Document Title: Assessing the Link Between Foreclosure and Crime Rates: A Multi-level Analysis of Neighborhoods Across Large U.S. Cities

Author(s): Eric P. Baumer, Kevin T. Wolff, Ashley N. Arnio, Joseph K. Chiapputo

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Abstract

Statement of Purpose

Levels of foreclosure increased substantially in many American communities during the latter half of the 2000s, leading to widespread speculation that higher rates of crime might emerge as a result. The primary purpose of this project was to evaluate the possible link between foreclosure and crime in America. The project addresses three specific questions: (1) Are levels of foreclosure significantly associated with crime rates across neighborhoods after controlling for other factors?; (2) Is any observed effect of foreclosure on neighborhood crime rates contingent on (i.e., moderated by) other neighborhood conditions, including preexisting structural disadvantage, pre-existing vacancy rates, or racial and ethnic context?; and (3) Does the effect of foreclosure rates on neighborhood crime levels *vary across cities in systematic ways*?

Methods

We address these questions by integrating neighborhood-level data on robbery and burglary gathered from local police agencies across the U.S., foreclosure data from RealtyTrac, and a wide variety of social, economic, and demographic control variables from multiple sources. Using census tracts to approximate neighborhoods, our general strategy was to regress 2009 neighborhood robbery and burglary rates on foreclosure rates measured for 2007-2008 (a period during which foreclosure spiked dramatically in the nation), while accounting for 2007 robbery and burglary rates and other control variables that capture differences in social, economic, and demographic context across American neighborhoods and cities for this period, including spatially lagged crime rates. Our analysis was based on more than 7,200 census tracts in over 60 large cities spread across 29 states. We addressed our core research questions with a series of multivariate multilevel and single-level regression models that account for the skewed nature of neighborhood crime patterns and the well-documented spatial dependence of crime.

Results

Our concluding answer to the first and most general question tackled in the project– whether levels foreclosure are significantly associated with crime rates across neighborhoods after controlling for other factors – defies a simple "yes" or "no" answer. This is not a function of the absence of an indication one way or another, but rather it stems from what we see as a major strength of the multi-city approach adopted in our research. In essence, *our project shows that the answer to the general question of whether foreclosure is associated with robbery and burglary rates is highly contingent on the city under investigation and, thus, it would be precarious to draw general conclusions from research on a single city.*

Overall, when we analyze our neighborhood-level data pooled across all cities, our findings indicate that neighborhood foreclosure rates are not significantly associated with neighborhood robbery rates across 63 cities. We do observe a small but significant positive "net" effect of foreclosure rates in 2007-2008 on burglary in 2009 in this pooled analysis, controlling for a wide array of other factors that include prior burglary levels and also burglary rates of surrounding neighborhoods. However, *the most uniform pattern we observe in our study is that the influence of neighborhood foreclosure rates on neighborhood crime during the last few years of the 2000s was highly contingent on city location. In particular, by analyzing each city separately, we show that neighborhood foreclosure is significantly associated with*

robbery and burglary only in a small number of selected cities; in the majority of the cities considered, foreclosure did not exert a significant main effect on either crime type.

We find some evidence that foreclosure was more likely to translate into elevated crime rates in cities with older housing stock but, for the most part, we conclude that the observed between-city variability in foreclosure effects is not highly systematic, at least not in ways that parallel the city-level attributes we considered. Further, the results of multiplicative models show little evidence that high neighborhood foreclosure rates were more criminogenic when accompanied by high levels of neighborhood socioeconomic disadvantage or other adverse conditions, though we find evidence in several cities that foreclosure was more likely to yield elevated property crime rates (most notably, burglary) in neighborhoods where Latinos and foreign born residents were more prevalent.

Conclusions

Our study highlights the general importance of analyzing the consequences of neighborhood conditions in a comparative context, and it also suggests more specifically that researchers and federal policy makers should be cautious in drawing strong conclusions about the relationship between foreclosure and crime from research on a single city. While we find that the foreclosure crisis yielded increases in burglary and robbery in some cities, in the vast majority of places this relationship did not take hold.

Though our research adds significantly to the existing knowledge base about the potential link between foreclosure and crime, additional research should further explore several issues. Among others, it would be useful to know whether different findings emerge in studies that replicate our research using smaller geographic areas (e.g., block groups, blocks, and street segments). Our analysis is based on census tracts as approximations of local neighborhoods; though common practice in social science research, census tracts are relatively large and heterogeneous compared to block groups and blocks, and the latter may prove to be more suitable for assessing the relationship between foreclosure and crime. Further, we focus on relatively short-term consequences of the contemporary foreclosure crisis, and so we acknowledge the possibility that the full consequences of the housing crises and recession, including the potential for increases in crime, may not have unfolded over the period encompassed within our study. Future research that explores longer-term consequences within multiple cities would be valuable to more fully assess this possibility. Subsequent research also should explore more nuanced indicators of foreclosure that capture occupancy status, duration of foreclosure, and the property conditions. Finally, it would be beneficial if future research were able to explicitly examine the implied mechanisms highlighted in extant theoretical discussions about foreclosure and crime. Research that integrates neighborhood-based survey data, systematic social observation, and measures of foreclosure and crime would be highly beneficial for advancing our theoretical understanding of these relationships.

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Executive Summary

Statement of Purpose

The abrupt increase in residential foreclosures observed in America during the mid-to-late 2000s has been implicated as one of the most important antecedents to the "Great Recession" in the U.S. (Mian, Sufi, & Trebbi, 2011). It has been linked to continued sluggishness in the global economy (Nanto, 2009), increased hypertension and anxiety (Bennett Scharoun-Lee, & Tucker-Seeley, 2009), and elevated rates of crime. National and local media were attracted almost immediately to the latter, as headlines across America relayed claims that "Homes abandoned via foreclosures [are] becoming havens for crime…" (Hirshon, 2009), and "Squalor, crime follow wave of foreclosures" (Associated Press, 2007). The primary purpose of this project was to evaluate the possibility of a significant link between foreclosure and crime in America.

The project addressed three specific questions: (1) Are foreclosure levels significantly associated with crime rates across neighborhoods (i.e., census tracts)[1] after controlling for other factors?; (2) Is any observed effect of foreclosure on neighborhood crime rates contingent on (i.e., moderated by) the other neighborhood conditions, including preexisting structural disadvantage, pre-existing vacancy rates, or racial and ethnic context?; and, (3) Does the effect of foreclosure rates on neighborhood crime levels vary across *cities* in systematic ways? For instance, is the magnitude of the effect of foreclosure on crime across neighborhoods contingent on city indicators of vulnerability, such as an aging housing stock, high rates of pre-existing vacancies, and high levels of unemployment and other forms of socioeconomic disadvantage, or the capacity for mitigating the adverse consequences of a housing crisis (e.g., housing affordability, the size of the police force)?

Rationale

The Influence of Foreclosure on Crime Rates

Drawing from theoretical perspectives that highlight problematic aspects of "broken

[1]We use the terms "neighborhood" and "census tracts" interchangeably, though it is important to acknowledge that the latter do not necessarily conform to the former.

windows," "incivilities," "routine activities," and "social disorganization," the extant theoretical literature implies that higher levels of foreclosure in a given area may increase crime through several possible mechanisms, including heightened disorder, weakened social organization and collective efficacy, and enhanced criminal opportunities. Additionally, the theoretical literature implies that each of the highlighted mechanisms through which foreclosure might increase crime can be considered highly *conditional*, moderated both by other neighborhood conditions and also broader city-level attributes. We consider both potential sources of conditional effects, but we focus largely on the possibility that there may be meaningful variation across cities in the estimated link between neighborhood-level rates of foreclosure and crime, the rationale for which we outline next.

City-Level Variation in the Influence of Foreclosure on Crime Rates

An important insight that has emerged from scholarship in the areas of political economy and urban sociology is that the broader contexts within which neighborhoods are situated can have important implications for how various social problems and/or economic shocks are experienced and perceived, which in turn has implications for their consequences. Two key features of city environments seem especially consequential for moderating the magnitude of the effects of foreclosure on crime across neighborhoods: (1) pre-existing or co-occurring vulnerabilities; and (2) the capacity for mitigating the adverse consequences of a housing crisis. We briefly elaborate on each of these features.

The extant theoretical literature suggests that the link between foreclosure and crime across neighborhoods may be conditioned by pre-existing or co-occurring vulnerabilities. The foreclosure crisis was a major part of the "Great Recession," and while most cities experienced symptoms of this significant economic decline, some were hit much harder than others. Even before the official onset of the most recent recession, however, U.S. cities differed considerably on a wide variety of social and economic indicators that may make them more or less vulnerable to a major foreclosure crisis. For example, the abrupt rise in foreclosures in the second half of the 2000s occurred in cities where there had been a relatively large volume of recent new construction and few existing vacancies (i.e., where housing markets had been robust in the earlier part of the decade), but it also happened in areas that already had an abundant supply of vacant homes and an "aging" housing stock (i.e., little new construction). These latter places may have been struggling already to attract new residents and keep crime rates low, and thus neighborhoods in these areas might be especially vulnerable to the potential negative consequences of high levels of foreclosure, including elevated crime rates.

Additionally, as some literature within the social disorganization and political economy traditions has highlighted (e.g., Crenson, 1983; Bursik & Grasmick, 1993), high-risk neighborhoods (e.g., those with high rates of foreclosure) may be less successful in efforts to garner useful external resources (e.g., foreclosure mitigation resources, support for maintaining and/or repurchasing vacant buildings) when embedded in a broader political context in which resources are highly strained, such as where vacancy rates were already quite high before the contemporary foreclosure crisis, or where rates of socioeconomic disadvantage were relatively high. Overall, these arguments suggest that the estimated effect of foreclosure on crime across neighborhoods may be stronger in cities with relatively little new construction, high rates of pre-existing vacancies, and high levels of unemployment and other forms of socioeconomic disadvantage.

A broader point often referenced in the literature is that cities differ significantly in their capacity to address social problems of all sorts (Logan & Molotch, 1987; Smith, Caris, & Wyly, 2001). During the 2000s, U.S. cities exhibited meaningful variation on a number of dimensions, some of which we just described as "vulnerabilities" that might amplify the criminogenic potential of high foreclosure neighborhoods. Admittedly, most of those factors also play a role in shaping city responses to a major economic downturn, including the foreclosure crisis. Two other features that seem particularly relevant for shaping the capacity for cities to mitigate the potentially adverse consequences of high neighborhood foreclosure rates are (1) the existing prospects for housing recovery, and, (2) the human resources available to address emerging crime problems. The theoretical frameworks reviewed above suggest that a high rate of foreclosure in a neighborhood is less likely to yield significant additional crime if foreclosed properties are reoccupied in short order, a prediction for which there is some empirical support (Cui, 2010; Ellen, Lacoe & Sharygin, 2011). This insight yields an expectation that foreclosure and crime may be less strongly related in cities where housing has remained relatively affordable. In such contexts it seems likely that home sales will rebound more quickly and foreclosed properties will remain vacant for shorter periods, which in turn should limit the likelihood that would-be offenders will congregate around such properties.

Cities also vary considerably with respect to their capacity to respond to growing crime problems, including those that might arise from an abrupt increase in unoccupied homes. The chief means by which they do so, of course, is through local policing efforts. The size of police forces differs significantly across cities, and though the existing literature on the link between crime rates and police size has generated inconsistent results (see Eck & Maguire, 2006, for an exhaustive review), some research has shown that larger police forces yield reductions in city crime rates (see Levitt, 1997). The foreclosure crisis spurred a large array of ameliorative efforts aimed at lessening the scope of the problem and minimizing collateral consequences, including elevated crime rates (e.g., the U.S. Housing and Urban Development [HUD] Neighborhood Stabilization Program [NSP]). However, these efforts were not directed at crime reduction *per se*, and most were not implemented on a large scale until the middle of 2009, several years into the housing decline and near the end of our study. In contrast, the types of criminal activities that foreclosed properties may give rise to—violent and non-violent property crimes, illicit drug activities, and various public order offenses—are the explicit focus of local police agencies, and therefore city differences in policing represent an important dimension of the urban environment that may have implications for the degree to which high neighborhood rates of foreclosure have translated into elevated crime rates. Specifically, all else equal, we anticipate the relationship between foreclosure and crime across neighborhoods to be weaker in cities in which the overall size of the police force was larger, increasing, or at least decreasing less significantly.

Methods

Sample & Data

At the onset of the project, *neighborhood-level* crime data were not readily available for a large number of cities for the period that encompassed the housing crisis. Thus, a major task during the project was to gather such data. Since there is no national repository of neighborhood crime data, this effort required direct data collection from local police agencies. We employed a multi-pronged sampling strategy designed to yield neighborhood-level data from a modest sized sample of relatively large cities across the U.S. In an initial stage of sampling, we sought data from the largest cities within the fifty most populous metropolitan areas. We supplemented this effort in a second stage of sampling from the population of large cities (those with populations of 100,000 or more) in other metropolitan areas. In total, we requested neighborhood data from 109 cities with 100,000 or more persons; we received data in some form or another from 78 cities (71.5% of those sampled), and data that could be integrated fully across sample entities for 67 cities (61.4% of the sampled cities).

The samples used in the analyses reported herein are further constrained by the specific design employed and the availability of other data elements. Specifically, we excluded three cities that did not provide the requisite crime data for both 2007 and 2009 (an important element of our design), so our maximum analysis sample is based on 64 cities. According to the 2005-2009 ACS census tract file, the 64 cities included in our sample contain 7,842 census tracts that fall wholly or partly within them (based on 2009 place definitions). To minimize potential distortions that might arise from computing crime and foreclosure rates on the basis of particularly small denominators, we exclude from the analysis census tracts with less than 100 persons or 100 housing units (n=295) and a small handful of tracts (n= 132) for which we were unable to obtain data on foreclosure or other data elements. After these data exclusions, the maximum analysis sample in our study consists of

7,415 census tracts within 64 cities and 29 states. The 64 cities are listed below.

Listing of cities included in multilevel analysis of foreclosure and crime (n=64).

City & State	City & State	City & State	City & State
Anchorage, AK	Orlando, FL	Lincoln, NE	Memphis, TN
Chandler, AZ	Pembroke Pines, FL	Las Vegas, NV	Arlington, TX
Glendale, AZ	St. Petersburg, FL	Albuquerque, NM	Austin, TX
Tempe, AZ	Tampa, FL	Rochester, NY	Carrollton, TX
Tucson, AZ	Atlanta, GA	Charlotte, NC	Dallas, TX
Chula Vista, CA	Chicago, IL	Greensboro, NC	Fort Worth, TX
Garden Grove, CA	Rockford, IL	Raleigh, NC	Houston, TX
Moreno Valley, CA	Evansville, IN	Akron, OH	Pasadena, TX
Oakland, CA	Fort Wayne, IN	Cincinnati, OH	Plano, TX
Sacramento, CA	Indianapolis, IN	Cleveland, OH	Waco, TX
San Diego, CA	Topeka, KS	Columbus, OH	Alexandria, VA
Aurora, CO	Lexington-Fayette, KY	Dayton, OH	Newport News, VA
Denver, CO	Baltimore, MD	Oklahoma City, OK	Richmond, VA
Fort Collins, CO	Sterling Heights, MI	Portland, OR	Bellevue, WA
Washington, DC	Minneapolis, MN	Philadelphia, PA	Madison, WI
Jacksonville, FL	St. Louis, MO	Pittsburgh, PA	Milwaukee, WI

Measures

Though the housing crisis began to unfold in many American communities as early as 2005, we focus on 2007-2009 because this is when actual foreclosure rates (i.e., not just notices of default) exhibited particularly notable spikes in most areas of the country. Our general strategy was to regress 2009 neighborhood crime rates on foreclosure rates measured for 2007-2008, while accounting for 2007 crime rates and other control variables. The bulk of the latter were drawn from the sole source of data on contemporary social, economic, and demographic context for American neighborhoods—the ACS pooled (2005-2009) census tract file—which we treat as reflective of conditions present at approximately the mid-point of the period covered in these data (i.e., 2007).

From a theoretical standpoint, high foreclosure rates should be salient for crimes strongly tied to economic motivations (e.g., acquisitive crimes). The study focuses on two forms of crime often committed for instrumental purposes (Felson, Baumer, & Messner, 2000; Baumer & Gustafson, 2007): robbery and burglary. As elaborated in the full report, though a variety of other crimes are potentially relevant to the foreclosure crisis as well, including domestic violence, drug offenses, and public order crimes, we limited our attention to robbery and burglary not only because we see these offenses as theoretically pertinent to the issue at hand, but also because of concerns about the validity and reliability of reported data on other crimes from the jurisdictions included in the analysis and in light of resource constraints associated with the project.

Our key explanatory variable is the number of residential foreclosures per 1,000 housing units in 2007-2008 for the sampled census tracts. These data represent actual foreclosures, defined here as Real Estate Owned [REO] transactions and foreclosure sales or auctions, within each census tract in our sample. We obtained address-level foreclosure data from RealtyTrac for our sample cities, and then geocoded these records to generate census tract foreclosure counts.[2] We constructed foreclosure rates by dividing the foreclosure counts by the total number of housing units in the census tracts, as estimated in the 2005-2009 American Community Survey (ACS) census tract data, and multiplying this quotient by 1000. We found very similar results if we used as a denominator the number of mortgages in the study areas, as estimated from Home Mortgage Disclosure Act (HMDA) data obtained through the Urban Institute National data repository (http://www.metrotrends.org/natdata/hmda/hmda_download.cfm).

Obtaining valid estimates of neighborhood foreclosure effects on crime levels requires that we simultaneously account for other neighborhood conditions that might be related both to the spatial distribution of foreclosure and to neighborhood variability in crime. We therefore include in our analysis a variety of neighborhood indicators that have been linked to foreclosure and which have emerged as robust predictors of neighborhood crime across several U.S. cities. Most of the control variables included in the study are drawn from the ACS pooled 2005-2009 census tract file,

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[2]The census tract foreclosure data presented here and used in our analysis differs in an important way from published RealtyTrac foreclosure estimates. Specifically, RealtyTrac routinely reports on total foreclosure filings, which includes "notices of default" (NODs) along with filings associated with foreclosure sales or REO proceedings. As a result, in many instances, a single foreclosed property is represented in published RealtyTrac data multiple times (e.g., first as an NOD and later as a sale notice). To avoid double counting and because we view foreclosure sales and REO proceedings as more pertinent to crime from a theoretical vantage point, our census tract measure of foreclosure excludes NODs.

and thus are available only at a single temporal point, which we assume to capture the mid-point of the period encompassed by these data (i.e., 2007). Drawing from prior neighborhood-level research (e.g., Peterson & Krivo, 2010) and extant theories about foreclosure and crime, we included multi-item scales of socioeconomic disadvantage, immigrant concentration, and residential stability, along with single-item measures of the level of pre-existing vacancies, divorce rates, and multiple measures of population structure (population size and density, percent 15-29, and percent non-Latino black). Additionally, we controlled for prior crime levels (measured in 2007) for focal neighborhoods, and contemporaneous crime rates for neighboring census tracts.

A key focus in our study is to assess whether the estimated effect of neighborhood foreclosure rates on neighborhood crime levels varies systematically across cities, and specifically whether the magnitude of the overall foreclosure slope estimated across cities is moderated by the city-level attributes described earlier. We thus included several city-level attributes that capture potentially important differences in conditions that may have made some cities more (or less) vulnerable or resistant to elevated neighborhood foreclosure rates. The measures included the relative age of the housing stock (percentage of housing units built between 2000 and 2007), pre-existing vacancy rates, a housing affordability index (AHI), poverty rates, racial composition, levels and changes in unemployment, and police force size per 100,000. These measures captured city conditions in 2008 and/or changes between 2007/8 and 2009.

Analytical Strategy

We addressed the substantive issues outlined above (i.e., whether there is a significant effect of foreclosure on robbery and burglary across neighborhoods, and whether the estimated neighborhood effect varies systematically across cities) with a series of single- and multi-level overdispersed count regression models that account for many potentially confounding factors, including spatially lagged neighborhood crime rates).

Our neighborhood-level data contain a considerable number of tracts with relatively small populations and low crime counts; these features yield highly skewed distributions for crime rates and a heterogeneous error variance, properties that violate assumptions of conventional linear regression models. We considered a variety of different alternatives that may be more appropriate in light of the distributional properties of our data, including Poisson and zero-inflated regression models (Hilbe 2011). Multiple tests (i.e., Pearson's dispersion statistics, z-score test, Lagrange multiplier test, and Poisson goodness of fit test) from preliminary Poisson models pointed to significant overdispersion. In light of this, we estimated a series of overdispersed Poisson, zero-inflated Poisson, and negative binomial regressions; these models yielded virtually identical results. Evaluation of AIC and BIC statistics revealed that overall model fit was slightly better for the negative binomial models. We therefore report the results of negative binomial regressions of crime on foreclosure and other factors for the individual city regressions presented below. At the time of our analysis, negative binomial regression models had not been fully incorporated into accessible multi-level analysis software; thus, for the pooled, multilevel specifications presented below, we present results for two-level overdispersed Poisson models, a strategy that has become common practice in studies of neighborhoods across multiple cities (see also Peterson & Krivo, 2010). The multi-level modelling strategy enables us to assess meaningful variability in neighborhood patterns across the sampled cities, while also accounting for the non-independence of census tracts within the same city. Given our focus on the potential between-city variability of neighborhood foreclosure effects, we report results from two-level random coefficient models in which both the intercept and the slopes are permitted to vary across cities. All of the estimations account for spatial autocorrelation of crime across neighborhoods within cities.

Results

Our concluding answer to the first and most general question tackled in the project– whether levels foreclosure are significantly associated with crime rates across neighborhoods after controlling for other factors – defies a simple "yes" or "no" answer. This is not a function of the absence of an indication one way or another, but rather it stems from what we see as a major strength of the multi-city approach adopted in our research. In essence, *our project shows that the answer to the general question of whether foreclosure is associated with robbery and burglary rates is highly contingent on the city under investigation and, thus, it would be precarious to draw general conclusions from research on a single city.*

Overall, when we analyze our neighborhood-level data pooled across all cities, our findings indicate that neighborhood foreclosure rates are not significantly associated with neighborhood robbery rates across 63 cities. We do observe a small but significant positive "net" effect of foreclosure rates in 2007-2008 on burglary in 2009 in this pooled analysis, controlling for a wide array of other factors that include prior burglary levels and also burglary rates of surrounding neighborhoods. Drawing firm conclusions from this pooled analysis across 7,000+ neighborhoods is tempting, but doing so would mask important nuances. *Indeed, the most uniform pattern we observed in our study was that the influence of neighborhood foreclosure rates on neighborhood crime during the last few years of the 2000s was highly contingent on city location.* We document this by highlighting statistically significant variance components in multilevel regression model that nest several thousand census tracts within our sample cities, which show that the estimated neighborhood slopes for foreclosure in both the burglary and robbery models exhibit considerable variability across the cities represented in our study. Further, we illuminate the theme of city-level variability in patterns of foreclosure coefficients, including main effects on robbery and burglary, in city-specific regression models that reveal some important insights about the nature of city-level variability in our study. *In particular, by analyzing each city separately, we show that neighborhood foreclosure is significantly associated with robbery and burglary only in a small number of selected cities; in the majority of the cities considered, foreclosure did not exert a significant main effect on either crime type.*

Our extended multilevel models explored a second important question advanced in the project, namely whether the effect of foreclosure rates on neighborhood crime levels varies across cities in *systematic ways*. For the most part, we conclude that the between-city variability in neighborhood foreclosure effects observed for robbery and burglary is not highly systematic, at least not in ways that parallel the city-level attributes we considered. Indeed, only one of the city-level factors we included–the percentage of housing units built between 2000 and 2007–emerged as a statistically significant and meaningful predictor of city-level variability in neighborhood foreclosure effects. We highlight the logic of this finding by showing that neighborhood foreclosure effects on burglary tended to be larger in cities that had experienced relatively little new housing construction during the first several years of the 2000s, but relatively weak in areas of significant recent housing construction. This may be a function of a heightened capacity for communities with newer housing stock to rebound quickly in the face of the foreclosure crisis, avoiding significant collateral consequences. We also acknowledge, however, that it is easy to find exceptions in both instances, and again the more typical finding that emerges from our study is that foreclosure and crime (robbery and burglary, at least) are not significantly related in the majority of U.S. cities we considered, at least overall.

Evaluating the main, or unconditional, effect of foreclosure is important, in our judgment, for it seems to square most directly with public discussions about a possible link between foreclosure and crime. And on that score, our study suggests that the widely presumed significant link between foreclosure and crime in the popular press is limited to select areas. We show that in the vast majority of places where no such link can be detected, at least as we attempt to measure and model it. Critics of this conclusion might argue that a focus on "main effects" is not sufficiently nuanced to detect foreclosure effects in practice, perhaps because they are evident only in *particular* types of places. The theoretical rationales pertinent to this line of thinking are not very well developed at present, but the basic issue is whether any observed effect of foreclosure on neighborhood crime rates is contingent on, moderated by, various other neighborhood conditions. This served as our final research question in the project, and we focused in particular on whether foreclosure effects on robbery and burglary during the heart of the housing crisis were contingent on preexisting structural disadvantages, pre-existing vacancy rates, and the prevailing racial and ethnic context.

The multiplicative models showed very little evidence that high neighborhood foreclosure rates were *more* criminogenic when accompanied by high levels of socioeconomic disadvantage or other adverse conditions. In fact, our models indicated that foreclosure was more likely to yield elevated crime rates in areas with *lower* rates of pre-existing vacancies. This may indicate something about the meaning of foreclosures in different neighborhood contexts. Specifically, perhaps in areas where there were many vacancies already, foreclosures did not add much to perceptions of decline and disorder, whereas in areas with few vacancies each additional foreclosure served as a symbolic and tangible cue for residents and offenders that the neighborhood was declining, and that informal social controls over crime were lessened. Alternatively, perhaps attractive opportunities for burglary and robbery are sufficiently depressed in areas with higher vacancy rates that even with elevated foreclosure rates, increased acquisitive crime does not follow. Unfortunately, we cannot address explicit mechanisms for the observed effects, but doing so would be a valuable component of subsequent research that explored in more detail the contexts in which foreclosure was more apt to translate into elevated crime rates.

Finally, though it is far from uniform across all of our cities, we find evidence in several cities that foreclosure was more likely to yield elevated property crime rates (most notably, burglary) in neighborhoods where Latinos and foreign born residents were more prevalent. It is not clear what this pattern reflects, but some scholars have suggested that Latino areas hit by the foreclosure crisis have had particular difficulties rebounding. For instance, Louden (2009) chronicles the very high rate of joblessness associated with seasonal work in such areas, and also long-standing barriers to home ownership that in these places may have limited the capacity for housing recovery and amplified the negative consequences of the housing bust and the "Great Recession." Whatever the reasons for this pattern, it highlights some potentially fruitful opportunities for resource allocation that could help alleviate the tendency for high levels of foreclosure to yield elevated crime rates in particular contexts.

The most dominant pattern that emerged from our detailed multiplicative models is that, in the majority of cities, there is no evidence of a significant link between neighborhood foreclosure and crime across the conditional patterns we considered. We do find evidence in many cities that the impact of foreclosure on crime is moderated by other neighborhood conditions, but the observed patterns do not reveal strong support for theoretical expectations. Clearly, our data do not support blanket statements about a significant link between foreclosure and crime, at least with respect to robbery and burglary. Though it is perhaps in some respects unsatisfying, the overall conclusion one draws appears to be highly contingent on the location in which the research is conducted, a conclusion that also highlights the importance of our multi-city neighborhood analysis.

Conclusions

Our study highlights the general importance of analyzing neighborhood conditions in a comparative context, and it also suggests specifically that researchers and federal policy makers should be cautious in drawing strong conclusions about the relationship between foreclosure and crime from research on a single city. We consider this a useful contribution to knowledge and encourage additional multi-city neighborhood investigations of foreclosure and crime. One natural extension of our work, for example, would consider longer-term impacts of the foreclosure crisis. We focused on relatively short-term consequences of the contemporary foreclosure crisis, but it is possible that the full consequences of this period, including those associated with potential increases in crime, may not have unfolded completely yet. Thus, future research that explores longer-term consequences within multiple cities would be valuable to more fully assess this possibility. It would be useful for any such effort to integrate more nuanced indicators of foreclosure (e.g., distinguishing between foreclosures that are sold quickly versus those that remain vacant for lengthy spells), and to consider small geographic areas, such as blocks or block groups, which may be more suitable for detecting significant foreclosure impacts. Additionally, an important ingredient in subsequent multi-city research should be the inclusion of information on policy prescriptions that have been implemented in response to the foreclosure crisis. Several billion dollars have been allocated for foreclosure remediation under the umbrella of several Federal policy efforts, such as the Neighborhood Stabilization Program (NSP), the Home Affordable Modification Program (HAMP), and the Home Affordable Foreclosure Alternatives (HAFA) program. It would be wise for the government to support research efforts to evaluate both the general efficacy of these policies, and whether or not they have lessened the impact of foreclosure on crime in jurisdictions in which such a connection appears to be significant.

We also see a major need for more detailed neighborhood data collection and analysis within cities, and this type of effort will probably require a tradeoff with the number of cities studied. Like most other neighborhood-level studies, our analysis cannot decipher the proximate mechanisms through which foreclosures translate (or do not translate) into higher crime rates. Our results suggest that there are city-level conditions under which high neighborhood foreclosure rates increase disorder and disorganization and reduce social controls, but without direct indicators of these constructs this remains highly speculative. Future research that integrates neighborhood-based survey data, systematic social observation, and measures of foreclosure and crime would be highly beneficial for advancing our theoretical understanding of these relationships. Assembling this type of data for a large number of cities is probably unrealistic because of logistical issues and cost considerations, but doing so in strategically selected places (e.g., perhaps a city in which foreclosures exhibit a relatively strong link to crime and other social ills, and a city in which no such connections are found) would advance substantially our understanding of the mechanisms that might link foreclosure to crime, and of the specific conditions that might make such a link more or less likely to arise.

Technical Report

I. Statement of the Problem

Housing foreclosure rates in America increased modestly during the 1980s and 1990s, but there was an especially sharp spike in foreclosure activity during the last several years of the 2000s (Elmer & Seelig, 1998; HUD, 2009; RealtyTrac, 2011). Many observers point to rampant mortgage fraud, an unprecedented extension of sub-prime mortgages, predatory lending practices, abrupt price depreciation, rising job losses, and an emerging recession as the major antecedents to the contemporary foreclosure crisis (Baumer, Arnio, & Wolf, 2013; Been, Chan, Ellen, & Madar., 2011; Crump et al., 2008; Gerardi, Ross, & Willen, 2011; Edmiston & Zalneraitis, 2007; Lucy & Herlitz, 2009). Whatever the causes, the housing bubble showed signs of weakening by mid-decade and foreclosure rates in many American communities rose precipitously during 2007 and 2008, and reached historically unprecedented levels by the end of the decade.

Figures 1a and 1b provide visual evidence of the rise in foreclosure rates across U.S. counties in the 48 contiguous states between 2006 and 2008, while also highlighting the substantial spatial variation associated with the housing crisis. Some states such as California, Nevada, Florida, Michigan, and Ohio were hit particularly hard, but the full weight of the foreclosure run-up during the latter half of the 2000s affected communities across the nation and was especially dramatic in some areas. For example, while foreclosure rates nation-wide remained below 1% of all households through 2008, there was considerable variability across local neighborhoods. Drawing on RealtyTrac (2009) data gathered for this project (described below), Figure 2 shows that for some neighborhoods in cities such as Cleveland and Las Vegas foreclosure rates exceeded 100 per 1,000 housing units (i.e., more than ten percent of housing units) during the same period. Even in cities where overall foreclosure rate were more modest in 2008, such as Chicago and Houston, several neighborhoods exhibited levels of foreclosure that were more than five times higher than the national average (see Figure 3).

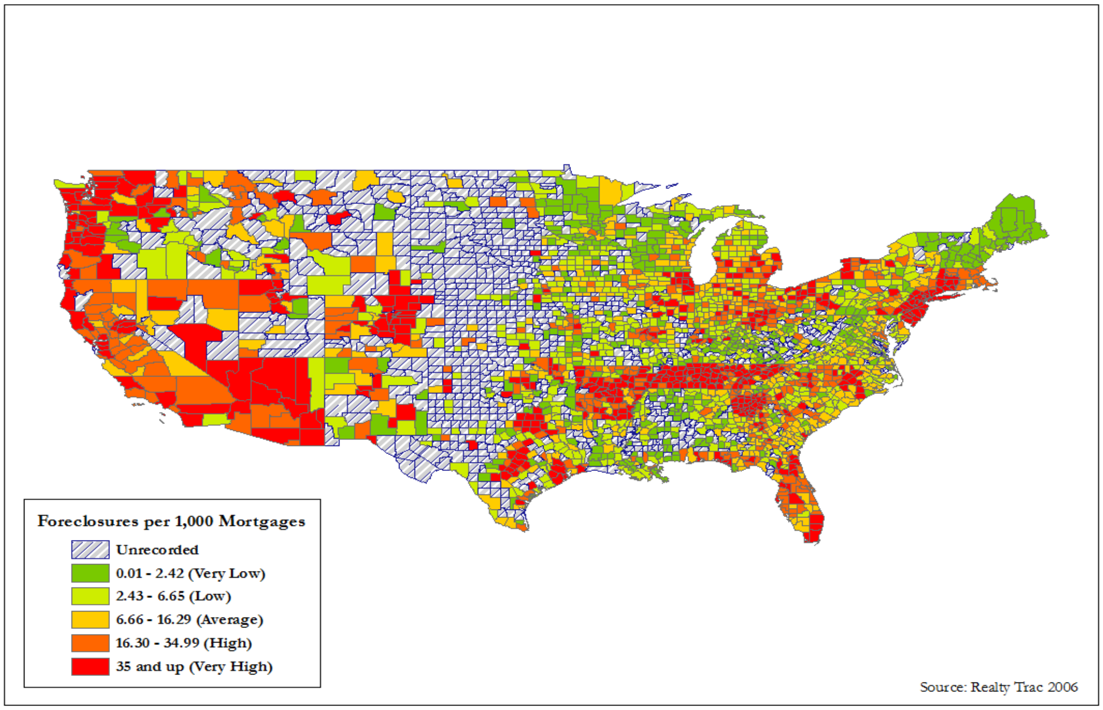


Figure 1a. Foreclosure Rates for U.S. Counties, 2006

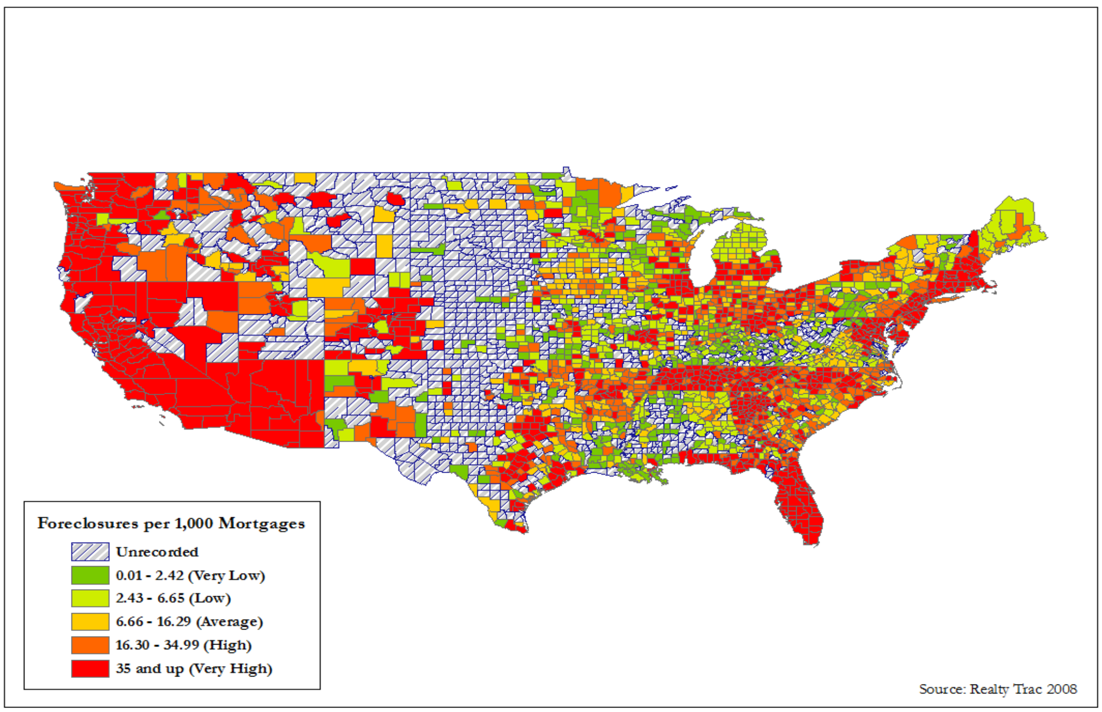


Figure 1b. Foreclosure Rates for U.S. Counties, 2008

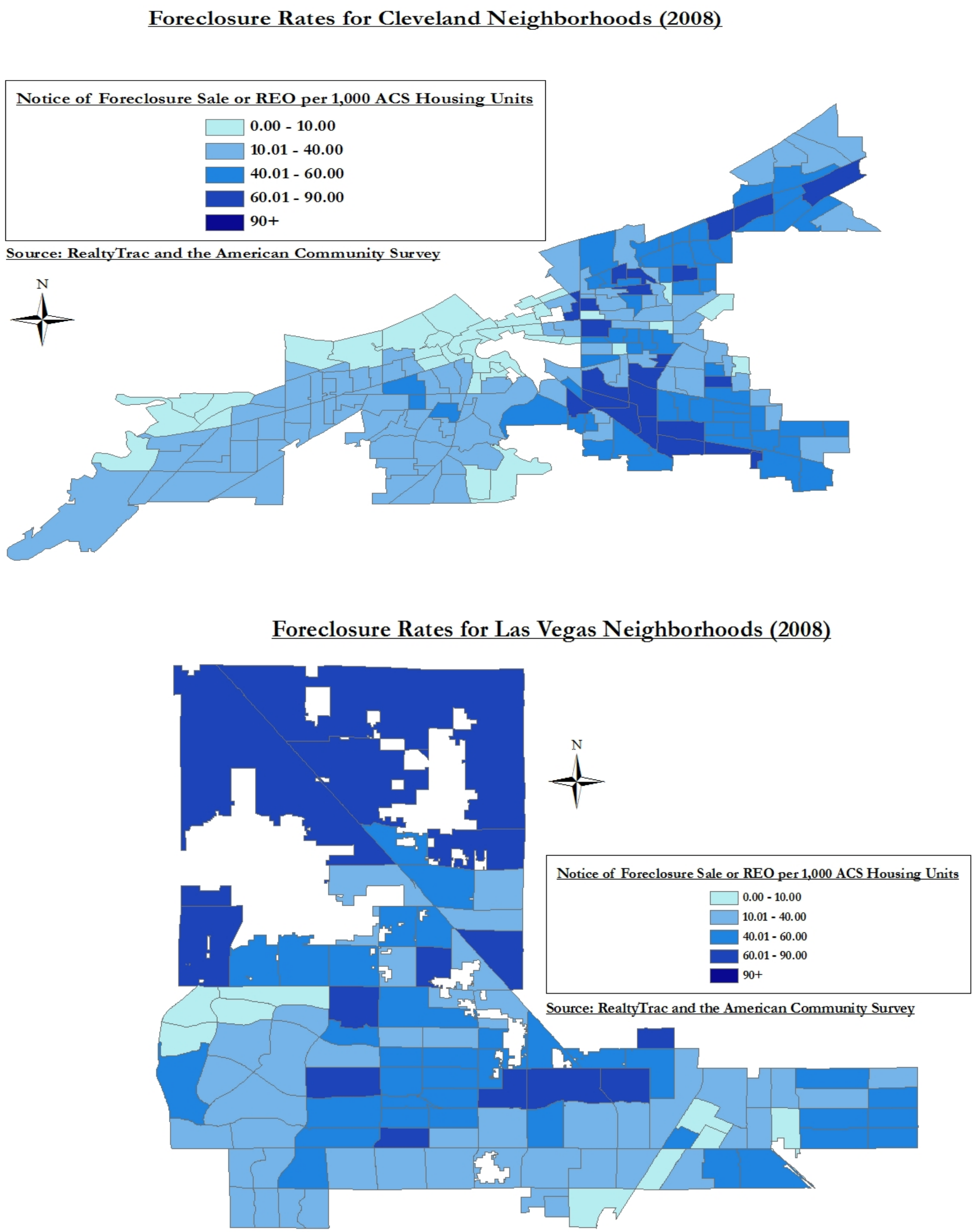
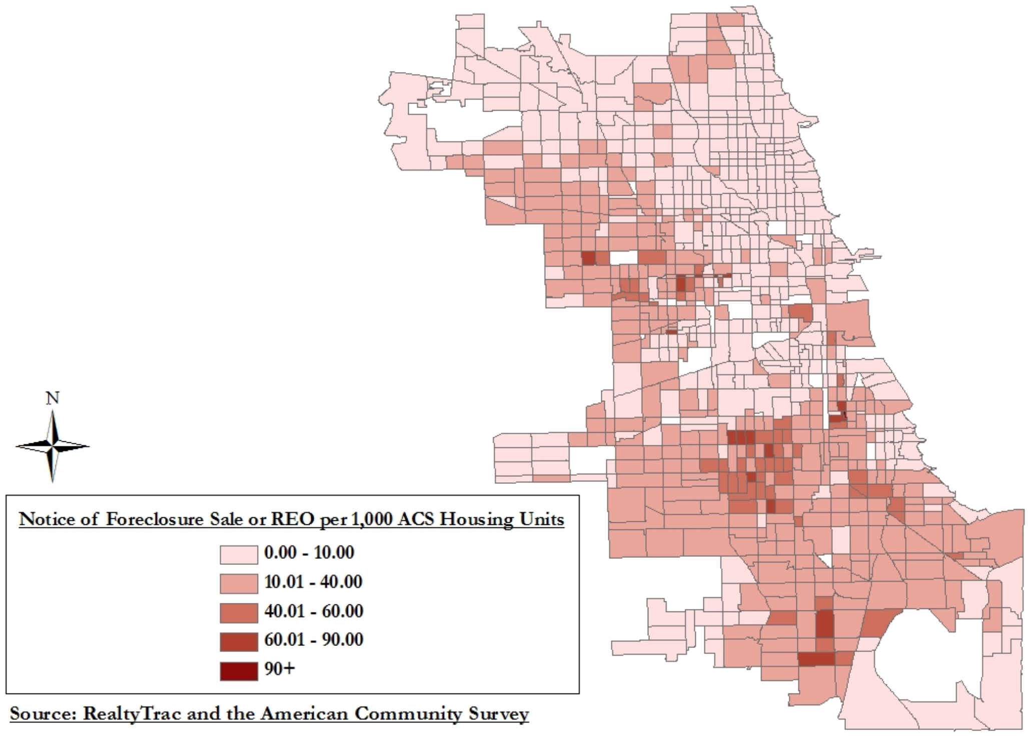


Figure 2. Neighborhood Variation in Foreclosure Rates (2008) in Cleveland and Las Vegas.

Foreclosure Rates for Chicago Neighborhoods (2008)



Foreclosure Rates for Houston Neighborhoods (2008)

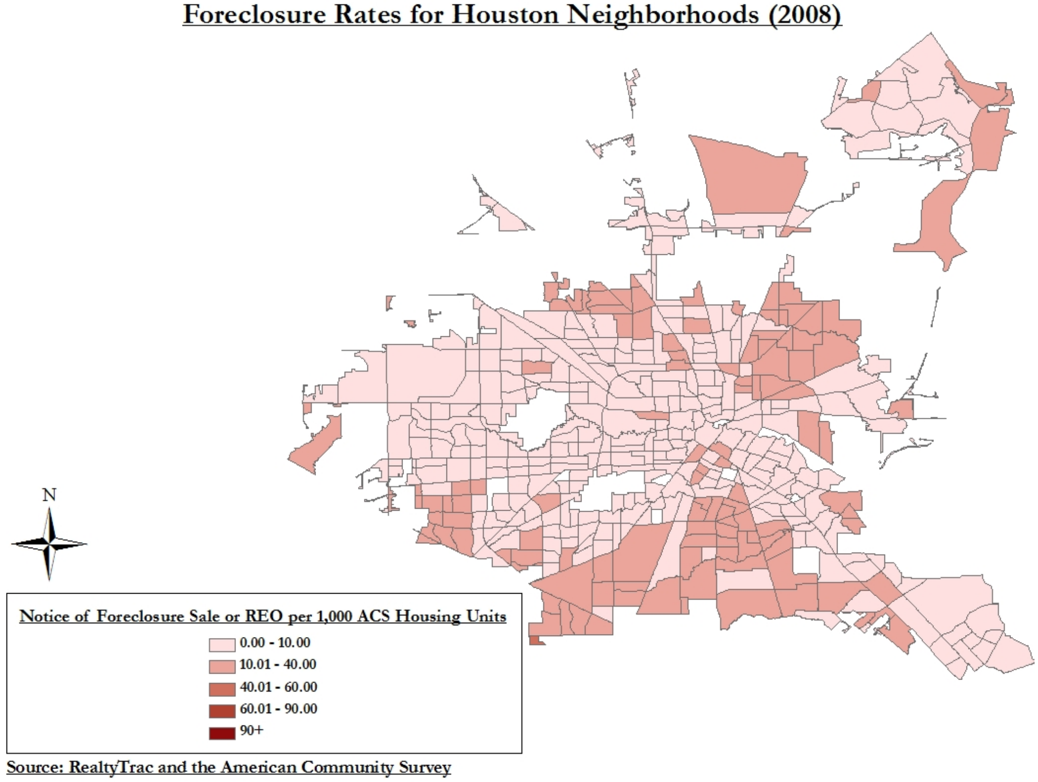


Figure 3. Neighborhood Variation in Foreclosure Rates (2008) in Chicago and Houston.

The abrupt increase in residential foreclosures observed in America since the mid-2000s has been implicated as a major—if not *the* major—impetus for the "Great Recession" in the U.S. (Mian, Sufi, & Trebbi, 2011). It also has been linked to continued sluggishness in the global economy (Nanto, 2009), increased hypertension and anxiety (Bennett, Scharoun-Lee, & Tucker-Seeley, 2009), and elevated rates of crime. National and local media were attracted almost immediately to the latter, as headlines across America relayed claims that "Homes abandoned via foreclosures [are] becoming havens for crime…" (Hirshon, 2009), and "Squalor, crime follow wave of foreclosures" (Associated Press, 2007). Such stories often emerged from visually persuasive images of foreclosed properties being neglected and quickly falling into disrepair, "squatters" settling in or congregating around homes abandoned from foreclosure, and scenes that portrayed a wide array of deviant and illicit conduct (e.g., drug and alcohol use, appliance and copper thefts) in places transformed by the housing crisis. These stories seemed to resonate with many Americans, especially those who resided in neighborhoods in which foreclosure rates were rising precipitously. They also were buttressed by signs that, despite relatively flat crime trends nationally (FBI, 2009), in some neighborhoods crime rates appeared to be increasing during the housing crisis. In fact, using data crime gathered for the project (described below), Figures 4 and 5 show that there were indeed some notable increases in levels of robbery and burglary—two crimes widely connected to rising foreclosures—during the period that defined the worst of the housing crisis (2007-2009). Figure 4 reveals that while burglary rates were unchanged or significantly lower in 2009 than in 2007 across many of the census tracts studied in our project, they also increased notably in a large proportion of tracts. For example, more than a quarter of the census tracts encompassed in Figure 4 show increases in burglary rates of 30% or more between 2007 and 2009. Figure 5 yields a largely parallel story, showing that robbery rates increased significantly between 2007 and 2009 in more than 20% of the census tracts we researched across more than sixty large U.S. cities.

In a context of widely publicized increases in foreclosure rates and at least a hint of evidence

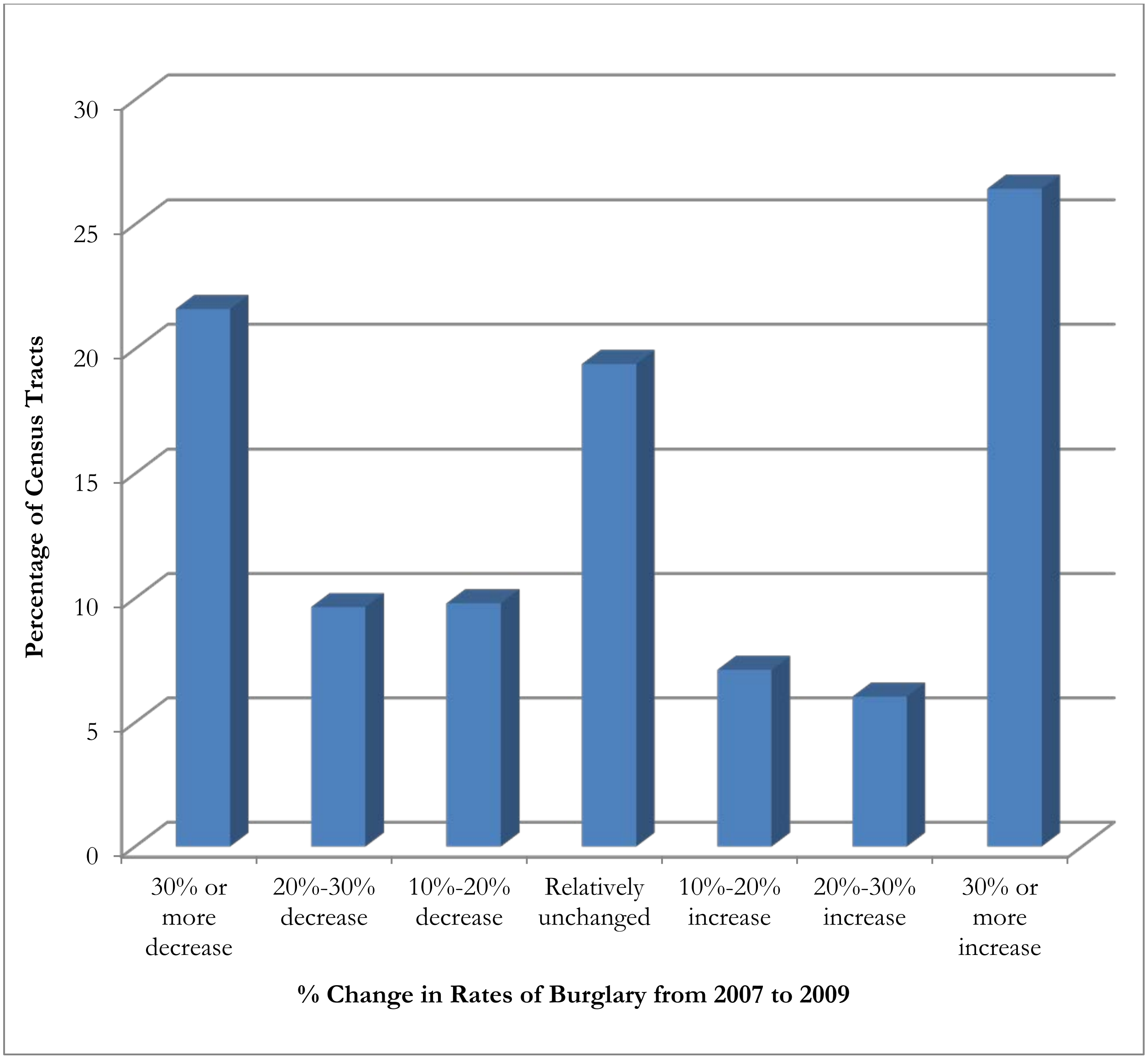


Figure 4. Neighborhood Variation in Recent Changes in Burglary Rates across 7,355 Census Tracts in 64 Large U.S. Cities.

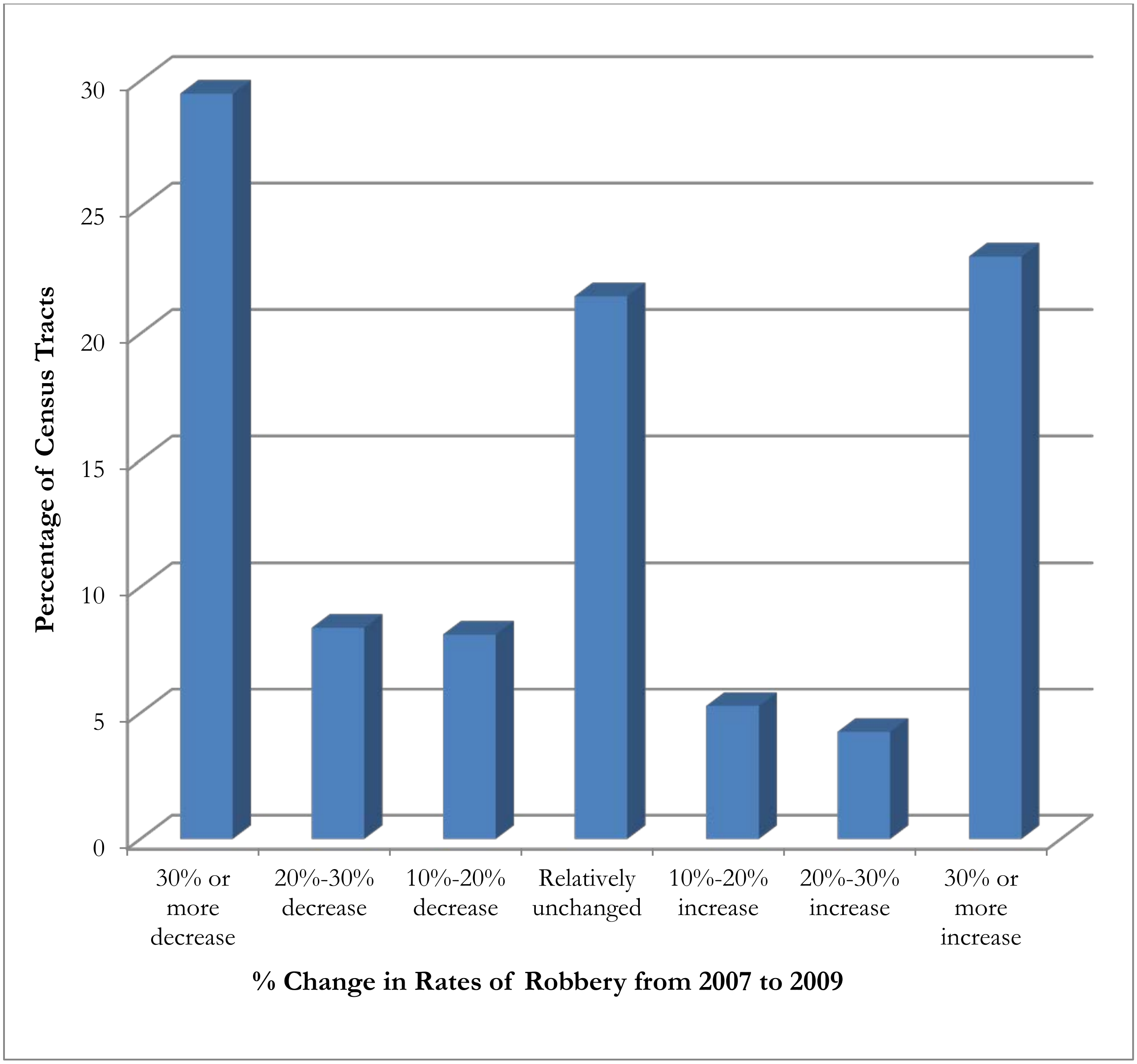


Figure 5. Neighborhood Variation in Recent Changes in Robbery Rates across 6,753 Census Tracts in 63 Large U.S. Cities.

that crime rates may be on the rise, it is not surprising that many representatives of the media and others highlighted a possible connection between the two. However, the presumption of a link between foreclosure and crime in America during the midst of the foreclosure crisis did not spring from a strong empirical foundation. In fact, as the nation stumbled to come to grips with the unprecedented rise in foreclosure and speculation mounted that it would yield elevated crime rates, the accumulated knowledge about a possible relationship between foreclosure and crime remained somewhat negligible, limited to a relatively small body of research on crime around vacant properties (see Krivo & Peterson, 1996; Spelman, 1993; Taylor & Covington, 1988) and a single neighborhood-level study of foreclosure and crime (Immergluck & Smith, 2006). While the available empirical evidence supported the general idea that the foreclosure crisis could yield higher crime rates, the paucity of systematic research directed explicitly on the matter made it a dubious enterprise to draw strong conclusions. Indeed, until very recently the most definitive evidence was Immergluck and Smith's (2006) pioneering research in Chicago, which is suggestive of a significant link between foreclosure and crime but is situated within an era that predated the contemporary housing bust (i.e., the early 2000s), was based on cross-sectional data, and did not account for the well-known spatial autocorrelation of crime.

Spurred by the recent housing crisis, a small but growing body of research has explored more directly a possible relationship between foreclosure and crime, with some of the studies encompassing the contemporary foreclosure crisis. Research on county-level patterns has supported the anticipated significant positive association between foreclosure and property crime (Arnio, Baumer, & Wolff, 2012; Goodstein & Lee, 2010), but the evidence reported in these studies may confound patterns that exist at smaller levels of aggregation, which seem better suited for evaluating whether the presence of foreclosed properties is contributing to area crime rates (see Hipp, 2007). A small handful of more localized studies of foreclosure and crime have emerged during the past few years that shed additional light on the issue (Arnio & Baumer, 2012; Cui, 2010; Ellen, Lacoe, &

Sharygin, 2011; Katz, Wallace, & Hedberg, 2012; Kirk & Hyra, 2012; Stucky, Ottensmann, & Payton, 2012; Teasdale, Clark, & Hinkle, 2011). Each of these studies focuses on a single, but different city (Akron, Chicago, Glendale, Indianapolis, New York City, Pittsburgh, and New York City, respectively), and they have applied different units of analysis (e.g., census tracts, locally defined neighborhoods, block-faces, and small spatial zones or rings around foreclosed properties), slightly different measures of foreclosure (i.e., all filings, REOs, REOs that remain vacant for pre-defined periods), and a wide variety of estimation strategies. Perhaps not surprisingly, the results have been inconsistent across studies. Some of the emerging studies have reported uniformly significant effects of foreclosure on crime (Teasdale et al., 2011), others report evidence of significant effects of foreclosure under some conditions (e.g., for *some* crime types, for *some* measures of foreclosure, for *some* periods, or for *some* neighborhood clusters) but not others (Arnio & Baumer, 2012; Cui, 2010; Ellen et al., 2011; Katz et al., 2012; Stucky et al., 2012), and some scholars report that foreclosure and crime are not significantly related (Kirk & Hyra, 2012).

The available research thus provides an ambiguous answer to the question of whether the contemporary foreclosure crisis has yielded increased crime rates. The variation in findings across studies thus far could reflect the noted differences in procedures, and as the number of studies in this area grows over time, closer scrutiny of those differences may help to extract a set of general conclusions supported by the most rigorous studies. It is also possible, however, that the observed differences in findings across existing "neighborhood-level" studies of foreclosure and crime to-date represent meaningful variability across cities. As elaborated in the next section, there are reasons to anticipate geographic variability in the relationship between foreclosure and crime, with the former more apt to lead to the latter in some contexts than others. This project contributes to the literature by examining the link between foreclosure and crime using a uniform set of procedures and a multilevel dataset that integrates information on neighborhood foreclosures, burglary and robbery, and other attributes during the heart of the contemporary foreclosure crisis for 60+ large cities.[3] The project addresses three specific questions: (1) Are levels foreclosure significantly associated with burglary and robbery rates across neighborhoods after controlling for other factors?; (2) Is any observed effect of foreclosure on neighborhood burglary and robbery rates contingent on (i.e., moderated by) the other neighborhood conditions, including preexisting structural disadvantage, pre-existing vacancy rates, or racial and ethnic context?; and (3) Does the effect of foreclosure rates on neighborhood levels of burglary and robbery vary across *cities* in systematic ways? For instance, is the magnitude of the effects of foreclosure on crime across neighborhoods contingent on city conditions such as pre-existing or co-occurring vulnerabilities (e.g., an aging housing stock, high rates of pre-existing vacancies, and high levels of unemployment and other forms of socioeconomic disadvantage), or the capacity for mitigating the adverse consequences of a housing crisis (e.g., housing affordability, the size of the police force).

As we elaborate below, we address these questions by estimating a series of single- and multi-level over-dispersed count regression models that specify 2009 neighborhood (i.e., census tract)[4] crime rates as a function of foreclosure rates measured for 2007-2008, while accounting for 2007 crime rates and other control variables (including spatially lagged neighborhood crime rates). As noted, we focus on assessing whether there is a significant effect of foreclosure on robbery and burglary across neighborhoods, and whether the estimated neighborhood effect varies systematically across cities.

[3]The data support neighborhood-level analyses of burglary rates for 64 cities. We were unable to obtain robbery data for Minneapolis; thus, our assessment of neighborhood robbery rates is restricted to 63 cities.

[4]We use the terms "neighborhood" and "census tracts" interchangeably throughout the report, though it is important to acknowledge that the latter do not necessarily conform to the former. Census tracts are commonly used to represent neighborhoods in social science research, and we do so in the present study to facilitate comparisons across multiple cities.

II. Theoretical Background

The Potential Criminogenic Effects of the Foreclosure Crisis

Most theoretical discussions of foreclosure and crime have borrowed heavily from the "broken-windows" thesis (e.g., Wilson & Kelling, 1982). Though there have been noteworthy revisions to this perspective (see Skogan (1990) and Taylor (2001) for overviews), the basic premise of what has become more widely known in the scholarly literature as the "incivility thesis" is that visual signs of abandonment in communities may give rise to heightened physical and social disorder. These conditions are likely to translate into higher levels of crime by encouraging residents to withdraw from public social interactions and social control efforts, yielding a larger volume of unregulated areas in which deviant activities can flourish.

The incivility thesis encompasses themes that are developed more fully within classic and contemporary explications of social disorganization theory and the routine activities perspective, both of which have been applied frequently to explain neighborhood-level variation in crime rates. Social disorganization theory emphasizes the potential destabilizing influence of significant population turnover, which is hypothesized to increase crime rates by disrupting communication among community residents, by impeding their capacity for reinforcing social norms about conventional behavior and organizing against social problems, and by reducing informal social control efforts (Shaw & McKay, 1942). Contemporary extensions of the perspective have elaborated on the implied mechanisms, highlighting how residents of socially disorganized communities tend to exhibit relatively low levels of "collective efficacy" (Sampson, Raudenbush, & Earls, 1997) and are less well equipped than others to garner external resources (e.g., police protection, social services, and other "public controls") that may be useful for combating crime (Bursik & Grasmick, 1993). The existing neighborhood-level studies of foreclosure and crime have drawn on these classic and contemporary arguments to highlight how the contemporary foreclosure crisis may stimulate higher crime rates because it has produced a relatively large volume of abrupt residential changes in many communities, which can disrupt social organization and weaken collective efficacy (Kirk & Hyra, 2012) and diminish the capacity for mobilizing formal social control efforts (Goodstein & Lee, 2010).

Arnio et al. (2012) suggest that elevated foreclosure rates also may translate into elevated neighborhood crime levels by altering opportunity structures and/or public interactions in ways that make crime more probable, a theme that is central to theoretical frameworks that highlight movement patterns of potential victims and offenders (e.g., routine activities theory and crime pattern theory). The routine activities perspective overlaps in key ways with the social disorganization framework (e.g., both describe how rapid ecological shifts can affect levels of guardianship and other forms of informal social control), but it also highlights the importance of how such conditions can shape the availability of "suitable targets," another key element for understanding community differences in crime rates (Cohen & Felson, 1979). Properties that have been foreclosed upon are often unoccupied for significant periods, an outcome particularly prevalent during the contemporary housing crisis given the long-term drought in home sales in many areas. This not only may depress guardianship levels, thereby increasing the chances that nearby properties are seen as attractive burglary targets, but foreclosed properties may themselves appear as attractive opportunities for theft (Brantingham & Brantingham, 1991). Consistent with this notion, the available evidence suggests that thefts of copper and appliances associated with burglaries rose precipitously as foreclosure rates hit historic highs in the last several years of the 2000s (Federal Bureau of Investigation [FBI], 2008; Von Fremd, 2009).

Beyond equating foreclosed properties as pertinent to "target attractiveness" for theft and burglary, the routine activities perspective suggests that foreclosures may be perceived as appealing "unguarded spaces" for potential offenders to congregate. This may yield elevated rates of a variety of deviant activities (e.g., substance abuse) that fuel other crimes, including violent crimes such as robbery, assault, and homicide (Felson & Cohen, 1980). In line with this possibility, studies of foreclosure and crime across block-faces in New York City (Ellen et al., 2011), block-groups in Indianapolis (Stuckey, Ottensmann, & Payton, 2012), and census tracts in Akron (Teasdale et al., 2011) show that that additional foreclosures (measured in various ways) yield an increase not only in property crimes, but also violent and public order offenses. Teasdale et al. (2011) also report significant effects of foreclosure on rates of drug violations and disorderly conduct.

In summary, the extant theoretical literature implies that higher levels of foreclosure in a given area may increase crime through several possible mechanisms, including heightened disorder, weakened social organization and collective efficacy, and enhanced criminal opportunities. These general linkages have a sound grounding in the extant theoretical literature, and though the data currently available to researchers does not permit definitive tests of the various perspectives, their application to the contemporary foreclosure crisis is theoretically plausible. At the same time, though, a broader reading of the theoretical literature implies that each of the highlighted mechanisms through which foreclosure might increase crime can be considered highly *conditional*. Some of the existing neighborhood-level research in single sites (see Immergluck and Smith's (2006) analysis of foreclosure and crime across Chicago census tracts and Stuckey et al.'s (2012) analysis across Indianapolis block-groups) have considered interactions between specified neighborhood conditions (e.g., foreclosure and socioeconomic disadvantage), and we also explore several of such possibilities in our analysis. But we focus more specifically on another potential form of conditional foreclosure effects—the possibility that there may be meaningful variation across cities in the estimated link between neighborhood-level rates of foreclosure and crime.

City-Level Variation in the Influence of Foreclosure on Crime Rates

An important insight that has emerged from scholarship in the areas of political economy and urban sociology is that the broader contexts within which neighborhoods are situated can have important implications for how various social problems and/or economic shocks are experienced and perceived, which in turn has implications for their consequences. Two key features of city environments seem especially consequential for moderating the magnitude of the effects of foreclosure on crime across neighborhoods: (1) pre-existing or co-occurring vulnerabilities; and (2) the capacity for mitigating the adverse consequences of a housing crisis. We briefly elaborate on each of these features.

The Possible Conditioning Role of City-Differences in "Vulnerability"

The extant theoretical literature also suggests that the link between foreclosure and crime across neighborhoods may be conditioned by pre-existing or co-occurring vulnerabilities. The foreclosure crisis was a partial stimulus to and a major part of the "Great Recession," and while most cities experienced symptoms of this significant economic decline, some were hit much harder than others. Even before the official onset of the most recent recession, however, U.S. cities differed considerably on a wide variety of social and economic indicators that may make them more, or less, vulnerable to a major foreclosure crisis. For example, the abrupt rise in foreclosures in the second half of the 2000s occurred in cities where there had been a relatively large volume of recent new construction and few existing vacancies (i.e., where housing markets had been robust in the earlier part of the decade), but it also happened in areas that already had an abundant supply of vacant homes and an "aging" housing stock (i.e., little new construction). These latter places may have been struggling already to attract new residents and keep crime rates low, and thus neighborhoods in these areas might be especially vulnerable to the potential negative consequences of high levels of foreclosure, including elevated crime rates. On the other hand, significant foreclosure activity in areas where the housing stock is relatively new may not yield the anticipated spiral of decay and widespread abandonment noted above, at least in the short-term, because the properties are likely to remain in relatively good condition and the areas are more likely retain their attractiveness to potential new buyers.

Additionally, as some literature within the social disorganization and political economy traditions has highlighted (Crenson, 1983; Bursik & Grasmick, 1993), high-risk neighborhoods (e.g., those with high rates of foreclosure) may be less successful in efforts to garner useful external resources (e.g., foreclosure mitigation resources, support for maintaining and/or repurchasing vacant buildings, etc.) when embedded in a broader political context in which resources are highly strained, such as where vacancy rates were already quite high before the contemporary foreclosure crisis, or where rates of socioeconomic disadvantage were relatively high. Overall, these arguments suggest that the estimated effect of foreclosure on crime across neighborhoods may be stronger in cities with relatively little new construction (i.e., an aging housing stock), high rates of pre-existing vacancies, and high levels of unemployment and other forms of socioeconomic disadvantage.

City Attributes that May Mitigate the Criminogenic Features of High Neighborhood Foreclosures

A broader point often referenced in the literature is that cities differ significantly in their capacity to address social problems of all sorts (Logan & Molotch, 1987; Smith, Caris, & Wyly, 2001). During the 2000s, U.S. cities exhibited meaningful variation on a number of dimensions, some of which we just described as "vulnerabilities" that might amplify the criminogenic potential of high foreclosure neighborhoods. Admittedly, most of those factors also play a role in shaping city responses to a major economic downturn, including the foreclosure crisis. Two other features that seem particularly relevant for shaping the capacity for cities to mitigate the potentially adverse consequences of high neighborhood foreclosure rates are (1) the existing prospects for housing recovery (e.g., where homes remain affordable), and (2) the human resources available to directly address emerging crime problems.

The theoretical frameworks reviewed above suggest that a high rate of foreclosure in a neighborhood is less likely to yield significant additional crime if foreclosed properties are reoccupied in short order, a prediction for which there is some empirical support (Cui, 2010; Ellen et al., 2011). This insight yields an expectation that foreclosure and crime may be less strongly related in cities where housing has remained relatively affordable. In such contexts it seems likely that home sales will rebound more quickly and foreclosed properties will remain vacant for shorter periods, which in turn should limit the likelihood that would-be offenders will congregate around such properties.

Cities also vary considerably with respect to their capacity to respond to growing crime problems, including those that might arise from an abrupt increase in unoccupied homes. The chief means by which they do so, of course, is through local policing efforts. The size of police forces differs significantly across cities, and though the existing literature on the link between crime rates and police size have generated inconsistent results (see Eck & Maguire, 2006, for an exhaustive review), some research has shown that larger police forces yield reductions in city crime rates (e.g., Levitt, 1997). The foreclosure crisis spurred a large array of ameliorative efforts aimed at lessening the scope of the problem and minimizing collateral consequences, including elevated crime rates (e.g., the U.S. Housing and Urban Development [HUD] Neighborhood Stabilization Program [NSP]). However, these efforts were not directed at crime reduction *per se*, and most were not implemented on a large scale until the middle of 2009, several years into the housing decline and near the end of our observation period. In contrast, the types of criminal activities that foreclosed properties may give rise to—illicit drug activities, violent and non-violent property crimes, and various public order offenses—are the explicit focus of local police agencies, and therefore city differences in policing represent an important dimension that may have implications for the degree to which high neighborhood rates of foreclosure have translated into higher crime rates. The cities included in our analysis differ in a number of important ways, including the relative size of their police forces and changes in police force size during the study period. Significant city-level differences in the number of police officers per capita have been documented in several previous studies (e.g., Levitt, 1997). Additionally, though the period observed in our study represents a relatively short duration, perhaps because of the significant strain on state and local budgets as a result of the "Great Recession," the data assembled for our research show that several of the cities included experienced notable declines (greater than 10 percent) in police force size per capita over the period. All else equal, we anticipate the relationship between foreclosure and crime across neighborhoods to be weaker in cities in which the overall size of the police force was larger and declining less significantly.

III. Methods

Sample & Data

As highlighted above, the project addresses three questions: (1) Are foreclosure levels significantly associated with crime rates across neighborhoods after controlling for other factors?; (2) Is any observed effect of foreclosure on neighborhood crime rates contingent on (i.e., moderated by) the other neighborhood conditions, including preexisting structural disadvantage, high unemployment, and the age of the housing stock; and (3) Does the effect of foreclosure rates on neighborhood crime levels vary across cities in systematic ways? These questions are addressed by integrating census tract-level data on crime rates gathered from local police agencies with foreclosure data from RealtyTrac, and a wide variety of social, economic, and demographic control variables from multiple source.

Our general strategy was to regress 2009 neighborhood crime rates on foreclosure rates measured for 2007-2008, while accounting for 2007 crime rates and other control variables. The bulk of the latter were drawn from the sole source of data on contemporary social, economic, and demographic context for American neighborhoods—the ACS pooled (2005-2009) census tract file—which we treat as reflective of conditions present at approximately the mid-point of the period covered in these data (i.e., 2007). Though the housing crisis began to unfold in many American communities as early as 2005, we focus on 2007-2009 because this is when foreclosure rates exhibit particularly notable spikes in most areas of the country.

A major objective of the study was to assemble neighborhood-level data on crime, foreclosure, and other factors for multiple cities across America. To facilitate a meaningful assessment of cross-city variability in neighborhood patterns in the context of the available resources for the project, we specifically suggested in the proposal that we would design our effort to yield a sample of approximately 50 cities. As we developed the sampling protocol for the project, we appreciated the potential utility of sampling from a wide variety of American cities (e.g., urban, suburban, and rural areas), but also recognized that obtaining neighborhood crime data from smaller law enforcement agencies might not be feasible with the time and funds available. Given these considerations, we chose to focus the project on relatively large cities, defined as those with 100,000 or more persons based on estimates drawn from the 2005-2007 American Community Survey (ACS); there were approximately 270 U.S. cities with populations of 100,000 during the middle of the decade. We considered drawing a random sample of cities from this universe, a strategy adopted by Peterson and Krivo (2010) in the National Neighborhood Crime Survey (NNCS), but determined that though this is a worthwhile strategy, one major disadvantage of doing so is that approximately 40 percent of U.S. cities with populations of 100,000 or more are located in just three states (California, Texas, and Florida). Thus, to avoid a sample that was dominated disproportionately by these states, and also to facilitate broader regional and state coverage, we defined our sampling frame in two stages. Both stages focused on the selection of large cities (those with 100,000 or more persons), but the first targeted cities from the 50 most populous metropolitan areas and the other targeted cities from other metropolitan areas.

In the first stage of sampling, we selected at least one large city (populations greater than 100,000) from each of the largest 50 metropolitan areas. For metropolitan areas with more than one such city, we chose one randomly. In cases where data were not provided by a selected city or were provided in a form that could not be meaningfully integrated with data from other cities (e.g., counts of crime within locally defined beats or neighborhoods that have important local value, but are not comparable to "neighborhood" definitions that could be applied across multiple cities), we randomly selected a replacement city. Overall, we requested data from 80 cities within the largest 50 metropolitan areas, obtaining data in some fashion from 58 (73%) of them, and data that could be meaningfully integrated with other cities (i.e., data that could be aggregated to census tracts) from 50 (61.7%) cities. Of the 80 cities included in our initial sampling frame, 62 had participated in the NNCS, which encompasses neighborhood data on crime and other conditions at the beginning of the 2000s. We wished to expand the breadth of our sample to include cities outside the largest U.S. metropolitan areas, while also facilitating more extensive linkages between our data and the NNCS. Thus, we also requested in a second stage of sampling data from the other 29 cities represented in the NNCS. In practice, these additional large cities were chosen randomly within regions from the universe of all cities with 100,000 or more persons located outside the largest 50 metropolitan areas. We received data in some form or another from 20 of these cities (68.9%), and data that could be meaningfully integrated with data from other jurisdictions from 17 (58.6%). In total, we requested neighborhood data in writing from 109 cities with 100,000 or more persons; we received data in some form or another from 78 cities (71.5% of those sampled), and data that could be integrated fully for 67 cities (61.4% of the sampled cities).[5]

The map in Figure 6 shows the 67 cities that define the maximum available sample for the analysis described herein. Though the sample is tilted toward the areas of the nation in which the largest metropolitan areas are concentrated (i.e., the Northeast), each of the regions is represented and the sample includes cities in states hit especially hard by the recent housing crisis (e.g., Nevada, Arizona, California, Florida) and those in which foreclosure rates were comparatively low (e.g., New Mexico, Pennsylvania, New York, North Carolina). The 67 cities denoted on Figure 6 define the universe of cities that provided data in a form that enabled us to generate the requisite census tract-level counts of robbery and burglary for two or more years during the study period (2005-2009).

The sample used for the analyses reported herein is further constrained by the specific design employed and the availability of other data elements. Specifically, we exclude Knoxville, TN, Columbus, OH, and Seattle, WA because the police agencies in these cities did not provide the

[5]We requested data from all agencies initially by sending a letter to the Chief of Police. Thirty-one of the contacted agencies did not provide data; of these, 15 declined to provide data, citing in many cases insufficient personnel to fulfill our request. Some of these agencies would have provided data if we were able to compensate them, but this is something the funds for the project were not intended to cover. The remainder of the cities for which we did not secure data (n=16) failed to respond to our initial contact and several follow-ups. Eleven cities provided data, but in a form that was not easily integrated with other cities. Most often, this was because cities submitted data aggregated by a geographic unit that was sensible for local reporting purposes (e.g., police beats, reporting districts, local neighborhoods), but which could not be matched to U.S. census tracts in a valid manner.

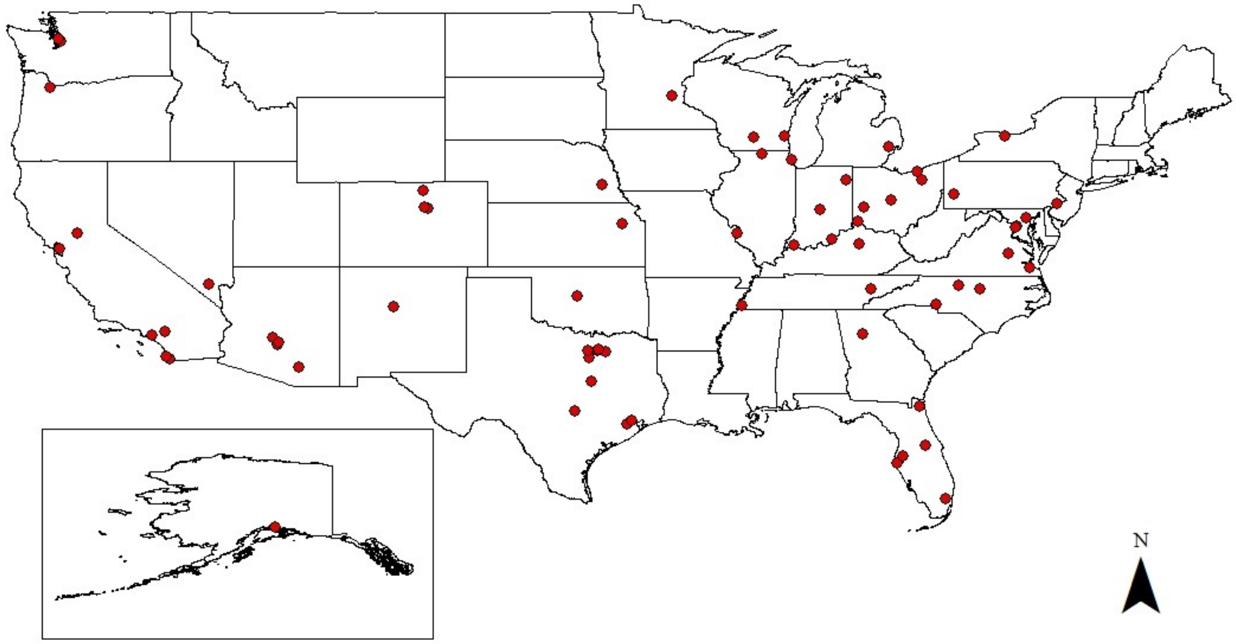


Figure 6. Cities encompassed in multilevel project on foreclosure and crime in America.

requisite crime data for both 2007 and 2009 (an important element of our design). According to the 2005-2009 ACS census tract file, these 64 cities included in our sample contain 7,842 census tracts that fall wholly or partly within them (based on 2009 place definitions). To minimize potential distortions that might arise from computing crime and foreclosure rates on the basis of particularly small denominators, we exclude from the analysis census tracts with less than 50 persons or 50 housing units (n=295) and a small handful of tracts (n= 132) for which we were unable to obtain data on foreclosure and other data elements. After these data exclusions, the maximum analysis sample consists of 7,415 census tracts within 64 cities and 29 states. The 64 cities are listed in Table 1. As we explain in more detail next, these 64 cities serve as our pooled sample for the analysis of foreclosure and burglary reported below. One city – Minneapolis – did not provide parallel crime counts for robbery, so this portion of our analysis is based on 7,294 census tracts within 63 cities.

Measures

We summarize the neighborhood (i.e., census tract) measures used in the study in Table 2, and we list the city-level variables considered in Table 3. Descriptive statistics also are provided in the tables. Most of the indicators are well represented in the literature on communities and crime, but because some are less prominent and others represent strategic choices made for purposes of the present research we elaborate on several key measures below.

<u>Dependent Variables</u>

From a theoretical standpoint, high foreclosure rates should be salient for crimes strongly tied to economic motivations (e.g., acquisitive crimes). We focus our attention in the study to two forms of crime often committed for instrumental purposes (Felson, Baumer, and Messner, 2000; Baumer and Gustafson, 2007): robbery and burglary.

We consider robbery and burglary particularly relevant from a theoretical vantage point, but acknowledge that a variety of other crimes are potentially relevant to the foreclosure crisis as well,

Table 1. Listing of cities included in multilevel analysis of foreclosure and crime (n=64).

City & State	City & State
Anchorage, AK	Lincoln, NE
Chandler, AZ	Las Vegas, NV
Glendale, AZ	Albuquerque, NM
Tempe, AZ	Rochester, NY
Tucson, AZ	Charlotte, NC
Chula Vista, CA	Greensboro, NC
Garden Grove, CA	Raleigh, NC
Moreno Valley, CA	Akron, OH
Oakland, CA	Cincinnati, OH
Sacramento, CA	Cleveland, OH
San Diego, CA	Columbus, OH
Aurora, CO	Dayton, OH
Denver, CO	Oklahoma City, OK
Fort Collins, CO	Portland, OR
Washington, DC	Philadelphia, PA
Jacksonville, FL	Pittsburgh, PA
Orlando, FL	Memphis, TN
Pembroke Pines, FL	Arlington, TX
St. Petersburg, FL	Austin, TX
Tampa, FL	Carrollton, TX
Atlanta, GA	Dallas, TX
Chicago, IL	Fort Worth, TX
Rockford, IL	Houston, TX
Evansville, IN	Pasadena, TX
Fort Wayne, IN	Plano, TX
Indianapolis, IN	Waco, TX
Topeka, KS	Alexandria, VA
Lexington-Fayette, KY	Newport News, VA
Baltimore, MD	Richmond, VA
Sterling Heights, MI	Bellevue, WA
Minneapolis, MN	Madison, WI
St. Louis, MO	Milwaukee, WI

including domestic violence, drug offenses, and public order crimes. We limit attention to robbery and burglary in this project for three main reasons. First, though the police agencies sampled for the project often provided us with data on a wide variety of crime types, in some instances it was clear that there were important differences across jurisdictions in how specified crimes were recorded and counted by local agencies. This was especially apparent for public-disorder crimes, for which agencies appear to use a wide variety of different offense labels and definitions. The data provided on robbery and burglary presented fewer of such concerns, presumably because they are UCR Part 1 crimes for which counting and recording rules have been institutionalized. Second, although there is little direct evidence on neighborhood variation in the validity of police-recorded crime data, in general robbery and burglary tend to be reported by citizens at relatively high rates compared to other crimes. Also, the extant research suggests fewer systematic neighborhood differences in crime reporting for robbery (Baumer, 2002) than assault. While we cannot say with certainty that other relevant crimes that we could have included in the study—domestic violence, drug offenses, and public order crimes— exhibit high levels of differential validity across neighborhoods, these offenses tend to have relatively low reporting rates overall, which heightens concerns that this may be the case.[6] Third, though we considered a more expansive approach even in light of the above mentioned considerations, it was not feasible to do so in light of resource constraints associated with the project. Even though we requested crime data from local agencies aggregated to census tracts, many of the jurisdictions included in our study provided us with address-level data, which required considerable processing by us to transform into census tract crime counts (i.e., data cleaning, geocoding, and aggregation). We had anticipated that some agencies would provide this type of granular data, but surprisingly this was the rule rather than the exception. To keep the project

[6]It is well known that many crimes go unreported to the police (Baumer & Lauritsen, 2010). The presence of under-reporting, per se, is not problematic for aggregate-levels of studies of police-based crime; the key issue is whether rates of under-reporting vary across communities systematically so that they are significantly correlated with theoretical variables of interest. The limited research on this issue suggests relatively little community variation in rates of police notification, especially for more serious crimes (for a review, see Baumer, 2002).

manageable and within budget, therefore, we opted to limit the project to two crimes that we considered suitable (as elaborated above) and for which we could reasonably allocate sufficient resources for the needed geocoding and data cleaning.

The specific crime measures used in the project reflect the number of robberies and burglaries known to (i.e., reported to and/or discovered by) the police.[7] As elaborated below, we address links between foreclosure and crime by modeling census tract robbery and burglary counts in 2009 using a multilevel Poisson-based framework, accounting for census tract differences in crime "risk" in the regression models by including population as an exposure variable, which yields interpretation of the covariate effects in terms of their influence on tract-level differences in crime rates (see Osgood, 2000).

Neighborhood Explanatory Variables

Our key explanatory variable is the number of residential foreclosures per 1,000 housing units in 2007-2008 for the sampled census tracts (*Neighborhood foreclosure rate*). There are numerous data options for measuring the prevalence of foreclosures in the U.S. (see Kan, 2008), including both local sources (county recorder's offices, tax assessor data, court filings, and newspaper filings) and national sources (RealtyTrac, CoreLogic, Foreclosures.com, DataQuick, and Mortgage Bankers Association of America). Given our interest in assessing the implications for crime during the foreclosure crisis across a large swath of American communities, we obtained the requisite data from one of the more commonly referenced sources in the housing industry–RealtyTrac. The data represent actual foreclosures (i.e., Real Estate Owned [REO] transactions and foreclosure sales or auctions) in 2007-2008 within each census tract in our sample. We obtained address-level foreclosure data from RealtyTrac for our sample cities, and then geocoded these records to generate

[7]We are aware of no research that directly examines the influence of community foreclosure rates on levels of police notification and/or police recording. However, if rates of police notification are depressed in areas hit hardest by foreclosure, our estimates of the relationship between rates of foreclosure and crime could be biased downward.

census tract foreclosure counts. We constructed foreclosure rates by dividing the foreclosure counts by the total number of housing units in the census tracts, as estimated in the 2005-2009 ACS census tract data, and multiplying this quotient by 1000.[8]

As Table 2 reveals, the mean foreclosure rate in 2007-2008 for the 7,415 tracts in our sample was 25.07 per 1,000, which not surprisingly is several times higher than the average "historical" rate of approximately one-half of a percent observed for much of the last half of the 1900s (Elmer and Seelig, 1998). Foreclosure rates also exhibit substantial variability across census tracts, with about one-quarter of the tracts in our sample experiencing foreclosure conditions in 2007-2008 that were at or below the recent historical average (a few—234—even experiencing no foreclosures), but also many (about 15 percent) that exhibit foreclosure rates more than 10 times higher.

Neighborhood Control Variables

Obtaining valid estimates of neighborhood foreclosure effects on crime levels requires that we simultaneously account for other neighborhood conditions that might be related both to the spatial distribution of foreclosure and to neighborhood variability in crime. We therefore include in our analysis a variety of neighborhood indicators that have been linked to foreclosure and which have emerged as robust predictors of neighborhood crime across several U.S. cities.[9] Most of the control variables are drawn from the ACS pooled 2005-2009 census tract file, and thus are available

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[8]We considered two alternative denominators as well, including an estimate of the number of mortgages granted between 2004 and 2006 (obtained from HUD) and the number of owner-occupied housing units with mortgages (obtained from the ACS). Foreclosure rates based on these denominators exhibit moderate-to-strong inter-item correlations with the housing-unit based measure used in our study (e.g., the within-year correlations range between .60 and .75). We use housing units to standardize the prevalence of foreclosure because this seems most consistent with the underlying research questions. To elaborate, a significant part of the theoretical rationale for expecting an empirical link between foreclosure rates and crime rates is that public perceptions of higher foreclosure rates might affect the social control behavior of residents and/or the offending calculus of would-be offenders. We assume that such perceptions are tied more closely to assessments of how prevalent foreclosure is in general (i.e., across all housing units), rather than a more selective assessment of foreclosure risk among housing units that contain a mortgage (something that is not typically visible).

[9]City-level differences in the validity of neighborhood-level crime models represents a potentially importance source of between-city variance in estimated neighborhood parameters. In light of this, we consulted available neighborhood-level crime studies based on data from a variety of cities to identify potentially important predictors.

Table 2. Description of neighborhood variables included in the multilevel analysis of foreclosure and crime (n=7,415 census tracts).

Variable	Variable definition and data source(s)	Mean	SD
Robbery count, 2009	Number of robberies known to the police. Data source: Local police agencies.	14.42	17.76
Burglary count, 2009	Number of burglaries known to the police. Data source: Local police agencies.	46.01	43.28
Foreclosure rate, 2007-08	Number of residential foreclosures (i.e., real estate owned transactions and foreclosure sales or auctions) per 1,000 housing units in 2007-2008. Data source: RealtyTrac	25.07	31.39
Socioeconomic disadvantage	Five-item standardized scale combining the percentage of families below the poverty level, 2005-2009; the percentage of households female-headed, 2005-2009; the percentage of families receiving public assistance or food stamps, 2005-2009; the percentage of the population ages 16-64 who are unemployed, 2005-2009, and the percentage of persons ages 16-64 who are not in the labor force, 2005-2009. Data source: American Community Survey (ACS)	.00	.83
Immigrant concentration	Two-item standardized scale combining the percentage of the population who are Latino, 2005-2009 and the percentage of the population who are foreign-born, 2005-2009. Data source: ACS	.00	.93
Residential stability	Three-item standardized scale combining the percentage of housing units owner-occupied, 2005-2009; the percentage of the population over one year old living in the same household one year ago, 2005-2009; and the percentage of owners and renters in occupied housing units that moved into their current residence prior to 2000 (computed by subtracting the combined percentages of owners and renters who had reported moving between 2000-2004 and after 2005 from 100). Data source: ACS	.00	.84
Preexisting vacancy rate	Percentage of housing units vacant 90 days or longer, as of the end of fourth quarter 2006. Data source: U.S. Department of Housing and Urban Development aggregated U.S. Postal Service data on address vacancies	4.75	4.91
Population size (logged)	Log transformed population size, 2005-2009. Data source: ACS	8.07	.73
Population density (logged)	Log transformed population density, 2005-2009. Data source: ACS and 2009 Census Tiger Files.	-6.21	.99
Percent non-Latino black	Percentage of the population who are non-Latino black, 2005-2009. Data source: ACS	29.34	33.19
Population ages 15-29	Percentage of the population ages 15-29, 2005-2009. Data source: ACS	23.89	9.83
Percent divorced	Percentage of the population ages 15 and older who are divorced, 2005-2009. Data source: ACS	11.63	5.20
Prior robbery rate, 2007	Number of robberies known to the police per 10,000 residents, 2007. Data sources: Local police agencies, ACS	52.21	79.18
Prior burglary rate, 2007	Number of burglaries known to the police per 10,000 residents, 2007. Data sources: Local police agencies, ACS	140.37	171.14

only at a single temporal point that can be described as the mid-point of the period encompassed by these data (i.e., 2007). Drawing from prior neighborhood-level research (e.g., Krivo et al., 2009), we use several measures to construct multi-item standardized indices of *residential stability*, *immigrant concentration*, and *socioeconomic disadvantage*. Our measure of residential stability is a three-item standardized scale combining the percentage of owner-occupied units; the percentage of the population over 1 year old living in the same household the previous year; and the percentage of owners and renters in occupied housing units that moved into their current residence prior to 2000 (α=.791). Immigrant concentration is a standardized index comprised of the percentage of the population that is foreign-born and the percentage of the population that is Latino (α=.846). Finally, we measure socioeconomic disadvantage with a five-item standardized index containing the percentage of families below the poverty level, the percentage of households headed by a female, the percentage of households receiving public assistance or food stamps, the percentage of persons 16 to 64 who are unemployed, and the percentage of persons 16 to 64 who are not in the labor force (α=.883).

We also consider several control variables drawn from the ACS that have been shown to be significant predictors of crime in previous neighborhood studies. As elaborated below, population size is included as an exposure variable in our count models, but we also include logged population size as a control variable because larger areas may exhibit higher crime rates independent of the fact that that the population at risk is greater (see also Baller, Zevenbergen, & Messner, 2009; Osgood, 2000). Past research also suggests that neighborhood crime rates tend to be higher in areas with greater population density. Thus, we include in our models a measure of population per square mile, derived from the 2009 Census Tiger files. Like population size, this indicator of population density was highly skewed, so to minimize the influence of outliers we include a log transformed measure of population density in our models of neighborhood crime. Additionally, we include from the ACS indicators of racial composition (percent non-Latino black), youthful age structure (percent ages 15-

29), and divorce rates (percent of population 15 and over who are divorced). We incorporate from the U.S. Department of Housing and Urban Development (HUD) the prevailing 90-day vacancy rate as of the end of 2006, the period just prior to when we observe foreclosure rates. Finally, all of the models estimated incorporate measures of prior crime rates, defined for the year 2007. Doing so helps to account for prior sources of 2009 crime levels not captured by the observed measures.

City-level Moderator Variables

A key focus in our study is to assess whether the estimated effect of neighborhood foreclosure rates on neighborhood crime levels varies systematically across cities, and specifically whether the magnitude of this slope is moderated by the city-level attributes described earlier. We thus include several city-level attributes that capture potentially important differences in conditions that may have some cities more (or less) vulnerable or resistant to elevated neighborhood foreclosure rates. The specific measures considered are displayed in Table 3, along with pertinent descriptive statistics (Appendix A provides correlations among the city measures).

As argued above, a high neighborhood foreclosure rate may have different consequences for crime depending on pre-existing "vulnerabilities." For instance, high neighborhood foreclosure rates may be more problematic for cities in which there had been relatively little new construction during the housing boom of the early 2000s, and where there was a larger supply of vacant houses prior to the housing bubble burst. We assess these possibilities by including as moderators city-level estimates from the 2008 ACS of the percentage of housing units built between 2000 and 2007 (*City percent housing built 2000-2007*), and city-level estimates of vacancy rates, averaged for 2006 and 2007 (*City pre-existing vacancy rate*). We also include indicators of structural disadvantage that may impede the capacity of cities to mitigate the potential crime generating properties of high foreclosure rates, namely the percentage of families below poverty (*City poverty rate*) and the percentage of the civilian labor force that were unemployed (*City unemployment rate*) in 2008, and the percentage change in unemployment rates between 2007-2009 (*City unemployment rate change*). The poverty data were drawn

Table 3. Description of city-level variables included in the multicity neighborhood analysis of foreclosure and crime (n=64 cities).			
Variable	**Variable definition and data source(s)**	**Mean**	**SD**
City percent housing units built, 2000-2007	The percentage of housing units built between 2000-2007. Data source: ACS	10.83	6.60
City preexisting vacancy rate	The average number of vacancies per 100 housing units, 2006-2007. Data Source: American Community Survey (ACS)	11.86	4.57
City housing affordability index (HAI)	Index computed by dividing the median family income in a given area by the income needed to qualify for a loan to purchase a median price home. Data Source: ACS	148.74	53.47
City police force size	The number of sworn police officers per 100,000 residents, 2008. Data Source: Uniform Crime Reporting Program (UCR)	357.88	369.79
City change in police force size	The percentage change in police force size between 2008-2009. Data Source: UCR	-2.47	6.78
City percent non-Latino black	The percentage of persons who identify as non-Latino black, 2008. Data source: ACS	21.89	16.85
City poverty rate	The percentage of families below the poverty level, 2008. Data source: ACS	12.66	5.11
City unemployment rate	The percentage of civilian labor force unemployed, 2008. Data source: BLS	5.88	1.53
City unemployment rate change	Percentage change in the unemployment rate, 2007-2009. Data source: BLS	101.75	38.09

from the ACS, while the unemployment data were taken from the Bureau of Labor Statistics (BLS). Given evidence that the foreclosure crisis may have been especially severe in areas with relatively large African American populations (see Rugh & Massey, 2010), coupled with extant theory that suggests greater vulnerabilities to external economic shocks in such communities (see Peterson & Krivo 2010), we include an indicator or racial context (*City percent non-Latino black*).

We also include as moderators several features of cities that may have served as buffers to the potentially criminogenic effects of high neighborhood foreclosure rates. The first is an overall indicator of housing affordability for our cities and three measures of the capacity of police to regulate crime. More specifically, we include a city housing affordability index (*City HAI*) based on a comparable measure developed by the National Association of Realtors (NAR). This index captures city differences in the capacity of a "typical family" to purchase a "typical home." The HAI is computed by dividing the median family income in a given area by the income needed to qualify for a loan for the median priced home. A value of 100 for a city indicates that a family with the median income is likely to qualify for a mortgage on a median-priced home, assuming prevailing loan arrangements and interest rates.[10] Cities with higher values on the index are places in which housing is relatively more affordable. Finally, we include two city policing measures included in the analysis—the number of sworn police offers per 100,000 residents (*City police size*) in 2008, and changes in police force size during the period (2007-2009) for which we observe potential foreclosure effects on crime (*City police force change*)—for purposes of evaluating whether high neighborhood foreclosure rates were less apt to translate into high crime rates where police resources were more plentiful and where they declined less significantly over the period.

[10]To construct the city-level HAI, we obtained median housing values for 2008 from the ACS to gauge median home prices, we assume a 20 percent down payment, a principal and payment that cannot exceed 25% of median family income, and the average U.S. interest rate (6.083%) for 2008 (see www.erate.com/mortgage_rates_history.htm). For more details on computing the HAI, see www.realtor.org/research/research/housinginx.

Analytical Strategy

We address the substantive issues outlined above (i.e., whether there is a significant effect of foreclosure on robbery and burglary across neighborhoods, and whether the estimated neighborhood effect varies systematically across cities) with a series of single- and multilevel regression models. Our neighborhood-level data contain a considerable number of tracts with relatively small populations and low crime counts; these features yield highly skewed distributions for crime rates and a heterogeneous error variance, properties that violate assumptions of conventional linear regression models. We considered a variety of different alternatives that may be more appropriate in light of the distributional properties of our data, including Poisson and zero-inflated regression models (Hilbe 2011). Multiple tests (i.e., Pearson's dispersion statistics, z-score test, Lagrange multiplier test, and Poisson goodness of fit test) from preliminary Poisson models pointed to significant overdispersion. In light of this, we estimated a series of overdispersed Poisson, zero-inflated Poisson, and negative binomial regressions; these models yielded virtually identical results. Evaluation of AIC and BIC statistics revealed that overall model fit was slightly better for the negative binomial models. We therefore report the results of negative binomial regressions of crime on foreclosure and other factors for the individual city regressions presented below. At the time of our analysis, negative binomial regression models had not been fully incorporated into accessible multi-level analysis software; thus, for the pooled, multilevel specifications presented below, we present results for two-level overdispersed Poisson models. This strategy has become common practice in studies of neighborhoods across multiple cities (see also Peterson & Krivo, 2010). The multi-level modelling strategy enables us to assess meaningful variability in neighborhood patterns across the sampled cities, while also accounting for the non-independence of census tracts within the same city. Given our focus on the potential between-city variability of neighborhood foreclosure effects, we report results from two-level random coefficient models in which both the intercept and the slopes are permitted to vary across cities.

Two other analytical issues warrant discussion before we report the results: (1) the choice of centering used in the multilevel specifications; and (2) the spatial dependence of crime. First, because our focus in the paper is on obtaining in a two-level hierarchical model an estimate of a level 1 relationship (i.e., the effect of neighborhood foreclosure rates on neighborhood crime rates) and evaluating the degree to which that relationship varies systematically across level 2 clustering units (i.e., cities), we group-mean center all of the neighborhood predictors in our analysis (see Raudenbush & Bryk, 2002). Second, it has been well established that many forms of crime exhibit significant geographic clustering across neighborhoods and other geographic units, and that this "spatial autocorrelation" is not merely a function of comparable clustering of social and economic attributes that are associated with crime (e.g., Morenoff, Sampson, & Raudenbush, 2001). Surprisingly, few of the recent studies of foreclosure and crime has explicitly accounted for spatial autocorrelation, which is potentially problematic because failing to account for spatial autocorrelation may lead to biased and inefficient regression estimates (Anselin, 1988). The underlying statistical theory and analytical tools for modeling spatial autocorrelation have been restricted primarily to single-level linear models, and they remain in early stages of development for application to multilevel and non-linear approaches (see Lambert, Brown, & Florax, 2010; Verbitsky, Savitz, & Raudenbush, 2009). Given this, we adopt a modified form of two-stage least squares (2SLS) approach explicated by Land and Deane (1992) to minimize the potential bias that can arise from including an endogenous spatial lag term. Specifically, using a standard contiguity matrix (e.g., five nearest neighbors) we computed spatially lagged measures of crime using the fitted values for crime from our multilevel Poisson models and then re-estimated these models with the spatial lag measures included (see also, Baller et al., 2009; Peterson & Krivo, 2010).

IV. Results

Multilevel Analysis for All Cities

We initiated our analysis with a bivariate multilevel specification that included only our key explanatory variable, neighborhood foreclosure rates. As shown in Table 4 (Panel A), under this specification we observe statistically significant positive bivariate effects of foreclosure rates on both robbery and burglary (shaded light gray). Further, inspection of the random effects variance components reveals that we find statistically significant variability across cities in the effects of neighborhood foreclosure rates (shaded dark gray).

The results shown in Panel A are suggestive, but Kirk and Hyra (2012) persuasively argue that such bivariate associations could be spurious given that foreclosure and crime tend to emerge from a common set of neighborhood conditions. This prospect is plausible in light of several significant inter-item correlations observed across the measures considered in our study (see Appendix A). Additionally, there is some evidence that high levels of crime may increase the prevalence of foreclosure, rather than or in addition to the reverse (Feinberg & Nickerson, 2002). Both of these possibilities motivate the estimation of multivariate regression models that account for other factors, including pre-existing crime levels. The model results presented in Panel B integrate the neighborhood-level control variables, while Panel C also incorporates spatially lagged measures of crime generated from the procedures described above. In both instances, we estimated models initially in which each of the neighborhood measures was specified as random across cities. Following Raudenbush and Bryk (2002), we set as fixed those slopes that were found to exhibit non-significant variation across cities. To facilitate a conservative estimation strategy, we used a one-tailed significance test ($p < .05$) to inform these decisions. Consistent with prior research, we observe statistically significant spatial lag effects, and so we focus our attention on the most complete specifications displayed in Table 4, which are reported in Panel C.

Though there are several interesting findings that emerge in Panel C, we emphasize three

Table 4. Hierarchical Overdispersed Poisson Regression of Neighborhood Crime on Foreclosure Rates.

Panel A. Bivariate Effects of Foreclosure Rate

	Model 1: Robbery			**Model 2: Burglary**		
Fixed Effects:	Coefficient	SE	t Ratio	Coefficient	SE	t Ratio
Foreclosure Rate	.005	.002	2.60*	.009	.001	6.14*
Intercept, γ_{00}	-6.11	.091	-67.23*	-4.66	.068	-68.91*

	Robbery			Burglary		
Random Effects:	SD	Variance	X^2	SD	Variance	X^2
Foreclosure Rate	.012	.0001	478.56*	.01	.0001	675.03*
Intercept, T_{00}	.699	.489	5281.43*	.533	.284	5227.90*
Neighborhood-Level, r	3.60	12.96		3.93	15.41	

Panel B. Multivariate Effects of Foreclosure Rate (no spatial lag for crime)

	Model 1: Robbery			**Model 2: Burglary**		
Fixed Effects:	Coefficient	SE	t Ratio	Coefficient	SE	t Ratio
Foreclosure Rate	-.0004	.0004	-.856	.002	.0004	4.72*
Population Size (logged)	-.149	.023	-6.48*	-.061	.009	-6.40*
Population Density (logged)	.113	.018	6.35*	.017	.011	1.50
Socioeconomic Disadvantage	.074	.020	3.72*	-.004	.020	-.204
Immigrant Concentration	.246	.019	13.24*	.054	.014	3.82*
Residential Stability	-.127	.014	-8.99*	-.079	.008	-9.57*
Percent Divorced	.024	.002	10.62*	.010	.001	8.14*
Percent Non-Latino Black	.009	.001	10.46*	.005	.001	7.34*
Percent Population Ages 15-29	.003	.001	3.06*	.0002	.001	.301
Pre-Existing Vacancy Rate	.018	.003	5.85*	.016	.003	5.17*
Prior Crime Rate	.011	.001	14.00*	.004	.0002	15.75*

	Robbery			Burglary		
Random Effects:	SD	Variance	X^2	SD	Variance	X^2
Foreclosure Rate	.002	.000004	87.38*	.002	.000004	112.65*
Population Size (logged)	.113	.013	112.61*	--	--	--
Population Density (logged)	.086	.008	105.49*	.059	.004	97.70*
Socioeconomic Disadvantage	.093	.009	81.54*	.109	.012	109.60*
Immigrant Concentration	.084	.007	94.94*	.777	.006	106.42*
Residential Stability	.050	.003	78.40	--	--	--
Percent Divorced	.012	.0001	106.86*	--	--	--
Percent Non-Latino Black	.005	.00002	165.80*	.004	.00002	177.51*
Percent Population Ages 15-29	--	--	--	--	--	--
Pre-Existing Vacancy Rate	.014	.0002	110.32*	.018	.0003	183.68*
Prior Crime Rate	.006	.00003	8483.44*	.002	.00000	1310.30*
Intercept, T_{00}	.787	.619	12086.945*	.572	.327	6463.168*
Neighborhood-Level, r	1.93	3.74		2.50	6.24	

Table 4. (Cont.)

Panel C. Multivariate Effects of Foreclosure Rate (with spatial lag for crime)

	Model 1: Robbery			Model 2: Burglary		
Fixed Effects:	Coefficient	SE	t Ratio	Coefficient	SE	t Ratio
Foreclosure Rate	-.0003	.0004	-.773	.001	.0003	3.70*
Population Size (logged)	-.089	.020	-4.52*	-.044	.009	-4.78*
Population Density (logged)	.063	.011	5.87*	-.002	.010	-.151
Socioeconomic Disadvantage	.051	.012	4.25*	.030	.020	-1.46
Immigrant Concentration	.174	.017	10.52*	.056	.011	5.03*
Residential Stability	-.108	.011	-9.78*	-.072	.008	-8.91*
Percent Divorced	.022	.002	11.00*	.010	.001	8.10*
Percent Non-Latino Black	.005	.0005	8.47*	.003	.001	5.45*
Percent Population Ages 15-29	.001	.001	1.51	-.004	.0007	-.647
Pre-Existing Vacancy Rate	.006	.002	3.30*	.008	.002	3.44*
Prior Crime Rate	.010	.001	13.85*	.003	.0002	15.79*
Spatially Lagged Crime	.419	.030	14.11*	.365	.033	10.97*
Intercept, γ_{00}	-6.25	.100	-62.32*	-4.67	.072	-64.42*
	Robbery			Burglary		
Random Effects:	SD	Variance	X^2	SD	Variance	X^2
Foreclosure Rate	.002	.000004	94.43*	.002	.000004	78.33*
Population Size (logged)	.087	.008	80.63*	--	--	--
Population Density (logged)	--	--	--	.051	.003	83.31*
Socioeconomic Disadvantage	--	--	--	.107	.012	87.52*
Immigrant Concentration	.066	.004	82.37*	.053	.003	79.10*
Residential Stability	--	--	--	--	--	--
Percent Divorced	.009	.0001	80.64*	--	--	--
Percent Non-Latino Black	.002	.00002	106.94*	.004	.00001	90.18*
Percent Population Ages 15-29	--	--	--	--	--	--
Pre-Existing Vacancy Rate	--	--	--	.011	.0001	103.64*
Prior Crime Rate	.005	.00003	8181.72*	.002	.000004	195.57*
Spatially Lagged Crime	.014	.019	98.24*	.179	.032	65.35
Intercept, T_{00}	.787	.620	12585.78*	.576	.332	4358.14*
Neighborhood-Level, r	1.91	3.65		2.46	6.05	

$^*p \leq .05$

Note: Robbery models are based on 7,294 tracts within 63 U.S. cities; burglary models are based on 7,415 tracts within 64 U.S. cities.

that are most central to our research questions. First, once we control for other neighborhood conditions, we find no significant association between neighborhood rates of foreclosure and robbery across the 7,000+ census tracts included in the study (Panel C, Model 1). This pattern is consistent with Kirk and Hyra's (2012) claim that the apparent tendency for areas of high foreclosure to have higher crime rates may reflect spuriousness.

Second, and contrary to the results for robbery, we do find a small, statistically significant effect of foreclosure on burglary ($b=.001$, $p < .05$) across these tracts, even after controlling for many other factors, including prior crime levels and contemporary levels of crime in neighboring census tracts.

Third, and perhaps most important, we observe statistically significant city-level variation in the estimated neighborhood foreclosure effects for both robbery and burglary. The "fixed effects" coefficients for foreclosure displayed in Panel C (shaded in light gray) reflect estimated neighborhood relationships *pooled across all cities* represented in our sample. In other words, they represent *average* neighborhood effects across the cities, generated from 60+ city-specific neighborhood foreclosure slope estimates. The corresponding random effects in the bottom half of the panel (shaded in darker gray) indicate whether the estimated neighborhood-level slopes exhibit significant between-city variability, and this information can be combined with the pooled estimates to compute 95% confidence intervals for the city-specific slopes (see Raudenbush & Bryk, 2002).

The variance components for our multilevel models reveal that several of the estimated slopes vary significantly across cities. Most notably, this is the case for the estimated effects of neighborhood foreclosure rates in both the robbery and burglary models. Even at the extremes the observed foreclosure effects are modest, a point to which we return below, but for now we emphasize that *the results imply a noteworthy range of estimates across cities*: for robbery, the 95% confidence interval for the city-specific foreclosure slopes is [-.004, .004], and for burglary the 95% confidence interval is [-.003, .005]. This is an important finding that may help to clarify the variability reported across previous studies in the estimated effects of foreclosure on crime. Applying the same empirical specification across cities, we observe a notable range of effects that include both positive and negative estimates. In short, the conclusions drawn about the link between foreclosure and crime are likely to be highly specific to the city under investigation, a point that we highlight further below.

Why might elevated neighborhood foreclosure rates yield higher neighborhood crime rates in some cities and not others? Why might the magnitude of positive (or negative) associations between foreclosure and crime vary across cities? As described above, the foreclosure crisis emerged during the 2000s in a wide variety of different contexts, and the extant literature suggests that some of those contexts may mitigate or amplify the mechanisms through which heightened foreclosures might yield elevated crime rates. Accordingly, we estimated random coefficient specifications for robbery and burglary rates that model the observed city-level variation in neighborhood foreclosure slopes as a function of several city-level attributes. We did so by employing specifications that were identical to those shown in Panel C of Table 4, except for the inclusion of city-level conditions as predictors of both city-level variability in the intercept (i.e., the average crime rate across cities, after adjusting for between-city neighborhood conditions) and as predictors of city-level variability in the neighborhood foreclosure slopes.

We considered a variety of different specifications for the city-level components of these models. In general, the substantive results were robust to alternative specifications and, in importantly, the findings do not appear to be unduly biased by multicollinearity (though some of the city-level variables are highly correlated, the results were stable across estimations that included or excluded such indicators in a step-wise fashion). We report in Table 5 the parameters of primary interest from the random coefficient models in which we evaluate the effects of city-level attributes on the cross-city crime intercepts and foreclosure slopes. The parameters shown represent the estimated city-level effects and the random components (of which we focus primarily on the

Table 5. Multilevel Overdispersed Poisson Models of City Variation in Neighborhood Foreclosure Effects on Crime.

	Robbery			Burglary		
Fixed Effects:	Coefficient	SE	t Ratio	Coefficient	SE	t Ratio
Intercept, γ_{00}	-7.024	.386	-18.220*	-5.492	.231	-23.739*
City percent housing units built, 2000-2007	.005	.009	.600	.026	.005	5.006*
City preexisting vacancy rate	.055	.018	3.126*	.018	.009	1.853
City housing affordability index	-.001	.001	-.784	.002	.001	3.420*
City police force size	-.0002	.0002	-1.130	-.00001	.00009	-.087
City change in police force size	1.404	.827	1.697	.627	.491	1.278
City percent non-Latino black	.010	.004	2.311*	.001	.002	.631
City poverty rate	-.028	.016	-1.746	-.014	.009	-1.437
City unemployment rate	.113	.041	2.769*	.043	.026	1.665
City unemployment rate change	-.002	.002	-1.475	-.001	.001	-.823
Foreclosure Rate, γ_{01}	.004	.005	.868	.008	.004	2.404*
City percent housing units built, 2000-2007	-.0003	.0001	-2.829*	-.0002	.0001	-2.391*
City preexisting vacancy rate	-.00005	.00017	-.294	-.0001	.0001	-1.005
City housing affordability index	.00001	.00001	.535	-.000001	.000009	-.027
City police force size	-.000001	.000001	-.587	.000001	.000001	.555
City change in police force size	-.02050	.00953	-2.158*	-.002	.007	-.346
City percent non-Latino black	.00007	.00005	1.502	-.00002	.00004	-.579
City poverty rate	-.00031	.00020	-1.566	-.0002	.0001	-1.228
City unemployment rate	.00032	.00039	.829	.00008	.0003	.266
City unemployment rate change	-.000002	.00002	-.101	-.00001	.00001	-.973

	Robbery			Burglary		
Random Effects:	SD	Variance	X^2	SD	Variance	X^2
Intercept, T_{00}	.555	.308	6994.666*	.529	.280	5161.417*
Foreclosure Rate	.002	.000003	78.635*	.002	.000004	74.971*
Population Size (logged)	.084	.007	80.863*	--	--	--
Population Density (logged)	--	--	--	.052	.003	89.503*
Socioeconomic Disadvantage	--	--	--	.107	.011	104.153*
Immigrant Concentration	.068	.005	83.209*	.061	.004	88.628*
Percent Divorced	.009	.00008	77.233	--	--	--
Percent Non-Latino Black	.002	.000005	115.973*	.004	.00001	121.260*
Pre-Existing Vacancy Rate	--	--	--	.014	.0002	146.423*
Prior Crime Rate	.005	.00003	7923.45*	.002	.000002	1051.670*
Spatially Lagged Crime	.138	.019	98.717*	--	--	--
Neighborhood, r	1.909	3.644		2.470	6.101	

*p ≤ .05

Note: Robbery models are based on 7,294 tracts within 63 U.S. cities; burglary models are based on 7,415 tracts within 64 U.S. cities.

reported variance of the neighborhood foreclosure effects).

The results reported in Table 5 indicate that the city attributes considered do not account for a notable portion of the city-level variation observed in the estimated foreclosure slopes. This is evidenced by the fact that the variance components for the average foreclosure slope are virtually unchanged from Table 4, Panel C. Nonetheless, the results highlight a modest, and statistically significant, role for selected variables.

The results in Table 5 under the sub-heading for "Foreclosure Rate, γ_{01}" reveal evidence that foreclosure effects on robbery were smaller in cities with larger values on the indicator of changes in police force size. Overall, police forces in the 63 cities in which we model neighborhood robbery rates declined by about 3 percent between 2008 and 2009. Our findings suggest that elevated foreclosure rates were less apt to translate into additional robberies in places that experienced smaller reductions in their police force (or which experienced greater increases). However, supplementary analyses in which we evaluated foreclosure effects in cities that experienced the greatest declines and the greatest growth in police force size during this period do not reveal strong evidence of a uniform protective effect of growth in policing. Instead, the city-level attribute that emerges as most pertinent to shaping whether neighborhoods with higher foreclosure rates in 2007-2008 experienced additional crime in 2009 beyond what was anticipated based on 2007 crime levels and other attributes was the age of the housing stock. Specifically, neighborhood foreclosure effects on both robbery and burglary are significantly weaker in cities where a larger proportion of housing units were built between 2000 and 2007, and significantly stronger where that proportion was lower. The logic of this pattern emerges most clearly for burglary, in part because as we discuss below, the evidence for "criminogenic" consequences of foreclosure are strongest for this crime type.

City-Specific Foreclosure Effects

To illustrate the logic of our primary finding from the multilevel models—that neighborhood foreclosure effects are conditioned by the age of city housing stocks—we show results for selected city-specific models of burglary in Tables 6 and 7. The specifications adopted in these "single-level" models closely parallel the most complete specifications used in the multilevel regressions reported in Table 4 (Panel C). However, in the city-specific models we adopt a more flexible estimation for the overdispersion parameter (a negative binomial specification, which was not available in the multilevel software used for the research) and, of course, by definition these models do not contain city random effects because they are based on a single city. Otherwise, the empirical specification adopted here is identical to what we report in our most comprehensive model in Table 4 (i.e., Panel C).

Table 6 shows results for negative binomial neighborhood models of burglary for four cities from our sample (Atlanta, Fort Worth, Las Vegas, and Moreno Valley) that experienced particularly high levels of new housing construction between 2000 and 2007, ranging from 18 percent (Atlanta) to 25 percent (Forth Worth) of housing units present in 2008 built during that period. Consistent with the logic of our multilevel regression model (see Table 5), foreclosure has a weak, statistically insignificant effect on burglary in these cities. It is noteworthy that two of these cities – Las Vegas and Moreno Valley – exhibit some of the highest foreclosure rates observed in American during this period. Our sample also includes cities where there was very little new housing construction during the 2000s. For instance, less than 3.5 percent of the housing units in the cities shown in Table 7 (Evansville, Philadelphia, Rochester, and Akron) were built between 2000 and 2007. These cities have a relatively "old" housing stock and, as argued above, it seems plausible to suggest that, all else equal, high neighborhood foreclosure rates in cities with an aging housing stock may be more apt to yield elevated crime rates. This is supported by the estimated foreclosure effects observed for the cities displayed in Table 7. In each case, the estimated effect of foreclosure is statistically significant and much larger than the effects observed in the cities in which there had been considerably new housing construction (compare to Table 6).

Table 6. Negative Binomial Regression Models of Burglary for Cities in which a Relatively Large Percentage of Housing Units were Built between 2000 and 2007.

	Atlanta	Fort Worth	Las Vegas	Moreno Valley
Foreclosure Rate	.001	-.0004	.001	.002
	(.001)	(.002)	(.002)	(.002)
Population Size (logged)	-.157*	-.076	-.198*	-.168
	(.075)	(.065)	(.069)	(.103)
Population Density (logged)	-.239*	.047	.039	.314*
	(.095)	(.041)	(.082)	(.123)
Socioeconomic Disadvantage	-.217*	-.152*	-.036	-.716*
	(.089)	(.067)	(.105)	(.252)
Immigrant Concentration	.223	.146*	.064	.168
	(.131)	(.045)	(.051)	(.170)
Residential Stability	-.052	-.043	-.034	-.565*
	(.092)	(.052)	(.072)	(.234)
Percent Divorced	.021*	.011	.019*	-.049*
	(.010)	(.007)	(.009)	(.018)
Percent Non-Latino Black	.010*	.008*	-.001	.004
	(.003)	(.002)	(.004)	(.009)
Percent Population Ages 15-29	.003	-.001	.012	-.016
	(.005)	(.005)	(.008)	(.023)
Pre-Existing Vacancy Rate	.006	.004	.017	-.234*
	(.010)	(.008)	(.018)	(.111)
Prior Burglary Rate	.002*	.003*	.004*	.005*
	(.001)	(.0004)	(.001)	(.001)
Spatial Lag	-.006*	-.001	.002	.004
	(.002)	(.002)	(.003)	(.004)
Constant	-5.324*	-4.103*	-3.874*	-1.323
	(.886)	(.783)	(.800)	(1.703)
Logged Alpha	-1.840*	-2.426*	-2.954*	-3.344*
	(.148)	(.149)	(.198)	(.421)
Neighborhood n	118	141	106	37

*p ≤ .05

Table 7. Negative Binomial Regression Models of Burglary for Cities in which a Relatively Small Percentage of Housing Units were Built between 2000 and 2007.

	Evansville	Philadelphia	Rochester	Akron
Foreclosure Rate	.014*	.008*	.015*	.008*
	(.005)	(.003)	(.007)	(.002)
Population Size (logged)	.019	-.192*	-.236*	.260*
	(.160)	(.054)	(.098)	(.092)
Population Density (logged)	-.410*	-.029	-.011	.017
	(.120)	(.046)	(.070)	(.072)
Socioeconomic Disadvantage	-.037	.060	.006	.100
	(.155)	(.041)	(.067)	(.095)
Immigrant Concentration	1.651*	.007	-.260*	-.212
	(.478)	(.060)	(.111)	(.222)
Residential Stability	.389*	-.175*	-.095	-.291*
	(.154)	(.045)	(.078)	(.106)
Percent Divorced	.026*	-.002	.007	.006
	(.012)	(.006)	(.009)	(.010)
Percent Non-Latino Black	.001	-.001	.003	.003
	(.004)	(.001)	(.002)	(.002)
Percent Population Ages 15-29	.032*	-.003	.009	-.009
	(.011)	(.003)	(.006)	(.006)
Pre-Existing Vacancy Rate	.069*	.027*	.009	.008
	(.023)	(.007)	(.009)	(.015)
Prior Burglary Rate	.003*	.003*	.003*	.002*
	(.001)	(.0004)	(.001)	(.001)
Spatial Lag	.035*	.001	.016*	.007*
	(.008)	(.003)	(.005)	(.003)
Constant	-9.744*	-3.867*	-4.264*	-7.272*
	(2.123)	(.654)	(.956)	(1.136)
Logged Alpha	-3.410*	-2.092*	-3.247*	-2.854*
	(.476)	(.103)	(.282)	(.254)
Neighborhood n	41	357	78	66

*p ≤ .05

Though the eight cities highlighted in Tables 6 and 7 fit with the logic of our multilevel models for burglary, we can also identify in our data places with relatively high levels of new housing construction in which there is a significant link between foreclosure and places with hardly any new housing where foreclosure is unrelated to crime. By far the most common finding that emerges in our project from both the pooled multilevel analysis reported above and our examination of city-specific models is that the high degree of variability in estimated neighborhood effects across cities does not appear follow a clear pattern, at least with respect to the city variables we have considered. To put it more plainly, we find that foreclosure is related to crime in some cities but not others, and that the magnitude of observed foreclosure effects varies significantly across cities. Some of this can be explained by city differences in the age of the housing stock, but for the most part the observed differences across cities are not captured by the city variables we considered. This prompted us to take a closer look at the cities in our sample, and to draw more definitive assessments about the cities in which foreclosure is (or is not) associated with crime. While the multilevel models are suitable for summarizing systematic patterns, they do so at the price of hiding some of the details about patterns in specific cities. Therefore, to supplement our pooled, multilevel models, we estimated neighborhood-level robbery and burglary models separately for all the cities in our sample, employing our most comprehensive specification (i.e., including all neighborhood control variables, prior crime, and spatially lagged crime). We summarize the results of these estimations in Table 8.

Panel A of Table 8 summarizes the three possible findings from the city-specific regressions, classifying each city (for each crime type) as exhibiting neighborhood foreclosure effects that were statistically non-significant, statistically significant and positive, or statistically significant and negative (we also comment on the magnitude of significant effects, where detected). Panel B lists the results for each city that form the basis of this overall summary.

While the multilevel models were useful for showing that there was statistically significant variability in the main effects of neighborhood foreclosure rates on crime, the results in Table 8

Table 8. Cross-City Summary of Neighborhood Effects of Foreclosure on Burglary and Robbery.

A. City Sample Summary of Foreclosure Main Effects

	Burglary	Robbery
% non-significant	76.6	87.3
% significant, positive	18.8	4.8
% significant, negative	4.7	7.9
Total	100.0	100.0

B. City-Specific Listing of Main Effects of Foreclosure on Crime Rates

City & State	Burglary	Robbery	City & State	Burglary	Robbery
Anchorage, AK	ns	*, negative	Lincoln, NE	*, positive	ns
Chandler, AZ	ns	ns	Las Vegas, NV	ns	ns
Glendale, AZ	ns	ns	Albuquerque, NM	ns	ns
Tempe, AZ	*, negative	ns	Rochester, NY	*, positive	ns
Tucson, AZ	ns	ns	Charlotte, NC	*, positive	ns
Chula Vista, CA	ns	ns	Greensboro, NC	ns	ns
Garden Grove, CA	ns	ns	Raleigh, NC	ns	ns
Moreno Valley, CA	ns	ns	Akron, OH	*, positive	ns
Oakland, CA	ns	ns	Cincinnati, OH	ns	ns
Sacramento, CA	ns	ns	Cleveland, OH	ns	ns
San Diego, CA	*, positive	ns	Columbus, OH	ns	ns
Aurora, CO	ns	ns	Dayton, OH	*, positive	*, positive
Denver, CO	ns	ns	Oklahoma City, OK	ns	ns
Fort Collins, CO	ns	ns	Portland, OR	ns	ns
Washington, DC	ns	ns	Philadelphia, PA	*, positive	*, positive
Jacksonville, FL	ns	ns	Pittsburgh, PA	*, positive	ns
Orlando, FL	ns	*, negative	Memphis, TN	ns	ns
Pembroke Pines, FL	ns	ns	Arlington, TX	*, negative	ns
St. Petersburg, FL	ns	ns	Austin, TX	ns	ns
Tampa, FL	ns	ns	Carrollton, TX	*, negative	ns
Atlanta, GA	ns	ns	Dallas, TX	ns	*, negative
Chicago, IL	*, positive	ns	Fort Worth, TX	ns	*, negative
Rockford, IL	ns	ns	Houston, TX	*, positive	ns
Evansville, IN	*, positive	*, positive	Pasadena, TX	ns	*, negative
Fort Wayne, IN	*, positive	ns	Plano, TX	ns	ns
Indianapolis, IN	ns	ns	Waco, TX	ns	ns
Topeka, KS	ns	ns	Alexandria, VA	ns	ns
Lexington-Fayette, KY	ns	ns	Newport News, VA	ns	ns
Baltimore, MD	ns	ns	Richmond, VA	ns	ns
Sterling Heights, MI	ns	ns	Bellevue, WA	ns	ns
Minneapolis, MN	ns	--	Madison, WI	ns	ns
St. Louis, MO	ns	ns	Milwaukee, WI	ns	ns

Note: ns =not statistically significant; -- =not estimated; *, positive =statistically significant and positive; *, negative =statistically significant and negative.

reveal a more vivid story. As the summary in Panel A shows, in the majority of the cities in our sample (more than 75%), we observe no statistically significant association between neighborhood foreclosure rates and crime after controlling for other factors. We find the anticipated significant positive effect of foreclosure on burglary rates in 12 of the 64 cities in which we estimated that relationship (18.8% of the sample), and a significant negative effect in a small number of cities. Thus, to sum up our findings for burglary to this point, we find evidence that foreclosure rates are associated with increases in burglary in selected cities, with a tendency for this to be more likely in cities with little recent housing construction, but the most consistent finding in our data is that foreclosure and burglary are not significantly related, at least under the specification applied in our analysis. We see a similar pattern for robbery, though in this case the search for a clear significant effect is even murkier. For 55 of the 63 cities (87.3%) in which we evaluated the link between foreclosure rates and robbery, we found the relationship to be statistically insignificant. We observe a significant association between foreclosure and robbery in 8 cities, but it is negative in 5 and positive in 3.

It is possible that census tracts are too large and heterogeneous to detect the impact of foreclosure on crime (Ellen et al., 2011), or that a more nuanced indicator of foreclosure activity that captured details such as the nature of occupancy patterns during foreclosure, the length (if any) of vacancy, and the condition of the property would yield different findings.[11] But, using the census tract and foreclosure data in hand we find little support for the presumed positive association between foreclosure and robbery that emerged from media accounts during the housing crisis. More generally, though there are important exceptions, for both robbery and burglary the most consistent pattern we see is that foreclosure did not yield significant increases in crime.

[11]Though our foreclosure data do not encompass such information, we estimated supplementary models in which we evaluated whether neighborhood foreclosure rates were more strongly related to crime in cities governed by judicial review procedures, where foreclosures often yield longer-term vacancies. We did not detect any significant differences in the magnitude of neighborhood foreclosure effects across jurisdictions governed by judicial vs. non-judicial proceedings.

Neighborhood Conditional Effects

One possible critique of the findings presented thus far is that they assume that foreclosure influences crime uniformly across geographic space within neighborhoods, or in other words that foreclosure effects are merely "additive." As other scholars have pointed out, high levels of foreclosure may represent a fundamentally different reality if accompanied by other neighborhood conditions that are potentially criminogenic (Immergluck & Smith, 2006; Arnio et al., 2012; Stucky et al., 2012). Immergluck and Smith (2006) argue that high foreclosure rates may be more likely to yield significant increases in crime rates in lower-income areas, compared to higher-income areas, because of greater pre-existing vulnerabilities for crime in the former places (see also Arnio et al., 2012; Stucky et al., 2012). We concur with such sentiments, but note that the logic of the theoretical frameworks outlined earlier in this report, and evidence from the broader literature on the consequences of foreclosure (e.g., Edmiston & Zalneraitis, 2007), suggests other factors in addition to community socioeconomic status that may condition the influence of foreclosure on crime. In particular, foreclosures may be more apt to increase criminal activity not only in contexts of high levels of resource deprivation, but also in areas with already high levels of vacancy prior to the foreclosure crisis, and in areas of concentrated minority presence (e.g., higher levels of percent non-Latino black and immigrant concentration). We explored these possibilities by re-estimating the models summarized in Table 8 after adding the pertinent interaction terms to test for possible conditional effects of foreclosure on robbery and burglary. Specifically, for each crime type and for each city in our sample, we estimated negative binomial regression models in which we considered the potential moderating role of neighborhood socioeconomic disadvantage, pre-existing vacancy rates, immigrant concentration, and percent non-Latino black.

In Tables 9 (burglary) and 10 (robbery), we summarize the overall patterns that emerge across all the cities for the multiplicative models we estimated. We report the key parameters associated with these estimations in Tables 11 through 20 for 10 cities that represent the different

Table 9. Cross-City Summary of Conditional Neighborhood Effects of Foreclosure on Burglary.

		Moderator Variable:					
City & State	**(1) Main Effect**	**(2) Concentrated Disadvantage**	**(3) Pre-Existing Vacancy Rate**	**(4) Immigrant Concentration**	**(5) Percent non-Latino Black**	**(6) One or More Moderating Effects**	**(7) Main Effect OR Moderating Effect**
Anchorage, AK	ns	ns	ns	ns	ns	no	no
Chandler, AZ	ns	ns	ns	ns	ns	no	no
Glendale, AZ	ns	ns	ns	ns	ns	no	no
Tempe, AZ	*, negative	ns	*, negative	ns	ns	yes	yes
Tucson, AZ	ns	ns	ns	ns	ns	no	no
Chula Vista, CA	ns	ns	ns	ns	ns	no	no
Garden Grove, CA	ns	*, positive	ns	*, positive	ns	yes	yes
Moreno Valley, CA	ns	*, negative	ns	ns	ns	yes	yes
Oakland, CA	ns	*, negative	ns	*, negative	ns	yes	yes
Sacramento, CA	ns	ns	ns	ns	ns	no	no
San Diego, CA	*, positive	ns	ns	ns	ns	no	yes
Aurora, CO	ns	ns	ns	ns	ns	no	no
Denver, CO	ns	ns	*, negative	ns	ns	yes	yes
Fort Collins, CO	ns	*, positive	ns	*, positive	ns	yes	yes
Washington, DC	ns	ns	ns	ns	ns	no	no
Jacksonville, FL	ns	ns	*, negative	ns	*, negative	yes	yes
Orlando, FL	ns	ns	ns	ns	ns	no	no
Pembroke Pines, FL	ns	ns	ns	ns	*, negative	yes	yes
St. Petersburg, FL	ns	ns	ns	*, positive	*, negative	yes	yes
Tampa, FL	ns	ns	ns	ns	ns	no	no
Atlanta, GA	ns	*, negative	ns	ns	*, negative	yes	yes
Chicago, IL	*, positive	*, negative	*, negative	*, positive	*, negative	yes	yes
Rockford, IL	ns	ns	*, negative	ns	ns	yes	yes
Evansville, IN	*, positive	ns	ns	ns	ns	no	yes
Fort Wayne, IN	*, positive	*, negative	ns	ns	ns	yes	yes
Indianapolis, IN	ns	ns	*, negative	ns	ns	yes	yes
Topeka, KS	ns	ns	ns	ns	ns	no	no
Lexington-Fayette, KY	ns	ns	ns	ns	ns	no	no
Baltimore, MD	ns	ns	ns	ns	ns	no	no
Sterling Heights, MI	ns	ns	ns	ns	ns	no	no
Minneapolis, MN	ns	ns	ns	ns	ns	no	no
St. Louis, MO	ns	ns	*, negative	ns	ns	yes	yes

Table 9. (Cont.)

City & State	(1) Main Effect	Moderator Variable: (2) Concentrated Disadvantage	(3) Pre-Existing Vacancy Rate	(4) Immigrant Concentration	(5) Percent non-Latino Black		(6) One or More Moderating Effects	(7) Main Effect OR Moderating Effect
Lincoln, NE	*, positive	ns	ns	ns	ns		no	yes
Las Vegas, NV	ns	ns	ns	ns	ns		no	no
Albuquerque, NM	ns	ns	ns	ns	ns		no	no
Rochester, NY	*, positive	ns	ns	ns	*, negative		yes	yes
Charlotte, NC	*, positive	ns	*, negative	ns	ns		yes	yes
Greensboro, NC	ns	ns	ns	*, positive	ns		yes	yes
Raleigh, NC	ns	ns	ns	ns	ns		no	no
Akron, OH	*, positive	*, negative	ns	ns	*, negative		yes	yes
Cincinnati, OH	ns	ns	ns	ns	ns		no	no
Cleveland, OH	ns	*, negative	ns	ns	*, negative		yes	yes
Columbus, OH	ns	*, negative	*, negative	ns	*, negative		yes	yes
Dayton, OH	*, positive	ns	*, negative	ns	ns		yes	yes
Oklahoma City, OK	ns	*, negative	ns	ns	*, negative		yes	yes
Portland, OR	ns	ns	ns	ns	ns		no	no
Philadelphia, PA	*, positive	ns	*, negative	ns	ns		yes	yes
Pittsburgh, PA	*, positive	ns	ns	ns	ns		no	yes
Memphis, TN	ns	ns	ns	ns	*, negative		yes	yes
Arlington, TX	*, negative	ns	ns	*, positive	ns		yes	yes
Austin, TX	ns	ns	*, negative	ns	ns		yes	yes
Carrollton, TX	*, negative	ns	ns	ns	ns		no	yes
Dallas, TX	ns	*, negative	ns	*, positive	*, negative		yes	yes
Fort Worth, TX	ns	ns	ns	ns	ns		no	no
Houston, TX	*, positive	ns	ns	*, positive	*, negative		yes	yes
Pasadena, TX	ns	ns	*, negative	ns	ns		yes	yes
Plano, TX	ns	ns	ns	ns	ns		no	no
Waco, TX	ns	ns	ns	ns	ns		no	no
Alexandria, VA	ns	*, negative	ns	*, negative	*, negative		yes	yes
Newport News, VA	ns	ns	ns	ns	*, negative		yes	yes
Richmond, VA	ns	ns	ns	ns	ns		no	no
Bellevue, WA	ns	ns	*, negative	ns	ns		yes	yes
Madison, WI	ns	ns	ns	ns	ns		no	no
Milwaukee, WI	ns	*, negative	*, negative	ns	*, negative		yes	yes
Summary						**Summary**		
% non-significant	**76.6**	**78.13**	**76.56**	**84.38**	**75.00**	**% no**	**46.88**	**39.06**
significant, positive	**18.8**	**3.13**	**0.00**	**14.06**	**0.00**	**% yes**	**53.13**	**60.94**
significant, negative	**4.7**	**18.75**	**23.44**	**1.56**	**25.00**			

Table 10. Cross-City Summary of Conditional Neighborhood Effects of Foreclosure on Robbery.							
		Moderator Variable:					
City & State	(1) Main Effect	(2) Concentrated Disadvantage	(3) Pre-Existing Vacancy Rate	(4) Immigrant Concentration	(5) Percent non-Latino Black	(6) One or More Moderating Effects	(7) Main Effect OR Moderating Effect
Anchorage, AK	*, negative	ns	ns	ns	ns	no	yes
Chandler, AZ	ns	ns	ns	ns	ns	no	no
Glendale, AZ	ns	ns	ns	ns	ns	no	no
Tempe, AZ	ns	ns	ns	ns	ns	no	no
Tucson, AZ	ns	*, positive	ns	ns	ns	yes	yes
Chula Vista, CA	ns	*, negative	ns	ns	ns	yes	yes
Garden Grove, CA	ns	ns	ns	ns	ns	no	no
Moreno Valley, CA	ns	ns	ns	ns	ns	no	no
Oakland, CA	ns	ns	ns	*, negative	ns	yes	yes
Sacramento, CA	ns	ns	ns	ns	ns	no	no
San Diego, CA	ns	*, positive	*, negative	ns	ns	yes	yes
Aurora, CO	ns	ns	ns	ns	ns	no	no
Denver, CO	ns	ns	ns	ns	ns	no	no
Fort Collins, CO	ns	*, positive	ns	*, positive	ns	yes	yes
Washington, DC	ns	ns	ns	ns	ns	no	no
Jacksonville, FL	ns	ns	ns	ns	ns	no	no
Orlando, FL	*, negative	ns	ns	ns	ns	no	yes
Pembroke Pines, FL	ns	ns	--	ns	ns	no	no
St. Petersburg, FL	ns	ns	*, negative	ns	ns	yes	yes
Tampa, FL	ns	ns	ns	ns	ns	no	no
Atlanta, GA	ns	ns	ns	ns	ns	no	no
Chicago, IL	ns	ns	*, negative	ns	ns	yes	yes
Rockford, IL	ns	ns	ns	ns	ns	no	no
Evansville, IN	*, positive	ns	ns	*, positive	ns	yes	yes
Fort Wayne, IN	ns	*, negative	ns	*, negative	ns	yes	yes
Indianapolis, IN	ns	ns	*, negative	ns	ns	yes	yes
Topeka, KS	ns	ns	ns	ns	ns	no	no
Lexington-Fayette, KY	ns	ns	ns	ns	ns	no	no
Baltimore, MD	ns	ns	ns	ns	ns	no	no
Sterling Heights, MI	ns	ns	ns	--	ns	no	no
Minneapolis, MN	--	--	--	--	--	--	--
St. Louis, MO	ns	ns	ns	ns	ns	no	no

Table 10. (Cont.)

City & State	(1) Main Effect	Moderator Variable: (2) Concentrated Disadvantage	(3) Pre-Existing Vacancy Rate	(4) Immigrant Concentration	(5) Percent non-Latino Black		(6) One or More Moderating Effects	(7) Main Effect OR Moderating Effect
Lincoln, NE	*, positive	ns	ns	ns	ns		no	yes
Las Vegas, NV	ns	ns	ns	ns	ns		no	no
Albuquerque, NM	ns	ns	ns	ns	ns		no	no
Rochester, NY	*, positive	ns	ns	ns	ns		no	yes
Charlotte, NC	*, positive	ns	ns	ns	ns		no	yes
Greensboro, NC	ns	ns	ns	ns	ns		no	no
Raleigh, NC	ns	ns	ns	*, negative	*, positive		yes	yes
Akron, OH	*, positive	ns	ns	ns	*, negative		yes	yes
Cincinnati, OH	ns	ns	ns	ns	ns		no	no
Cleveland, OH	ns	*, negative	*, negative	ns	*, negative		yes	yes
Columbus, OH	ns	*, negative	*, negative	*, positive	*, negative		yes	yes
Dayton, OH	*, positive	ns	ns	ns	ns		no	yes
Oklahoma City, OK	ns	ns	ns	ns	ns		no	no
Portland, OR	ns	ns	ns	ns	ns		no	no
Philadelphia, PA	*, positive	*, negative	*, negative	ns	*, negative		yes	yes
Pittsburgh, PA	*, positive	ns	*, negative	*, positive	ns		yes	yes
Memphis, TN	ns	ns	ns	ns	ns		no	no
Arlington, TX	*, negative	ns	ns	ns	ns		no	yes
Austin, TX	ns	ns	ns	ns	ns		no	no
Carrollton, TX	*, negative	ns	ns	ns	*, negative		yes	yes
Dallas, TX	ns	ns	*, negative	*, positive	*, negative		yes	yes
Fort Worth, TX	ns	ns	ns	*, positive	ns		no	no
Houston, TX	*, positive	ns	ns	ns	*, negative		yes	yes
Pasadena, TX	ns	ns	ns	ns	*, positive		yes	yes
Plano, TX	ns	ns	ns	ns	ns		no	no
Waco, TX	ns	ns	ns	ns	ns		no	no
Alexandria, VA	ns	ns	ns	ns	ns		no	no
Newport News, VA	ns	ns	ns	ns	ns		no	no
Richmond, VA	ns	ns	ns	ns	ns		no	no
Bellevue, WA	ns	ns	ns	ns	ns		no	no
Madison, WI	ns	ns	ns	ns	ns		no	no
Milwaukee, WI	ns	ns	*, negative	*, positive	*, negative		yes	yes
						Summary		
% non-significant	87.3	87.30	83.87	83.87	84.13	**% no**	**66.67**	**60.94**
significant, positive	4.8	4.76	0.00	11.29	3.17	**% yes**	**33.33**	**44.44**
significant, negative	7.9	7.94	16.13	4.84	12.70			
Total	100.0	100.00	100.00	100.00	100.00			

geographic areas from which our sample of cities was drawn, and which also illustrate the basic patterns found. Overall, the results in Tables 9-20 help to illuminate four noteworthy findings that emerge from our assessment of the association between neighborhood foreclosure and crime: (1) in most cities there is no evidence of additive or multiplicative effects of foreclosure on crime; (2) there is very little evidence that high neighborhood foreclosure rates were more criminogenic when accompanied by high levels of socioeconomic disadvantage or other adverse conditions; (3) we find evidence that in some cities foreclosure was more likely to yield elevated property crime rates (most notably, burglary) in neighborhoods where Latinos and foreign born residents were more prevalent; and (4) foreclosure was more likely to yield elevated crime rates in areas with lower rates of pre-existing vacancies.

Tables 9 and 10 show a summary of city-by-city results for main effects (the first column), evidence relevant to moderating effects (columns 2-5), and two final summary columns in which we tally whether each city reveals any evidence of one or more moderating effects (column 6) and whether they exhibit either a main effect or a conditional effect of foreclosure rates (column 7). We provide some summary measures for each column at the bottom of the tables.

We see from Tables 9 and 10 that many cities exhibit no main or conditional effects of foreclosure on burglary (40% of the sample) or robbery (60% of the sample). Tables 11-13 illustrate this type of pattern for three cities in our sample—Cincinnati, Washington, DC, and Richmond. Though it is possible that foreclosure influenced robbery and burglary in these cities in more complex ways than covered in our analysis, or that foreclosure was problematic for other types of offending we did not consider, based on the data and models examined in the study we would conclude that there is no evidence of a link between foreclosure and crime in these cities or, as just noted, the many others like it for which parallel patterns emerge.

The predominant pattern in our data is for either no or little evidence of significant foreclosure effects, but we do observe several instances where the existence and/or magnitude of

Table 11. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Cincinnati Census Tracts (n=118).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.002	.003	.005*	-.010	.002	.008	.008	.010	.011	.006
	(.002)	(.002)	(.002)	(.007)	(.002)	(.005)	(.006)	(.006)	(.017)	(.006)
Disadvantage X Foreclosure	--	-.001	--	--	--	--	.0004	--	--	--
	--	(.002)	--	--	--	--	(.004)	--	--	--
Vacancy X Foreclosure	--	--	-.0003	--	--	--	--	-.0002	--	--
	--	--	(.0002)	--	--	--	--	(.001)	--	--
Immigrant Concentration X Foreclosur	--	--	--	-.016	--	--	--	--	.003	--
	--	--	--	(.008)	--	--	--	--	(.022)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	-.00001	--	--	--	--	.0001
	--	--	--	--	(.0001)	--	--	--	--	(.0001)
Constant	-4.882*	-4.875*	-4.849*	-4.636*	-4.895*	-5.573*	-5.585*	-5.533*	-5.614*	-5.529*
	(.600)	(.596)	(.588)	(.606)	(.606)	(1.733)	(1.74)	(1.731)	(1.751)	(1.730)
Logged Alpha	-2.792*	-2.814*	-2.853*	-2.839*	-2.794*	-1.079*	-1.079*	-1.081*	-1.080*	-1.085*
	(.189)	(.192)	(.193)	(.192)	(.190)	(.211)	(.211)	(.211)	(.211)	(.212)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 12. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Washington, DC Census Tracts (n=171).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	-.015	-.017	-.011	.001	.014	.005	.005	.005	.014	.029
	(.015)	(.015)	(.016)	(.018)	(.033)	(.014)	(.014)	(.016)	(.017)	(.030)
Disadvantage X Foreclosure	--	.008	--	--	--	--	-.001	--	--	--
	--	(.017)	--	--	--	--	(.016)	--	--	--
Vacancy X Foreclosure	--	--	-.002	--	--	--	--	-.0003	--	--
	--	--	(.004)	--	--	--	--	(.0038)	--	--
Immigrant Concentration X Foreclosure	--	--	--	.034	--	--	--	--	.020	--
	--	--	--	(.022)	--	--	--	--	(.020)	--
Percent Non-Latino Black X Foreclosur	--	--	--	--	-.001	--	--	--	--	-.0005
	--	--	--	--	(.001)	--	--	--	--	(.0005)
Constant	-4.26*	-4.29*	-4.03*	-4.17*	3.91*	-1.76	-1.76	-1.71	-1.75	-1.54
	(1.24)	(1.24)	(1.32)	(1.23)	(1.28)	(1.16)	(1.16)	(1.26)	(1.16)	(1.19)
Logged Alpha	-1.70	-17.0	-1.70	-1.72	-1.71	-1.75	-1.75	-1.75	-1.76	-1.76
	(.142)	(.142)	(.142)	(.143)	(.143)	(.143)	(.142)	(.143)	(.143)	(.143)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 13. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Richmond Census Tracts (n=65).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	-.007	.021	-.009	.028	-.080	.008	-.020	.009	.033	.017
	(.029)	(.038)	(.029)	(.082)	(.085)	(.036)	(.046)	(.036)	(.076)	(.078)
Disadvantage X Foreclosure	--	-.034	--	--	--	--	.036	--	--	--
	--	(.031)	--	--	--	--	(.036)	--	--	--
Vacancy X Foreclosure	--	--	.004	--	--	--	--	-.003	--	--
	--	--	(.006)	--	--	--	--	(.007)	--	--
Immigrant Concentration X Foreclosure	--	--	--	.045	--	--	--	--	.035	--
	--	--	--	(.098)	--	--	--	--	(.094)	--
Percent Non-Latino Black X Foreclosure	--	--	--	--	.001	--	--	--	--	-.0001
	--	--	--	--	(.001)	--	--	--	--	(.001)
Constant	-5.06	-5.75*	-5.22*	-5.15	-5.96*	-6.25*	-5.75	-6.06*	-6.27*	-6.08
	(2.65)	(2.72)	(2.64)	(2.65)	(2.87)	(3.00)	(3.03)	(3.02)	(2.99)	(3.22)
Logged Alpha	-2.05	-2.11	-2.19	-2.08	-2.05	-14.24	-14.27	-14.22	-14.30	-13.64
	(.711)	(.737)	(.764)	(.729)	(.708)	(13.41)	(695.33)	(1214.57)	(1448.44)	(1078.21)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

neighborhood foreclosure effects are conditioned by other neighborhood conditions. In particular, we find some evidence that high neighborhood levels of foreclosure were more likely to translate into elevated burglary (and, to a lesser extent, robbery) rates in areas in which Latinos and foreign born persons were more populous. Table 9 shows that this was the case for burglary in nine cities and for robbery in seven cities. Tables 14-16 illustrate the nature of such patterns for Houston, St. Petersburg, and Chicago. In each case, we see that the effect of foreclosure on burglary increases substantially as neighborhood levels of immigrant concentration increase. We observed similar patterns for robbery in cities such as Dallas, Pittsburgh, and Milwaukee (see Table 10, column 4). These findings are consistent with the general idea that communities with larger minority populations may confront difficulties securing public resources to combat crime related to external shocks, such as the foreclosure crisis (e.g., Bursik and Grasmick, 1993). However, it is important to reiterate that, in most cities, foreclosure is not related to elevated crime rates, nor do we observe a general pattern by which foreclosure effects are amplified by a high concentration of Latinos and foreign born persons. Further, we must acknowledge that our study is not well suited for uncovering the reasons *why* foreclosure effects were stronger in areas of high immigrant concentration in selected cities.

Notwithstanding the tendency for foreclosure effects to be amplified in areas of concentrated Latino and foreign born presence, we find little evidence that foreclosure was more strongly related to crime in neighborhoods with pre-existing vulnerabilities. Indeed, we found very few instances in which levels of concentrated disadvantage amplified neighborhood foreclosure effects. Tucson and San Diego are exceptions to this, as we display in Tables 17 and 18, but we also observe more instances in which foreclosure effects appear to have been larger in areas with *lower* rates of neighborhood disadvantage (see Tables 9 and 10). Consistent with this theme, one of the relatively common patterns to emerge from our analysis of conditioning effects is that high neighborhood *foreclosure rates are more likely to yield elevated burglary and robbery rates in areas with low rates of* *pre-existing vacancies*. We observe this pattern in almost a quarter of the cities for which we analyze neighborhood burglary, and fully 16% of the cities in which we examine robbery. Examples include cities such as Houston, St. Petersburg, Chicago, which we highlighted in Tables 14-16, but also in San Diego (robbery), Oakland (robbery), and Denver (burglary). The models for the latter three cities are shown in Tables 18-20. In each of these cases, contrary to notions that the foreclosure crisis may have been more detrimental in areas with pre-existing vulnerabilities, the results suggest that elevated foreclosures contributed to additional crime more so in neighborhoods that had *relatively few vacancies*. Though our data do not provide a means by which to test the mechanisms through which such effects operate, the findings are consistent with the idea that perhaps elevated foreclosures do not add significantly to perceptions of disorder and social disorganization in areas already facing a high rate of housing vacancy. Paradoxically, foreclosures may be more influential for crime in areas that are relatively stable (see also Stucky et al., 2012).

Table 14. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Houston Census Tracts (n=419).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.007*	.007*	.007*	.002	.011*	-.003	-.003	-.003	-.006	-.001
	(.002)	(.002)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Disadvantage X Foreclosure	--	-.002	--	--	--	--	.002	--	--	--
	--	(.003)	--	--	--	--	(.004)	--	--	--
Vacancy X Foreclosure	--	--	-0.0003	--	--	--	--	.0004	--	--
	--	--	(.001)	--	--	--	--	(.001)	--	--
Immigrant Concentration X Foreclosur	--	--	--	.009*	--	--	--	--	.004	--
	--	--	--	(.002)	--	--	--	--	(.003)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	-.0003*	--	--	--	--	-.0002*
	--	--	--	--	(.0001)	--	--	--	--	(.0001)
Constant	-4.307*	-4.327*	-4.282*	-4.119	-4.257*	-5.442*	-5.424*	-5.480*	-5.364*	-5.406*
	(.615)	(.616)	(.617)	(.605)	(.605)	(.810)	(.811)	(.813)	(.809)	(.805)
Logged Alpha	-1.458	-1.486	-1.486	1.531	-1.531	-1.124	-1.124	-1.125	-1.130	-1.142
	(.073)	(.073)	(.073)	(.074)	(.074)	(.084)	(.084)	(.084)	(.084)	(.085)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 15. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across St. Petersburg Census Tracts (n=64).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.003	.007	.004	.025*	.011	-008	-.005	-.007	-.002	-.004
	(.005)	(.006)	(.005)	(.010)	(.006)	(.006)	(.007)	(.006)	(.013)	(.007)
Disadvantage X Foreclosure	--	-.006	--	--	--	--	-.003	--	--	--
	--	(.005)	--	--	--	--	(.006)	--	--	--
Vacancy X Foreclosure	--	--	-.001	--	--	--	--	-.002*	--	--
	--	--	(.001)	--	--	--	--	(.001)	--	--
Immigrant Concentration X Foreclosur	--	--	--	.034*	--	--	--	--	.008	--
	--	--	--	(.014)	--	--	--	--	(.017)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	-.0002*	--	--	--	--	-.0001
	--	--	--	--	(.0001)	--	--	--	--	(.0001)
Constant	-4.45*	-4.31*	-3.98*	-4.46*	-3.54*	-3.26	-3.30*	-2.32	-3.28	-3.01
	(1.46)	(1.44)	(1.48)	(1.38)	(1.44)	(.1.69)	(1.69)	(1.70)	(1.69)	(1.70)
Logged Alpha	-2.34	-2.37	-2.37	-2.43	-2.43	-2.50	-2.52	-2.69	-2.51	-2.56
	(.213)	(.213)	(.213)	(.215)	(.217)	(.432)	(.436)	(.493)	(.433)	(.455)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 16. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Chicago Census Tracts (n=831).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.002*	.005*	.005*	.004*	.007*	.001	.002	.003*	.002	.003
	(.001)	(.002)	(.001)	(.001)	(.002)	(.001)	(.002)	(.001)	(.001)	(.002)
Disadvantage X Foreclosure	--	-.002*	--	--	--	--	-.001	--	--	--
	--	(.001)	--	--	--	--	(.001)	--	--	--
Vacancy X Foreclosure	--	--	-.001*	--	--	--	--	-.001*	--	--
		--	(.0001)	--	--	--	--	(.0002)	--	--
Immigrant Concentration X Foreclosur	--	--	--	.003*	--	--	--	--	.002	--
	--	--	--	(.001)	--	--	--	--	(.001)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	-.0001*	--	--	--	--	-.00004
	--	--	--	--	(.00003)	--	--	--	--	(.00004)
Constant	-4.603*	-4.555*	-4.556*	-4.567*	-4.498*	-5.204*	-5.183*	-5.162*	-5.179*	-5.156*
	(.338)	(.337)	(.336)	(.336)	(.338)	(.396)	(.396)	(.395)	(.396)	(.398)
Logged Alpha	-1.887*	-1.900*	-1.909*	-1.898*	-1.902*	-1.639*	-1.640*	-1.655*	-1.642*	-1.642*
	(.066)	(.067)	(.067)	(.067)	(.067)	(.075)	(.075)	(.075)	(.075)	(.075)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 17. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Tucson Census Tracts (n=114).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	-.002	-.002	-.002	-.003	.020	-.005	-.007*	-.006	-.010	.013
	(.003)	(.003)	(.003)	(.003)	(.017)	(.003)	(.003)	(.003)	(.005)	(.022)
Disadvantage X Foreclosure	--	.001	--	--	--	--	.014*	--	--	--
	--	(.005)	--	--	--	--	(.006)	--	--	--
Vacancy X Foreclosure	--	--	.0007	--	--	--	--	-.0004	--	--
	--	--	(.0007)	--	--	--	--	(.001)	--	--
Immigrant Concentration X Foreclosur	--	--	--	.0005	--	--	--	--	.004	--
	--	--	--	(.002)	--	--	--	--	(.003)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	.001	--	--	--	--	.0007
	--	--	--	--	(.0006)	--	--	--	--	(.0008)
Constant	-5.52*	-5.52*	-5.59*	-5.51*	-6.01*	-5.74*	-5.76*	-5.68*	-5.64*	-6.14*
	(.779)	(.778)	(.775)	(.780)	(.857)	(1.13)	(1.07)	(1.15)	(1.14)	(4.23)
Logged Alpha	-2.75	-2.76	-2.78	-2.76	-2.78	-3.12	-3.47	-3.10	-3.17	-3.12
	(.208)	(.209)	(.210)	(.208)	(.210)	(.493)	(.663)	(.488)	(.513)	(.489)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 18. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across San Diego Census Tracts (n=267).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.003*	.004*	-.004	.003	.004	.002	.004	-.028	-.002	-.002
	(.001)	(.002)	(.009)	(.002)	(.003)	(.003)	(.003)	(.015)	(.004)	(.005)
Disadvantage X Foreclosure	--	.001	--	--	--	--	.010*	--	--	--
	--	(.002)	--	--	--	--	(.004)	--	--	--
Vacancy X Foreclosure	--	--	-.001	--	--	--	--	-.007*	--	--
	--	--	(.002)	--	--	--	--	(.003)	--	--
Immigrant Concentration X Foreclosur	--	--	--	.0005	--	--	--	--	.003	--
	--	--	--	(.001)	--	--	--	--	(.002)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	.00004	--	--	--	--	-.0001
	--	--	--	--	(.0001)	--	--	--	--	(.002)
Constant	-4.65*	-4.72*	-4.56*	-4.67*	-4.71*	-8.06*	-8.69*	-7.37*	-8.12*	-8.05*
	(.666)	(.677)	(.699)	(.667)	(.682)	(1.28)	(1.28)	(1.31)	(1.27)	(1.30)
Logged Alpha	-2.16	-2.16	-2.16	-2.16	-2.16	-1.26	-1.33	-1.29	-1.26	-1.26
	(.121)	(.121)	(.121)	(.121)	(.121)	(.160)	(.165)	(.161)	(.162)	(.160)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 19. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Oakland Census Tracts (n=104).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.001	.004	-.001	.005*	.002	.001	.0005	.0002*	.007	-.001
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.003)	(.003)	(.002)
Disadvantage X Foreclosure	--	-.006*	--	--	--	--	.0006	--	--	--
	--	(.002)	--	--	--	--	(.003)	--	--	--
Vacancy X Foreclosure	--	--	-.001	--	--	--	--	-.0002*	--	--
	--	--	(.001)	--	--	--	--	(.0009)	--	--
Immigrant Concentration X Foreclosur	--	--	--	-.003*	--	--	--	--	-.005	--
	--	--	--	(.001)	--	--	--	--	(.002)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	-.00001	--	--	--	--	.0001
	--	--	--	--	(.00007)	--	--	--	--	(.0001)
Constant	-4.80*	-4.92*	-4.82*	-4.91*	-4.78*	-4.47*	-4.46*	-4.47*	-4.68*	-4.55*
	(.818)	(.794)	(.804)	(.800)	(.822)	(1.06)	(1.06)	(1.06)	(1.02)	(1.04)
Logged Alpha	-2.68	-2.76	-2.72	-2.74	-2.68	-2.25	-2.25	-2.25	-2.39	2.32
	(.196)	(.202)	(.198)	(.200)	(.196)	(.226)	(.227)	(.226)	(.234)	(.232)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

Table 20. Negative Binomial Regression Models of Foreclosure Effects on Burglary and Robbery across Denver Census Tracts (n=135).

	Burglary					Robbery				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreclosure Rate	.0002	-.0001	-.0002	.002	.001	.0005	.0004	.0004	.002	-.001
	(.001)	(.001)	(.001)	(.002)	(.001)	(.002)	(.002)	(.002)	(.004)	(.002)
Disadvantage X Foreclosure	--	-.003	--	--	--	--	-.002	--	--	--
	--	(.002)	--	--	--	--	(.003)	--	--	--
Vacancy X Foreclosure	--	--	-.001*	--	--	--	--	.0001	--	--
	--	--	(.0002)	--	--	--	--	(.0004)	--	--
Immigrant Concentration X Foreclosur	--	--	--	-.001	--	--	--	--	-.001	--
	--	--	--	(.001)	--	--	--	--	(.002)	--
Percent Non-Latino Black X Foreclosu	--	--	--	--	.0001	--	--	--	--	-.0001
	--	--	--	--	(.0001)	--	--	--	--	(.0001)
Constant	-4.694*	-4.521*	-4.633*	4.518*	-4.584*	-6.555*	-6.530*	-6.547*	-6.543*	-6.793*
	(.823)	(.822)	(.812)	(.832)	(.822)	(1.368)	(1.374)	(1.365)	(1.372)	(1.363)
Logged Alpha	-2.499	-2.534	-2.569	-2.514	-2.514	-1.927	-1.924	-1.932	-1.922	-1.977
	(.169)	(.172)	(.173)	(.170)	(.169)	(.258)	(.257)	(.260)	(.257)	(.264)

*p ≤ .05; Note: models also include all neighborhood control variables included in study.

V. Conclusions

This project contributed to the scientific literature by examining the link between foreclosure and crime using a uniform set of procedures and a multilevel dataset that integrates information on neighborhood foreclosures, crime, and other attributes during the heart of the contemporary foreclosure crisis for more than sixty large U.S. cities. The project addressed three specific questions: (1) Are foreclosure levels significantly associated with crime rates across neighborhoods after controlling for other factors?; (2) Is any observed effect of foreclosure on neighborhood crime rates contingent on (i.e., moderated by) the other neighborhood conditions, including preexisting structural disadvantage, pre-existing vacancy rates, or racial and ethnic context?; and (3) Does the effect of foreclosure rates on neighborhood crime levels vary across cities in systematic ways? For instance, is the magnitude of the effects of foreclosure on crime across neighborhoods contingent on city conditions such as pre-existing or co-occurring vulnerabilities (e.g., an aging housing stock, high rates of pre-existing vacancies, and high levels of unemployment and other forms of socioeconomic disadvantage), or the capacity for mitigating the adverse consequences of a housing crisis (e.g., housing affordability, the size of the police force).

The contemporary foreclosure crisis that proliferated across America during the late 2000s fueled speculation that a variety of adverse consequences may emerge in the neighborhoods that have been hit hardest. At the commencement of this project, a growing body of research had begun to explore whether foreclosure rates during this period have stimulated higher rates of crime, but the findings were mixed. The inconsistency across studies in units of analysis, definitions and measures of foreclosure, and analytical strategies made it difficult to discern a general pattern from the findings reported in prior work, or to determine whether perhaps foreclosures may yield crime in some settings but not others. We advance understanding of the issue by applying a uniform empirical approach to neighborhood-level data across many cities—64 for our analysis of burglary, and 63 for our analysis of robbery.

Our concluding answer to the first and most general question tackled in the project–whether levels foreclosure are significantly associated with crime rates across neighborhoods after controlling for other factors – defies a simple "yes" or "no" answer. This is not a function of the absence of an indication one way or another, but rather it stems from what we see as a major strength of the multi-city approach adopted in our research. In essence, *our project shows that the answer to the general question of whether foreclosure is associated with robbery and burglary rates is highly contingent on the city under investigation and, thus, it would be precarious to draw general conclusions from research on a single city.*

Overall, when we analyze our neighborhood-level data pooled across all cities, our findings indicate that neighborhood foreclosure rates are not significantly associated with neighborhood robbery rates across 63 cities. We do observe a small but significant positive "net" effect of foreclosure rates in 2007-2008 on burglary in 2009 in this pooled analysis, controlling for a wide array of other factors that include prior burglary levels and also burglary rates of surrounding neighborhoods. Drawing firm conclusions from this pooled analysis across 7,000+ neighborhoods is tempting, but doing so would mask important nuances. *Indeed, the most uniform pattern we observed in our study was that the influence of neighborhood foreclosure rates on neighborhood crime during the last few years of the 2000s was highly contingent on city location.* We document this by highlighting statistically significant variance components in multilevel regression model that nest several thousand census tracts within our sample cities, which show that the estimated neighborhood slopes for foreclosure in both the burglary and robbery models exhibit considerable variability across the cities represented in our study. Further, we illuminate the theme of city-level variability in patterns of foreclosure coefficients, including main effects on robbery and burglary, in city-specific regression models that reveal some important insights about the nature of city-level variability in our study. *In particular, by analyzing each city separately, we show that neighborhood foreclosure is significantly associated with robbery and burglary only in a small number of selected cities; in the majority of the cities considered, foreclosure did not exert a significant main effect on either crime type.*

Our extended multilevel models explored a second important question advanced in the project, namely whether the effect of foreclosure rates on neighborhood crime levels vary across cities in systematic ways. For the most part, we conclude that the significant between-city variability in neighborhood foreclosure effects on robbery and burglary is not highly systematic, at least not in ways that parallel the city-level attributes we considered. Indeed, only one of the city-level factors we included – the percentage of housing units built between 2000 and 2007– emerged as a statistically significant and meaningful predictor of city-level variability in neighborhood foreclosure effects. We highlighted the logic of this finding by showing that neighborhood foreclosure effects on burglary tended to be relatively strong in cities that had experienced relatively little new housing construction during the first several years of the 2000s, and relatively weak in areas of significant recent housing construction. We also acknowledged, however, that it is easy to find exceptions in both instances, and while we must acknowledge that it is conceivable that a more nuanced indicator of foreclosure activity that captured details such as the nature of occupancy patterns during foreclosure, the length (if any) of vacancy, and the condition of the property would yield different findings, the most typical finding that emerges from the measures used in our study is that foreclosure and crime (robbery and burglary, at least) are not significantly related in the majority of U.S. cities we considered, at least overall.

Evaluating the main, or unconditional, effect of foreclosure is important, in our judgment, for it seems to square most directly with public discussions about a possible link between foreclosure and crime. And on that score, our study suggests that the widely presumed significant link between foreclosure and crime in the popular press is limited to selected areas. We show that there are plenty of places where no such link can be detected, at least as we attempt to measure and model it. Critics of this conclusion might suggest that a focus on "main effects" is not sufficiently nuanced to detect the adverse consequences of foreclosure in practice, perhaps because such consequences are likely only under specific types of accompanying conditions. The theoretical rationales pertinent to this line of thinking are not very well developed at present, but the basic issue is whether any observed effect of foreclosure on neighborhood crime rates is contingent on (i.e., moderated by) various *other* neighborhood conditions. This served as our final research question in the project, and we focused in particular on whether foreclosure effects on robbery and burglary during the heart of the housing crisis were contingent on preexisting structural disadvantage, pre-existing vacancy rates, or racial and ethnic context.

Most discussion in the literature to-date suggests that foreclosure effects may be amplified when accompanied by other neighborhood conditions (e.g., high levels of socioeconomic disadvantage and pre-existing vacancies, a relatively large minority presence) that have been linked to an increased likelihood of criminal behavior. We explored the possibility of such contingent effects by estimating a series of multiplicative models for each of the cities in our study. We provided a summary of the results for these estimations (e.g., Tables 9 and 10), along with results for selected cities that illustrate the key patterns observed.

The more detailed multiplicative models further bolster the conclusion that in many cities, there is no evidence of a significant link between neighborhood foreclosure and crime, a pattern that held for 40% of the cities for which we estimated burglary models and 60% of the cities for which we estimated robbery models. Clearly, our data do not support blanket statements about a significant link between foreclosure and crime, at least with respect to robbery and burglary. These analyses reinforce the idea that the overall conclusion one draws appears to be highly contingent on the location in which the study is conducted.

The multiplicative models also showed very little evidence that high neighborhood foreclosure rates were *more* criminogenic when accompanied by high levels of socioeconomic disadvantage or other adverse conditions. In fact, our models indicated that foreclosure was more likely to yield elevated crime rates in areas with *lower* rates of pre-existing vacancies. This may indicate something about the meaning of foreclosures in different neighborhood contexts.

Specifically, perhaps in areas where there were many vacancies already, foreclosures did not add much to perceptions of decline and disorder, whereas in areas with few vacancies each additional foreclosure served as a symbolic and tangible cue for residents and offenders that the neighborhood was declining, and that informal social controls over crime were lessened. Alternatively, perhaps attractive opportunities for burglary and robbery are sufficiently depressed in areas with higher vacancy rates that even with elevated foreclosure rates, increased acquisitive crime does not follow. Unfortunately, we cannot address explicit mechanisms for the observed effects, but doing so would be a valuable component of subsequent research that explored in more detail the contexts in which foreclosure was more apt to translate into elevated crime rates.

Finally, though it is far from uniform across all of our cities, we find evidence in several cities that foreclosure was more likely to yield elevated property crime rates (most notably, burglary) in neighborhoods where Latinos and foreign born residents were more prevalent. It is not clear what this pattern reflects, but some scholars have suggested that Latino areas hit by the foreclosure crisis have had particular difficulties rebounding. For instance, Louden (2009) chronicles the very high rate of joblessness associated with seasonal work in such areas, and also long-standing barriers to home ownership that in these places that may have limited the capacity for housing recovery and amplified the negative consequences of the housing bust. Whatever the reasons for this pattern, it highlights some potentially fruitful opportunities for resource allocation that could help alleviate the tendency for high levels of foreclosure to yield elevated crime rates.

Overall, our study highlights the general importance of analyzing neighborhood conditions in a comparative context, and it also suggests more specifically that researchers and federal policy makers should be cautious in drawing strong conclusions about the relationship between foreclosure and crime from research on any given single city. We consider this a useful contribution to knowledge and encourage additional multi-city neighborhood investigations of foreclosure and crime. One natural extension of our work, for example, would consider longer-term impacts of the foreclosure crisis. We focused on relatively short-term consequences of the contemporary foreclosure crisis, but it is possible that the full consequences of this period, including those associated with potential increases in crime, may not have unfolded completely yet. Thus, future research that explores longer-term consequences within multiple cities would be valuable to more fully assess this possibility. It would be useful for any such research to integrate more nuanced indicators of foreclosure (e.g., distinguishing between foreclosures that are sold quickly versus those that remain vacant for lengthy spells), and to also consider refined geographic definitions of neighborhoods (e.g., block groups, blocks, street segments) that might yield different patterns. Additionally, an important ingredient in subsequent multi-city research should be the inclusion of information on policy prescriptions that have been implemented in response to the foreclosure crisis. Several billion dollars have been allocated for foreclosure remediation under the umbrella of several Federal policy efforts (e.g., NSP, HAMP, HARP, and HAFA). It would be wise for the government to support research efforts to evaluate both the general efficacy of these policies, and whether or not they have lessened the impact of foreclosure on crime in jurisdictions in which such a connection appears to be significant.

We also see a major need for more detailed neighborhood data collection and analysis within cities, and this type of effort will probably require a tradeoff with the number of cities studies. Like most other neighborhood-level studies, our analysis cannot decipher the proximate mechanisms through which foreclosures translate (or do not translate) into higher crime rates. Our results suggest that there are city-level conditions under which high neighborhood foreclosure rates increase disorder and disorganization and reduce social control, but without direct indicators of these constructs this remains highly speculative. Future research that integrates neighborhood-based survey data, systematic social observation, and measures of foreclosure and crime would be highly beneficial for advancing our theoretical understanding of these relationships. Assembling this type of data for a large number of cities is probably unrealistic because of logistical issues and cost, but doing so in strategically selected places (e.g., perhaps a city in which foreclosures exhibit a relatively strong link to crime and other social ills, and a city in which no such connections are found) would advance substantially our understanding of the mechanisms that might link foreclosure to crime, and of the specific conditions that might make such a link more or less likely to arise.

Appendix A. Bivariate correlations

	Neighborhood Variables (n=7,415)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Foreclosure Rate	1.000											
(2)	Population Size (logged)	-.054*	1.000										
(3)	Population Density (logged)	-.006	.249*	1.000									
(4)	Socioeconomic Disadvantage	.334*	-.199*	.147*	1.000								
(5)	Immigrant Concentration	-.009	.213*	.165*	-.060*	1.000							
(6)	Residential Stability	.088*	.050*	-.098*	-.200*	-.095*	1.000						
(7)	Percent Divorced	.103*	-.155*	-.173*	.080*	-.200*	-.107*	1.000					
(8)	Percent Non-Latino Black	.318*	-.204*	.111*	.691*	-.399*	-.060*	.114*	1.000				
(9)	Percent Population Ages 15-29	-.090*	.046*	.182*	.073*	.074*	-.579*	-.218*	-.029*	1.000			
(10)	Pre-Existing Vacancy Rate	.308*	-.323*	.022	.530*	-.187*	-.192*	.166*	.453*	.022	1.000		
(11)	Prior Robbery Rate	.132*	-.371*	-.018	.337*	-.047*	-.215*	.117*	.346*	.063*	.340*	1.000	
(12)	Prior Burglary Rate	.190*	-.320*	-.226*	.265*	-.072*	-.158*	.183*	.248*	.029*	.352*	.659*	1.000

	City Variables (n=64)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	City percent housing units built, 2000-2007	1.000								
(2)	City preexisting vacancy rate	-.368*	1.000							
(3)	City housing affordability index	-.158	.269*	1.000						
(4)	City police force size	.016	.400*	-.086	1.000					
(5)	City change in police force size	-.074	-.078	.206	-.343*	1.000				
(6)	City percent non-Latino black	-.345*	.712*	.045	.466*	-.132	1.000			
(7)	City poverty rate	-.520*	.687*	.188	.248*	-.197	.614*	1.000		
(8)	City unemployment rate	-.249*	.362*	-.130	.050	-.223	.417*	.554*	1.000	
(9)	City unemployment rate change	.320*	-.257*	-.467*	-.151	-.069	-.249*	-.392*	.005	1.000

*p ≤ .05

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VII. Dissemination of Research Findings

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