial lagged effects included.

As expected, in all models, going from the Poisson model to the generalized model (the GCE variant) reduces the statistical significance of the parameters of interest (i.e., the Chi square values are typically lower). A common shortcoming of the Poisson model is that it forces the mean and variance of the recovered rate to be the same (termed equi-dispersion). Allowing over-dispersion typically yields more robust estimates and provides for better coverage (more believable standard errors). In effect, in the presence of over-dispersion, the Poisson model yields results that are overly optimistic and oftentimes misleading. The GCE accounts for this and yields overdispersion parameters that are typically statistically significant.

Going from the static GCE model to the dynamic variant also yields some interesting findings. In all of the models, the fixed effect terms are statistically significant suggesting that there is sufficient amount of time-stable effects in the census tracts. If these effects are ignored, then one runs the risk of mistaking time-stable differences as substantive effects.

In all the models, the crime series (violent, property, and all) show strong trending (across years) and seasonal (across quarters) variation. Typically, quarters 2, 3 and 4 have more crime than quarter 1 (the omitted category). For the foreclosures series, the temporal trends are evident. However, the seasonal variation is evident in only the inventory series not the sales series (for Washington, DC). The Miami sales series does display seasonal variation.

Finally, as expected, when the temporal and spatial lagged terms are statistically significant, they tend to be positive but small. This suggests that the spatial and temporal dynamics are stable (i.e., a small increase in crime or foreclosures spills over to the next period and to the surrounding areas).

Appendix B. Detailed Model Results

Table B.1: Model estimates for the links between crime (all) and foreclosures (sales), Washington, DC.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	3.8549	0.0061	394836.72	0.00	177.9900	-0.1631	0.0024	4739.82	0.00	-2905.4669	-0.0823	0.0142	33.77	0.00	-9.7552
Y2004	-0.1337	0.0073	332.80	0.00	-6.1710	0.0075	0.0020	13.32	0.00	133.2737	-0.0501	0.0050	102.07	0.00	-5.9408
Y2005	-0.1989	0.0075	711.59	0.00	-9.1844	0.0056	0.0021	7.29	0.01	99.3287	-0.0751	0.0052	206.99	0.00	-8.9070
Y2006	-0.1637	0.0074	491.44	0.00	-7.5597	0.0054	0.0021	6.71	0.01	95.5140	-0.0610	0.0052	136.08	0.00	-7.2363
Y2007	-0.1204	0.0073	272.11	0.00	-5.5604	0.0052	0.0021	6.25	0.01	92.3474	-0.0443	0.0051	76.59	0.00	-5.2518
Y2008	-0.1129	0.0073	239.93	0.00	-5.2109	0.0070	0.0021	11.72	0.00	125.1136	-0.0412	0.0051	64.68	0.00	-4.8797
Y2009	-0.1514	0.0074	422.94	0.00	-6.9898	0.0034	0.0022	2.55	0.11	61.3889	-0.0566	0.0051	124.45	0.00	-6.7081
Y2010	-0.2558	0.0076	1140.21	0.00	-11.8116	0.0060	0.0021	8.44	0.00	106.5739	-0.0972	0.0055	314.47	0.00	-11.5180
Q2	0.1601	0.0055	855.07	0.00	7.3932	-0.0017	0.0003	31.04	0.00	-30.0675	0.0631	0.0038	280.64	0.00	7.4808
Q3	0.1918	0.0054	1244.87	0.00	8.8564	-0.0009	0.0002	12.83	0.00	-15.3516	0.0758	0.0039	373.40	0.00	8.9863
Q4	0.1062	0.0055	367.04	0.00	4.9052	-0.0014	0.0003	26.39	0.00	-25.7989	0.0426	0.0038	126.79	0.00	5.0553
Crim (Tlag 1)											-0.0018	0.0019	0.92	0.34	-0.2169
Crim (Slag 1)											0.0006	0.0038	0.03	0.86	0.0770
Forc											0.0008	0.0019	0.20	0.65	0.1003
Forc (Slag 1)											0.0002	0.0025	0.01	0.94	0.0237
Foreclosures Equation															
Intercept	-0.2982	0.0541	30.39	0.00	-0.1306	-0.0177	0.0484	0.13	0.71	-0.0172	-1.1340	0.1285	77.85	0.00	-0.5030
Y2004	-0.2131	0.0628	11.53	0.00	-0.0933	-0.0014	0.0522	0.00	0.98	-0.0013	-0.1408	0.0639	4.85	0.03	-0.0624
Y2005	-0.6251	0.0711	77.37	0.00	-0.2737	-0.0024	0.0522	0.00	0.96	-0.0023	-0.3877	0.0818	22.44	0.00	-0.1720
Y2006	-0.9172	0.0785	136.43	0.00	-0.4016	-0.0029	0.0522	0.00	0.96	-0.0028	-0.5381	0.1018	27.96	0.00	-0.2387
Y2007	-0.7549	0.0742	103.50	0.00	-0.3305	-0.0026	0.0522	0.00	0.96	-0.0025	-0.4115	0.0956	18.52	0.00	-0.1826
Y2008	-0.9040	0.0782	133.80	0.00	-0.3958	-0.0029	0.0522	0.00	0.96	-0.0028	-0.5209	0.1015	26.36	0.00	-0.2311
Y2009	-0.5676	0.0698	66.20	0.00	-0.2485	-0.0023	0.0522	0.00	0.97	-0.0022	-0.2949	0.0852	11.98	0.00	-0.1308
Y2010	-0.7930	0.0752	111.28	0.00	-0.3472	-0.0027	0.0522	0.00	0.96	-0.0026	-0.4661	0.0930	25.11	0.00	-0.2068
Q2	0.0999	0.0543	3.39	0.07	0.0438	-0.0040	0.0369	0.01	0.91	-0.0039	0.1087	0.0548	3.94	0.05	0.0482
Q3	-0.0031	0.0556	0.00	0.96	-0.0014	-0.0045	0.0369	0.01	0.90	-0.0043	-0.0123	0.0554	0.05	0.82	-0.0055
Q4	-0.0314	0.0560	0.31	0.58	-0.0137	-0.0046	0.0369	0.02	0.90	-0.0044	-0.0073	0.0561	0.02	0.90	-0.0032
Forc (Tlag 1)											0.2769	0.0794	12.16	0.00	0.1228
Forc (Slag 1)											0.1420	0.0401	12.52	0.00	0.0630
Auxiliary Parameters															
Fixed Effects (Crim)											0.4022	0.0079	2563.55	0.00	
Fixed Effects (Forc)											2.0485	0.2289	80.05	0.00	
Dispersion (Crim)						0.0261	0.0003	#########	0.00		-0.3825	0.0072	7341.83	0.00	
Dispersion (Forc)						-1.0036	0.0383	0.01	0.92		-0.9797	0.0583	0.12	0.73	

Table B.2: Model estimates for the links between crime (property) and foreclosures (sales), Washington, DC.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	3.6003	0.0070	266585.60	0.00	128.4365	-0.1429	0.0026	3051.59	0.00	-862.0110	-0.0932	0.0146	40.94	0.00	-8.8958
Y2004	-0.1270	0.0083	233.34	0.00	-4.5300	0.0096	0.0017	32.56	0.00	57.8910	-0.0460	0.0055	70.61	0.00	-4.3914
Y2005	-0.2161	0.0085	643.99	0.00	-7.7102	0.0075	0.0017	19.07	0.00	45.4638	-0.0783	0.0058	181.66	0.00	-7.4741
Y2006	-0.1761	0.0084	437.16	0.00	-6.2830	0.0077	0.0017	20.13	0.00	46.5417	-0.0626	0.0058	116.07	0.00	-5.9705
Y2007	-0.1284	0.0083	238.45	0.00	-4.5811	0.0096	0.0017	32.70	0.00	58.0132	-0.0451	0.0056	64.65	0.00	-4.3072
Y2008	-0.1058	0.0083	163.88	0.00	-3.7751	0.0084	0.0017	24.35	0.00	50.6392	-0.0363	0.0056	41.28	0.00	-3.4619
Y2009	-0.1429	0.0083	292.89	0.00	-5.0968	0.0065	0.0018	13.56	0.00	39.3409	-0.0510	0.0056	83.53	0.00	-4.8695
Y2010	-0.2550	0.0086	876.91	0.00	-9.0955	0.0070	0.0017	16.15	0.00	42.3501	-0.0925	0.0060	236.42	0.00	-8.8214
Q2	0.1580	0.0062	643.99	0.00	5.6379	0.0359	0.0022	264.14	0.00	216.5140	0.0593	0.0041	205.40	0.00	5.6566
Q3	0.1878	0.0062	921.40	0.00	6.6981	0.0351	0.0022	251.48	0.00	211.4914	0.0708	0.0043	272.87	0.00	6.7550
Q4	0.1060	0.0063	282.96	0.00	3.7828	0.0377	0.0022	291.39	0.00	227.5668	0.0404	0.0042	92.96	0.00	3.8552
Crim (Tlag 1)											-0.0010	0.0023	0.18	0.67	-0.0912
Crim (Slag 1)											0.0004	0.0043	0.01	0.92	0.0413
Forc											0.0006	0.0021	0.09	0.76	0.0607
Forc (Slag 1)											0.0020	0.0029	0.49	0.48	0.1914
Foreclosures Equation															
Intercept	-0.2982	0.0541	30.39	0.00	-0.1306	-0.0227	0.0485	0.22	0.64	-0.0219	-1.4346	0.1383	107.61	0.00	-0.6300
Y2004	-0.2131	0.0628	11.53	0.00	-0.0933	-0.0017	0.0524	0.00	0.97	-0.0017	-0.1651	0.0638	6.69	0.01	-0.0725
Y2005	-0.6251	0.0711	77.38	0.00	-0.2737	-0.0030	0.0524	0.00	0.95	-0.0029	-0.4702	0.0814	33.33	0.00	-0.2065
Y2006	-0.9172	0.0785	136.43	0.00	-0.4016	-0.0037	0.0524	0.00	0.94	-0.0036	-0.6836	0.1010	45.83	0.00	-0.3002
Y2007	-0.7549	0.0742	103.50	0.00	-0.3305	-0.0034	0.0524	0.00	0.95	-0.0032	-0.5593	0.0946	34.96	0.00	-0.2456
Y2008	-0.9040	0.0782	133.80	0.00	-0.3958	-0.0037	0.0524	0.00	0.94	-0.0036	-0.6723	0.1015	43.92	0.00	-0.2953
Y2009	-0.5676	0.0698	66.20	0.00	-0.2485	-0.0029	0.0524	0.00	0.96	-0.0028	-0.4195	0.0843	24.79	0.00	-0.1842
Y2010	-0.7930	0.0752	111.28	0.00	-0.3472	-0.0034	0.0524	0.00	0.95	-0.0033	-0.5916	0.0932	40.27	0.00	-0.2598
Q2	0.0999	0.0543	3.39	0.07	0.0438	-0.0051	0.0371	0.02	0.89	-0.0049	0.0786	0.0544	2.08	0.15	0.0345
Q3	-0.0031	0.0556	0.00	0.96	-0.0014	-0.0057	0.0371	0.02	0.88	-0.0055	-0.0067	0.0559	0.01	0.90	-0.0029
Q4	-0.0314	0.0560	0.31	0.58	-0.0138	-0.0059	0.0371	0.02	0.87	-0.0057	-0.0242	0.0560	0.19	0.66	-0.0106
Forc (Tlag 1)											0.0442	0.0806	0.30	0.58	0.0194
Forc (Slag 1)											0.2286	0.0401	32.52	0.00	0.1004
Auxiliary Parameters															
Fixed Effects (Crim)											0.3874	0.0079	2417.70	0.00	
Fixed Effects (Forc)											2.7415	0.2405	129.98	0.00	
Dispersion (Crim)						0.0158	0.0003	12748.30	0.00		-0.3645	0.007	8353.55	0.00	
Dispersion (Forc)						-1.0046	0.0385	0.01	0.91		-1.0262	0.0586	0.20	0.65	

Table B.3: Model estimates for the links between crime (violent) and foreclosures (sales), Washington, DC.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	2.3620	0.0129	33492.96	0.00	24.7925	0.1002	0.0101	97.88	0.00	7.1172	-0.4371	0.0267	268.01	0.00	-6.1274
Y2004	-0.1568	0.0155	102.29	0.00	-1.6458	-0.0225	0.0059	14.57	0.00	-1.6017	-0.1040	0.0142	53.27	0.00	-1.4574
Y2005	-0.1421	0.0154	84.71	0.00	-1.4919	-0.0204	0.0059	12.04	0.00	-1.4463	-0.0915	0.0144	40.21	0.00	-1.2823
Y2006	-0.1224	0.0154	63.49	0.00	-1.2848	-0.0174	0.0058	8.99	0.00	-1.2391	-0.0753	0.0148	25.89	0.00	-1.0551
Y2007	-0.0935	0.0152	37.64	0.00	-0.9817	-0.0132	0.0057	5.30	0.02	-0.9396	-0.0547	0.0145	14.28	0.00	-0.7663
Y2008	-0.1373	0.0154	79.24	0.00	-1.4411	-0.0196	0.0059	11.25	0.00	-1.3953	-0.0862	0.0148	33.73	0.00	-1.2080
Y2009	-0.1811	0.0156	134.61	0.00	-1.9006	-0.0262	0.0060	19.23	0.00	-1.8616	-0.1206	0.0145	68.80	0.00	-1.6901
Y2010	-0.2588	0.0159	263.33	0.00	-2.7162	-0.0382	0.0062	37.95	0.00	-2.7170	-0.1772	0.0152	135.66	0.00	-2.4842
Q2	0.1673	0.0115	211.64	0.00	1.7559	0.0253	0.0045	31.51	0.00	1.7973	0.1259	0.0106	141.43	0.00	1.7643
Q3	0.2056	0.0114	325.37	0.00	2.1584	0.0308	0.0045	47.56	0.00	2.1873	0.1573	0.0111	201.36	0.00	2.2045
Q4	0.1070	0.0117	84.13	0.00	1.1228	0.0164	0.0046	12.85	0.00	1.1676	0.0864	0.0110	61.94	0.00	1.2118
Crim (Tlag 1)											-0.0181	0.0081	4.97	0.03	-0.2533
Crim (Slag 1)											0.0223	0.0095	5.49	0.02	0.3122
Forc											0.0011	0.0052	0.04	0.84	0.0152
Forc (Slag 1)											0.0042	0.0077	0.29	0.59	0.0583
Foreclosures Equation															
Intercept	-0.2982	0.0541	30.38	0.00	-0.1305	-0.9798	0.0499	386.22	0.00	-0.7222	-1.4467	0.1398	107.06	0.00	-0.6269
Y2004	-0.2131	0.0628	11.53	0.00	-0.0933	-0.1078	0.0451	5.73	0.02	-0.0795	-0.1651	0.0643	6.59	0.01	-0.0716
Y2005	-0.6251	0.0711	77.38	0.00	-0.2737	-0.3525	0.0559	39.82	0.00	-0.2599	-0.4805	0.0827	33.75	0.00	-0.2082
Y2006	-0.9172	0.0785	136.44	0.00	-0.4016	-0.5520	0.0653	71.45	0.00	-0.4069	-0.7009	0.1030	46.29	0.00	-0.3037
Y2007	-0.7549	0.0742	103.51	0.00	-0.3305	-0.4387	0.0599	53.66	0.00	-0.3234	-0.5734	0.0964	35.35	0.00	-0.2485
Y2008	-0.9041	0.0782	133.81	0.00	-0.3958	-0.5426	0.0648	70.01	0.00	-0.4000	-0.6896	0.1035	44.36	0.00	-0.2988
Y2009	-0.5676	0.0698	66.21	0.00	-0.2485	-0.3157	0.0542	33.95	0.00	-0.2327	-0.4296	0.0857	25.10	0.00	-0.1861
Y2010	-0.7931	0.0752	111.29	0.00	-0.3472	-0.4648	0.0611	57.83	0.00	-0.3426	-0.6062	0.0950	40.72	0.00	-0.2627
Q2	0.0999	0.0543	3.39	0.07	0.0437	0.0585	0.0416	1.98	0.16	0.0431	0.0816	0.0549	2.21	0.14	0.0354
Q3	-0.0032	0.0556	0.00	0.95	-0.0014	-0.0019	0.0431	0.00	0.97	-0.0014	-0.0046	0.0562	0.01	0.93	-0.0020
Q4	-0.0314	0.0560	0.31	0.57	-0.0138	-0.0190	0.0436	0.19	0.66	-0.0140	-0.0232	0.0564	0.17	0.68	-0.0101
Forc (Tlag 1)											0.0390	0.0822	0.22	0.64	0.0169
Forc (Slag 1)											0.2105	0.0405	27.00	0.00	0.0912
Auxiliary Parameters															
Fixed Effects (Crim)											0.8655	0.0197	1932.95	0.00	
Fixed Effects (Forc)											2.7252	0.2426	126.21	0.00	
Dispersion (Crim)						-0.0712	0.0034	74325.24	0.00		-0.7348	0.0149	315.79	0.00	
Dispersion (Forc)						0.1590	0.0361	1029.04	0.00		-1.0241	0.0594	0.16	0.69	

Table B.4: Model estimates for the links between crime (all) and foreclosures (inventory), Washington, DC.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	3.8549	0.0061	394834.25	0.00	177.9897	0.1377	0.0047	867.30	0.00	114.2569	-0.0863	0.0144	36.12	0.00	-10.2338
Y2004	-0.1336	0.0073	332.78	0.00	-6.1708	-0.0073	0.0017	17.91	0.00	-6.0190	-0.0500	0.0049	102.03	0.00	-5.9247
Y2005	-0.1989	0.0075	711.55	0.00	-9.1842	-0.0109	0.0018	38.40	0.00	-9.0642	-0.0751	0.0051	212.65	0.00	-8.8989
Y2006	-0.1637	0.0074	491.41	0.00	-7.5595	-0.0089	0.0017	26.49	0.00	-7.4132	-0.0612	0.0051	146.45	0.00	-7.2533
Y2007	-0.1204	0.0073	272.09	0.00	-5.5602	-0.0065	0.0017	14.63	0.00	-5.4110	-0.0447	0.0049	83.03	0.00	-5.3002
Y2008	-0.1129	0.0073	239.91	0.00	-5.2107	-0.0061	0.0017	12.90	0.00	-5.0643	-0.0423	0.0049	75.07	0.00	-5.0156
Y2009	-0.1514	0.0074	422.91	0.00	-6.9896	-0.0082	0.0017	22.79	0.00	-6.8392	-0.0579	0.0050	133.14	0.00	-6.8624
Y2010	-0.2558	0.0076	1140.18	0.00	-11.8114	-0.0142	0.0018	61.53	0.00	-11.7808	-0.0988	0.0054	338.39	0.00	-11.7110
Q2	0.1601	0.0055	855.09	0.00	7.3933	0.0090	0.0013	47.42	0.00	7.5031	0.0632	0.0038	281.19	0.00	7.4870
Q3	0.1918	0.0054	1244.90	0.00	8.8565	0.0108	0.0013	68.09	0.00	8.9369	0.0757	0.0039	372.44	0.00	8.9788
Q4	0.1062	0.0055	367.05	0.00	4.9052	0.0061	0.0013	20.77	0.00	5.0277	0.0426	0.0038	126.28	0.00	5.0451
Crim (Tlag 1)											-0.0020	0.0019	1.04	0.31	-0.2313
Crim (Slag 1)											0.0010	0.0038	0.06	0.80	0.1138
Forc											0.0007	0.0014	0.26	0.61	0.0868
Forc (Slag 1)											0.0005	0.0018	0.08	0.78	0.0594
Foreclosures Equation															
Intercept	1.7930	0.0171	11003.80	0.00	11.8925	-0.2063	0.0077	723.64	0.00	-16.7269	-0.8661	0.0382	513.80	0.00	-4.8775
Y2004	-0.1680	0.0216	60.70	0.00	-1.1145	-0.0213	0.0077	7.60	0.01	-1.7251	-0.2167	0.0248	76.53	0.00	-1.2201
Y2005	-0.5072	0.0238	453.74	0.00	-3.3641	-0.0765	0.0096	62.90	0.00	-6.2028	-0.5907	0.0287	423.24	0.00	-3.3266
Y2006	-0.6414	0.0249	665.97	0.00	-4.2544	-0.1035	0.0106	94.93	0.00	-8.3955	-0.7347	0.0310	560.36	0.00	-4.1375
Y2007	-0.3106	0.0224	191.46	0.00	-2.0599	-0.0423	0.0084	25.20	0.00	-3.4334	-0.3665	0.0257	204.07	0.00	-2.0638
Y2008	0.1303	0.0200	42.42	0.00	0.8642	0.0141	0.0066	4.54	0.03	1.1411	0.1205	0.0236	26.03	0.00	0.6787
Y2009	0.5622	0.0183	944.86	0.00	3.7289	0.0480	0.0058	67.78	0.00	3.8908	0.5986	0.0286	439.01	0.00	3.3713
Y2010	0.6424	0.0180	1269.36	0.00	4.2611	0.0524	0.0058	81.23	0.00	4.2462	0.6832	0.0308	492.06	0.00	3.8477
Q2	0.0256	0.0143	3.18	0.07	0.1696	0.0022	0.0042	0.28	0.60	0.1796	0.0119	0.0164	0.52	0.47	0.0668
Q3	0.0540	0.0142	14.37	0.00	0.3581	0.0045	0.0041	1.21	0.27	0.3689	0.0433	0.0165	6.89	0.01	0.2441
Q4	0.0712	0.0142	25.21	0.00	0.4723	0.0059	0.0041	2.07	0.15	0.4774	0.0618	0.0166	13.78	0.00	0.3479
Forc (Tlag 1)											0.0516	0.0159	10.55	0.00	0.2907
Forc (Slag 1)											0.0212	0.0086	6.14	0.01	0.1195
Auxiliary Parameters															
Fixed Effects (Crim)											0.4025	0.0080	2535.36	0.00	
Fixed Effects (Forc)											1.3896	0.0341	1658.51	0.00	
Dispersion (Crim)						-0.0392	0.0011	726343.83	0.00		-0.3825	0.0072	7341.51	0.00	
Dispersion (Forc)						0.0228	0.0022	216322.79	0.00		-1.1920	0.0255	56.91	0.00	

Table B.5: Model estimates for the links between crime (property) and foreclosures (inventory), Washington, DC.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	3.6003	0.0070	266585.50	0.00	128.4365	0.1397	0.0053	686.43	0.00	76.0153	-0.0992	0.0154	41.56	0.00	-9.4659
Y2004	-0.1270	0.0083	233.34	0.00	-4.5300	-0.0081	0.0021	14.75	0.00	-4.3997	-0.0464	0.0055	71.78	0.00	-4.4223
Y2005	-0.2161	0.0085	643.98	0.00	-7.7102	-0.0140	0.0022	40.90	0.00	-7.6214	-0.0791	0.0058	189.04	0.00	-7.5427
Y2006	-0.1761	0.0084	437.15	0.00	-6.2830	-0.0113	0.0022	27.72	0.00	-6.1611	-0.0639	0.0056	128.23	0.00	-6.0936
Y2007	-0.1284	0.0083	238.45	0.00	-4.5811	-0.0082	0.0021	15.07	0.00	-4.4506	-0.0467	0.0055	72.98	0.00	-4.4513
Y2008	-0.1058	0.0083	163.88	0.00	-3.7751	-0.0067	0.0021	10.33	0.00	-3.6504	-0.0390	0.0054	52.26	0.00	-3.7229
Y2009	-0.1429	0.0083	292.89	0.00	-5.0968	-0.0091	0.0021	18.52	0.00	-4.9645	-0.0536	0.0055	94.30	0.00	-5.1158
Y2010	-0.2550	0.0086	876.91	0.00	-9.0955	-0.0166	0.0022	55.73	0.00	-9.0623	-0.0957	0.0059	265.36	0.00	-9.1284
Q2	0.1580	0.0062	643.99	0.00	5.6379	0.0105	0.0016	42.14	0.00	5.7260	0.0592	0.0041	205.39	0.00	5.6521
Q3	0.1878	0.0062	921.40	0.00	6.6981	0.0124	0.0016	59.53	0.00	6.7635	0.0704	0.0043	269.30	0.00	6.7135
Q4	0.1060	0.0063	282.96	0.00	3.7828	0.0071	0.0016	18.88	0.00	3.8815	0.0399	0.0042	90.71	0.00	3.8088
Crim (Tlag 1)											-0.0007	0.0023	0.10	0.75	-0.0691
Crim (Slag 1)											0.0012	0.0043	0.08	0.78	0.1139
Forc											0.0011	0.0016	0.46	0.50	0.1031
Forc (Slag 1)											0.0007	0.0020	0.11	0.75	0.0630
Foreclosures Equation															
Intercept	1.7930	0.0171	11003.85	0.00	11.8925	-0.2063	0.0077	710.20	0.00	-16.6932	-0.8661	0.0382	514.04	0.00	-4.8789
Y2004	-0.1681	0.0216	60.72	0.00	-1.1147	-0.0213	0.0077	7.63	0.01	-1.7243	-0.2165	0.0248	76.44	0.00	-1.2195
Y2005	-0.5072	0.0238	453.77	0.00	-3.3642	-0.0765	0.0096	62.93	0.00	-6.1933	-0.5909	0.0287	423.55	0.00	-3.3284
Y2006	-0.6414	0.0249	666.02	0.00	-4.2545	-0.1036	0.0106	94.97	0.00	-8.3839	-0.7351	0.0310	560.91	0.00	-4.1407
Y2007	-0.3106	0.0224	191.50	0.00	-2.0601	-0.0424	0.0084	25.22	0.00	-3.4280	-0.3667	0.0257	204.30	0.00	-2.0653
Y2008	0.1303	0.0200	42.42	0.00	0.8641	0.0141	0.0066	4.54	0.03	1.1375	0.1208	0.0236	26.15	0.00	0.6805
Y2009	0.5622	0.0183	944.81	0.00	3.7288	0.0480	0.0058	67.57	0.00	3.8806	0.5994	0.0286	439.82	0.00	3.3763
Y2010	0.6424	0.0180	1269.31	0.00	4.2610	0.0524	0.0058	81.14	0.00	4.2360	0.6841	0.0308	492.95	0.00	3.8535
Q2	0.0256	0.0143	3.19	0.07	0.1698	0.0022	0.0042	0.28	0.60	0.1803	0.0120	0.0164	0.53	0.47	0.0676
Q3	0.0540	0.0142	14.39	0.00	0.3583	0.0046	0.0041	1.21	0.27	0.3691	0.0435	0.0165	6.95	0.01	0.2452
Q4	0.0712	0.0142	25.23	0.00	0.4725	0.0059	0.0041	2.08	0.15	0.4776	0.0620	0.0166	13.87	0.00	0.3492
Forc (Tlag 1)											0.0514	0.0159	10.47	0.00	0.2895
Forc (Slag 1)											0.0204	0.0086	5.70	0.02	0.1152
Auxiliary Parameters															
Fixed Effects (Crim)											0.3870	0.0079	2409.06	0.00	
Fixed Effects (Forc)											1.3901	0.0341	1658.89	0.00	
Dispersion (Crim)						-0.0437	0.0014	498123.60	0.00		-0.3644	0.0070	8353.48	0.00	
Dispersion (Forc)						0.0228	0.0022	208686.21	0.00		-1.1919	0.0255	56.82	0.00	

Table B.6: Model estimates for the links between crime (violent) and foreclosures (inventory), Washington, DC.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	2.3620	0.0129	33492.75	0.00	24.7924	0.1002	0.0101	97.89	0.00	7.1176	-0.4454	0.0250	317.00	0.00	-6.2436
Y2004	-0.1568	0.0155	102.29	0.00	-1.6458	-0.0226	0.0059	14.57	0.00	-1.6022	-0.1046	0.0142	54.01	0.00	-1.4656
Y2005	-0.1421	0.0154	84.71	0.00	-1.4919	-0.0204	0.0059	12.04	0.00	-1.4467	-0.0934	0.0142	43.28	0.00	-1.3093
Y2006	-0.1224	0.0154	63.49	0.00	-1.2848	-0.0174	0.0058	9.00	0.00	-1.2395	-0.0784	0.0142	30.47	0.00	-1.0995
Y2007	-0.0935	0.0152	37.64	0.00	-0.9817	-0.0132	0.0057	5.31	0.02	-0.9400	-0.0578	0.0140	17.15	0.00	-0.8108
Y2008	-0.1373	0.0154	79.24	0.00	-1.4411	-0.0196	0.0059	11.26	0.00	-1.3956	-0.0911	0.0141	41.66	0.00	-1.2775
Y2009	-0.1811	0.0156	134.61	0.00	-1.9006	-0.0262	0.0060	19.24	0.00	-1.8621	-0.1247	0.0145	73.61	0.00	-1.7481
Y2010	-0.2588	0.0159	263.33	0.00	-2.7162	-0.0383	0.0062	37.97	0.00	-2.7175	-0.1826	0.0151	146.01	0.00	-2.5598
Q2	0.1673	0.0115	211.65	0.00	1.7560	0.0253	0.0045	31.50	0.00	1.7972	0.1260	0.0106	141.35	0.00	1.7658
Q3	0.2056	0.0114	325.39	0.00	2.1584	0.0308	0.0045	47.56	0.00	2.1873	0.1567	0.0111	200.02	0.00	2.1962
Q4	0.1070	0.0117	84.14	0.00	1.1228	0.0164	0.0046	12.85	0.00	1.1676	0.0858	0.0110	61.19	0.00	1.2032
Crim (Tlag 1)											-0.0179	0.0081	4.87	0.03	-0.2510
Crim (Slag 1)											0.0239	0.0097	6.08	0.01	0.3353
Forc											0.0035	0.0041	0.73	0.39	0.0489
Forc (Slag 1)											-0.0011	0.0056	0.04	0.85	-0.0151
Foreclosures Equation															
Intercept	1.7930	0.0171	11003.62	0.00	11.8925	-0.2072	0.0080	668.50	0.00	-16.5749	-0.8645	0.0382	511.98	0.00	-4.8682
Y2004	-0.1681	0.0216	60.71	0.00	-1.1146	-0.0212	0.0077	7.58	0.01	-1.6983	-0.2171	0.0248	76.85	0.00	-1.2227
Y2005	-0.5072	0.0238	453.74	0.00	-3.3641	-0.0763	0.0096	62.60	0.00	-6.1074	-0.5908	0.0287	423.36	0.00	-3.3271
Y2006	-0.6414	0.0249	666.00	0.00	-4.2545	-0.1033	0.0106	94.42	0.00	-8.2676	-0.7346	0.0310	560.25	0.00	-4.1370
Y2007	-0.3106	0.0224	191.48	0.00	-2.0601	-0.0422	0.0084	25.11	0.00	-3.3801	-0.3666	0.0257	204.26	0.00	-2.0647
Y2008	0.1303	0.0200	42.42	0.00	0.8642	0.0140	0.0066	4.53	0.03	1.1221	0.1200	0.0236	25.80	0.00	0.6757
Y2009	0.5622	0.0183	944.84	0.00	3.7289	0.0478	0.0058	66.91	0.00	3.8265	0.5978	0.0286	438.00	0.00	3.3664
Y2010	0.6424	0.0180	1269.34	0.00	4.2611	0.0523	0.0058	80.96	0.00	4.1832	0.6821	0.0308	490.76	0.00	3.8412
Q2	0.0256	0.0143	3.19	0.07	0.1698	0.0022	0.0042	0.28	0.60	0.1778	0.0114	0.0164	0.48	0.49	0.0641
Q3	0.0540	0.0142	14.39	0.00	0.3583	0.0046	0.0042	1.21	0.27	0.3663	0.0428	0.0165	6.73	0.01	0.2413
Q4	0.0712	0.0142	25.23	0.00	0.4725	0.0059	0.0041	2.09	0.15	0.4757	0.0613	0.0166	13.55	0.00	0.3449
Forc (Tlag 1)											0.0526	0.0159	10.93	0.00	0.2961
Forc (Slag 1)											0.0214	0.0086	6.24	0.01	0.1205
Auxiliary Parameters															
Fixed Effects (Crim)											0.8644	0.0197	1924.66	0.00	
Fixed Effects (Forc)											1.3884	0.0341	1657.08	0.00	
Dispersion (Crim)						-0.0712	0.0034	74325.12	0.00		-0.7348	0.0149	315.84	0.00	
Dispersion (Forc)						0.0231	0.0024	184257.05	0.00		-1.1921	0.0255	56.95	0.00	

Table B.7: Model estimates for the links between crime (all) and foreclosures (sales), Miami, FL.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	4.2300	0.0076	311915.50	0.00	256.2196	0.0756	0.0028	730.07	0.00	134.2039	0.1075	0.0300	12.80	0.00	15.7974
Y2004	-0.0863	0.0077	124.36	0.00	-5.2260	-0.0028	0.0014	4.04	0.04	-4.9574	-0.1698	0.0301	31.75	0.00	-24.9523
Y2005	-0.1536	0.0078	388.89	0.00	-9.3043	-0.0051	0.0014	12.92	0.00	-8.9695	-0.1925	0.0298	41.60	0.00	-28.2868
Y2006	-0.1916	0.0078	600.42	0.00	-11.6072	-0.0064	0.0014	20.20	0.00	-11.2919	-0.2070	0.0295	49.11	0.00	-30.4304
Y2007	-0.1171	0.0078	227.55	0.00	-7.0909	-0.0038	0.0014	7.47	0.01	-6.7764	-0.1839	0.0297	38.43	0.00	-27.0312
Y2008	-0.1175	0.0078	229.04	0.00	-7.1143	-0.0038	0.0014	7.52	0.01	-6.7993	-0.1881	0.0300	39.42	0.00	-27.6505
Y2009	-0.1907	0.0078	594.62	0.00	-11.5498	-0.0063	0.0014	20.00	0.00	-11.2335	-0.2164	0.0297	53.28	0.00	-31.8090
Y2010	-0.2584	0.0079	1076.11	0.00	-15.6527	-0.0087	0.0014	36.94	0.00	-15.4769	-0.2446	0.0295	68.80	0.00	-35.9518
Y2011	-0.2896	0.0108	720.15	0.00	-17.5410	-0.0099	0.0020	24.17	0.00	-17.6075	-0.2539	0.0294	74.61	0.00	-37.3100
Q2	0.0426	0.0038	125.04	0.00	2.5783	0.0015	0.0007	4.28	0.04	2.5922	0.0182	0.0027	47.00	0.00	2.6821
Q3	0.0475	0.0038	155.97	0.00	2.8761	0.0016	0.0007	5.34	0.02	2.8882	0.0187	0.0027	48.94	0.00	2.7526
Q4	0.0328	0.0038	73.84	0.00	1.9861	0.0011	0.0007	2.54	0.11	2.0015	0.0132	0.0025	27.21	0.00	1.9422
Crim (Tlag 1)											0.0306	0.0067	20.64	0.00	4.4993
Crim (Slag 1)											0.0009	0.0022	0.17	0.68	0.1322
Forc											0.0023	0.0019	1.55	0.21	0.3453
Forc (Slag 1)											0.0014	0.0029	0.22	0.64	0.2035
Foreclosures Equation															
Intercept	-0.5745	0.0650	78.07	0.00	-1.8150	-0.8836	0.0472	350.11	0.00	-22.9932	-1.5110	0.0733	425.29	0.00	-11.3418
Y2004	-0.2390	0.0720	11.03	0.00	-0.7551	-0.1125	0.0538	4.37	0.04	-2.9277	-0.1535	0.0601	6.52	0.01	-1.1519
Y2005	-0.9993	0.0808	153.07	0.00	-3.1571	-0.6365	0.0642	98.30	0.00	-16.5640	-0.7594	0.0706	115.54	0.00	-5.7003
Y2006	-0.9099	0.0794	131.27	0.00	-2.8749	-0.5688	0.0626	82.58	0.00	-14.8019	-0.6843	0.0692	97.69	0.00	-5.1364
Y2007	0.7874	0.0665	140.24	0.00	2.4878	0.3769	0.0483	60.83	0.00	9.8076	0.5040	0.0562	80.31	0.00	3.7836
Y2008	1.8039	0.0644	783.89	0.00	5.6994	0.6271	0.0472	176.31	0.00	16.3199	0.9951	0.0630	249.31	0.00	7.4699
Y2009	1.7727	0.0645	756.08	0.00	5.6007	0.6222	0.0472	173.48	0.00	16.1903	0.9822	0.0641	235.06	0.00	7.3729
Y2010	2.4764	0.0638	1504.43	0.00	7.8241	0.7047	0.0474	221.39	0.00	18.3393	1.2685	0.0708	321.40	0.00	9.5216
Y2011	1.8858	0.0710	704.73	0.00	5.9582	0.6318	0.0492	164.66	0.00	16.4411	1.0365	0.0793	170.93	0.00	7.7806
Q2	0.4941	0.0177	775.73	0.00	1.5612	0.0743	0.0075	99.39	0.00	1.9333	0.2170	0.0137	251.68	0.00	1.6287
Q3	0.5770	0.0175	1090.41	0.00	1.8229	0.0828	0.0074	124.70	0.00	2.1537	0.2529	0.0183	190.82	0.00	1.8984
Q4	0.3275	0.0183	318.82	0.00	1.0347	0.0541	0.0077	49.36	0.00	1.4068	0.1483	0.0194	58.74	0.00	1.1134
Forc (Tlag 1)											-0.0031	0.0168	0.04	0.85	-0.0236
Forc (Slag 1)											-0.0069	0.0084	0.67	0.41	-0.0519
Auxiliary Parameters															
Fixed Effects (Crim)											-0.6091	0.0088	4839.72	0.00	
Fixed Effects (Forc)											-0.4619	0.0228	411.55	0.00	
Dispersion (Crim)						-0.0202	0.0006	30459.11	0.00		-0.4071	0.0059	9945.56	0.00	
Dispersion (Forc)						0.0070	0.0036	77954.47	0.00		-0.3368	0.0100	4367.59	0.00	

Table B.8: Model estimates for the links between crime (property) and foreclosures (sales), Miami, FL.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	4.0703	0.0082	246605.13	0.00	212.9348	0.0937	0.0033	822.74	0.00	118.1023	0.0470	0.0326	2.07	0.15	5.9381
Y2004	-0.0806	0.0084	92.43	0.00	-4.2176	-0.0032	0.0017	3.68	0.06	-4.0324	-0.1236	0.0323	14.66	0.00	-15.6144
Y2005	-0.1425	0.0084	285.10	0.00	-7.4530	-0.0057	0.0017	11.60	0.00	-7.2335	-0.1458	0.0320	20.81	0.00	-18.4187
Y2006	-0.1725	0.0085	415.19	0.00	-9.0221	-0.0070	0.0017	17.06	0.00	-8.8178	-0.1576	0.0317	24.75	0.00	-19.9050
Y2007	-0.0949	0.0084	127.60	0.00	-4.9623	-0.0038	0.0017	5.11	0.02	-4.7616	-0.1307	0.0319	16.80	0.00	-16.5130
Y2008	-0.0983	0.0084	136.98	0.00	-5.1432	-0.0039	0.0017	5.49	0.02	-4.9395	-0.1348	0.0322	17.51	0.00	-17.0305
Y2009	-0.1647	0.0085	379.20	0.00	-8.6153	-0.0067	0.0017	15.54	0.00	-8.4049	-0.1610	0.0319	25.49	0.00	-20.3313
Y2010	-0.2221	0.0085	681.11	0.00	-11.6172	-0.0091	0.0017	28.40	0.00	-11.4864	-0.1849	0.0317	33.95	0.00	-23.3593
Y2011	-0.2511	0.0116	470.83	0.00	-13.1345	-0.0104	0.0024	19.28	0.00	-13.1452	-0.1947	0.0316	37.84	0.00	-24.5900
Q2	0.0304	0.0041	55.16	0.00	1.5911	0.0013	0.0008	2.30	0.13	1.5988	0.0130	0.0028	20.72	0.00	1.6381
Q3	0.0375	0.0041	84.18	0.00	1.9622	0.0016	0.0008	3.50	0.06	1.9685	0.0150	0.0029	27.08	0.00	1.8893
Q4	0.0292	0.0041	50.70	0.00	1.5259	0.0012	0.0008	2.12	0.15	1.5337	0.0118	0.0027	18.71	0.00	1.4870
Crim (Tlag 1)											0.0214	0.0075	8.14	0.00	2.7052
Crim (Slag 1)											0.0025	0.0025	0.98	0.32	0.3104
Forc											0.0021	0.0020	1.12	0.29	0.2683
Forc (Slag 1)											0.0005	0.0031	0.02	0.88	0.0609
Foreclosures Equation															
Intercept	-0.5745	0.0650	78.07	0.00	-1.8150	-0.8836	0.0472	350.11	0.00	-22.9929	-1.4836	0.0729	413.69	0.00	-11.1015
Y2004	-0.2390	0.0720	11.03	0.00	-0.7551	-0.1125	0.0538	4.37	0.04	-2.9280	-0.1528	0.0602	6.45	0.01	-1.1433
Y2005	-0.9993	0.0808	153.07	0.00	-3.1572	-0.6365	0.0642	98.29	0.00	-16.5632	-0.7497	0.0707	112.48	0.00	-5.6100
Y2006	-0.9099	0.0794	131.27	0.00	-2.8749	-0.5688	0.0626	82.58	0.00	-14.8027	-0.6746	0.0693	94.81	0.00	-5.0481
Y2007	0.7874	0.0665	140.24	0.00	2.4878	0.3769	0.0483	60.83	0.00	9.8073	0.4941	0.0562	77.19	0.00	3.6971
Y2008	1.8039	0.0644	783.89	0.00	5.6994	0.6271	0.0472	176.31	0.00	16.3196	0.9716	0.0627	239.97	0.00	7.2706
Y2009	1.7727	0.0645	756.08	0.00	5.6007	0.6221	0.0472	173.48	0.00	16.1900	0.9581	0.0638	225.63	0.00	7.1692
Y2010	2.4764	0.0638	1504.44	0.00	7.8241	0.7047	0.0474	221.39	0.00	18.3390	1.2361	0.0702	309.93	0.00	9.2500
Y2011	1.8858	0.0710	704.74	0.00	5.9582	0.6318	0.0492	164.66	0.00	16.4408	1.0031	0.0788	161.87	0.00	7.5060
Q2	0.4941	0.0177	775.74	0.00	1.5612	0.0743	0.0075	99.39	0.00	1.9333	0.2123	0.0136	243.30	0.00	1.5885
Q3	0.5770	0.0175	1090.42	0.00	1.8229	0.0828	0.0074	124.70	0.00	2.1537	0.2440	0.0182	180.78	0.00	1.8262
Q4	0.3275	0.0183	318.83	0.00	1.0347	0.0541	0.0077	49.36	0.00	1.4068	0.1402	0.0193	52.99	0.00	1.0495
Forc (Tlag 1)											0.0040	0.0168	0.06	0.81	0.0296
Forc (Slag 1)											-0.0001	0.0084	0.00	0.99	-0.0007
Auxiliary Parameters															
Fixed Effects (Crim)											0.4028	0.0095	1808.62	0.00	
Fixed Effects (Forc)											0.5276	0.0226	543.73	0.00	
Dispersion (Crim)						-0.0258	0.0007	20707.27	0.00		-0.4083	0.0060	9781.24	0.00	
Dispersion (Forc)						0.0070	0.0036	77954.85	0.00		-0.3381	0.0101	4323.07	0.00	

Table B.9: Model estimates for the links between crime (violent) and foreclosures (sales), Miami, FL.

	CE - Static					GCE - Static					GCE - Dynamic				
	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal	Parm	ase	ChiSq	pval	Marginal
Crime Equation															
Intercept	2.3139	0.0199	13587.96	0.00	19.1080	-0.2939	0.0140	438.96	0.00	-8.3334	-0.0868	0.0449	3.74	0.05	-1.0913
Y2004	-0.1205	0.0201	36.03	0.00	-0.9952	-0.0305	0.0131	5.39	0.02	-0.8637	-0.2474	0.0423	34.18	0.00	-3.1112
Y2005	-0.2199	0.0203	117.57	0.00	-1.8160	-0.0308	0.0132	5.46	0.02	-0.8730	-0.3071	0.0421	53.28	0.00	-3.8628
Y2006	-0.3071	0.0205	225.01	0.00	-2.5363	-0.0382	0.0138	7.72	0.01	-1.0838	-0.3593	0.0410	76.90	0.00	-4.5195
Y2007	-0.2520	0.0204	153.34	0.00	-2.0810	-0.0319	0.0134	5.71	0.02	-0.9058	-0.3232	0.0408	62.70	0.00	-4.0651
Y2008	-0.2328	0.0203	131.38	0.00	-1.9223	-0.0310	0.0132	5.51	0.02	-0.8783	-0.3118	0.0432	52.08	0.00	-3.9218
Y2009	-0.3504	0.0206	289.97	0.00	-2.8937	-0.0434	0.0139	9.80	0.00	-1.2299	-0.3846	0.0424	82.11	0.00	-4.8369
Y2010	-0.4898	0.0209	547.31	0.00	-4.0444	-0.0588	0.0141	17.32	0.00	-1.6680	-0.4689	0.0437	114.87	0.00	-5.8971
Y2011	-0.5436	0.0302	324.19	0.00	-4.4893	-0.0329	0.0154	4.56	0.03	-0.9327	-0.5006	0.0443	127.50	0.00	-6.2964
Q2	0.1198	0.0103	134.38	0.00	0.9892	-0.0385	0.0064	36.10	0.00	-1.0925	0.0868	0.0092	88.37	0.00	1.0918
Q3	0.1114	0.0104	115.69	0.00	0.9197	-0.0401	0.0065	38.60	0.00	-1.1365	0.0741	0.0092	64.31	0.00	0.9323
Q4	0.0565	0.0105	29.05	0.00	0.4669	-0.0481	0.0067	52.32	0.00	-1.3645	0.0383	0.0088	18.99	0.00	0.4817
Crim (Tlag 1)											0.0596	0.0140	18.13	0.00	0.7494
Crim (Slag 1)											-0.0045	0.0062	0.53	0.47	-0.0571
Forc											0.0157	0.0074	4.48	0.03	0.1969
Forc (Slag 1)											-0.0165	0.0113	2.13	0.14	-0.2072
Foreclosures Equation															
Intercept	-0.5745	0.0650	78.07	0.00	-1.8150	-0.0527	0.0504	1.09	0.30	-0.0930	-1.5165	0.0733	428.01	0.00	-11.3925
Y2004	-0.2390	0.0720	11.03	0.00	-0.7550	-0.0560	0.0494	1.28	0.26	-0.0988	-0.1532	0.0601	6.50	0.01	-1.1507
Y2005	-0.9993	0.0808	153.07	0.00	-3.1571	-0.0627	0.0495	1.61	0.20	-0.1107	-0.7603	0.0706	115.88	0.00	-5.7119
Y2006	-0.9099	0.0794	131.27	0.00	-2.8749	-0.0621	0.0494	1.58	0.21	-0.1097	-0.6854	0.0692	98.06	0.00	-5.1488
Y2007	0.7874	0.0665	140.24	0.00	2.4878	-0.0334	0.0492	0.46	0.50	-0.0590	0.5055	0.0562	80.79	0.00	3.7975
Y2008	1.8039	0.0644	783.89	0.00	5.6994	0.0283	0.0488	0.34	0.56	0.0499	0.9987	0.0630	250.93	0.00	7.5027
Y2009	1.7727	0.0645	756.08	0.00	5.6007	0.0253	0.0488	0.27	0.60	0.0447	0.9861	0.0641	236.79	0.00	7.4078
Y2010	2.4764	0.0638	1504.43	0.00	7.8241	0.1200	0.0483	6.18	0.01	0.2118	1.2733	0.0708	323.49	0.00	9.5659
Y2011	1.8858	0.0710	704.73	0.00	5.9582	0.0021	0.0631	0.00	0.97	0.0037	1.0428	0.0793	172.87	0.00	7.8343
Q2	0.4941	0.0177	775.72	0.00	1.5612	0.0031	0.0221	0.02	0.89	0.0055	0.2175	0.0137	252.76	0.00	1.6340
Q3	0.5770	0.0175	1090.41	0.00	1.8229	0.0128	0.0220	0.34	0.56	0.0227	0.2544	0.0183	192.85	0.00	1.9115
Q4	0.3275	0.0183	318.82	0.00	1.0347	-0.0261	0.0224	1.36	0.24	-0.0460	0.1501	0.0194	60.10	0.00	1.1275
Forc (Tlag 1)											-0.0051	0.0168	0.09	0.76	-0.0383
Forc (Slag 1)											-0.0070	0.0084	0.69	0.41	-0.0526
Auxiliary Parameters															
Fixed Effects (Crim)											0.6807	0.0192	1256.95	0.00	
Fixed Effects (Forc)											0.5403	0.0228	562.48	0.00	
Dispersion (Crim)						0.0541	0.0014	548297.72	0.00		-0.6308	0.0111	1107.41	0.00	
Dispersion (Forc)						-0.5521	0.0199	507.59	0.00		-0.3365	0.0100	4378.57	0.00	