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Do Foreclosures Cause Crime?

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In the last few years, the mortgage foreclosure crisis has uprooted millions of households and destabilized myriad communities around the country. News stories have reported growing concerns about the effects of these foreclosed homes on surrounding communities and on crime in particular.[1] But we have little hard evidence that foreclosures actually lead to increased criminal activity. This paper aims to fill this gap by examining whether and how elevated rates of foreclosure affect different types of crime in the immediately surrounding area, using a unique dataset of point-specific, longitudinal crime and foreclosure data from New York City.

Foreclosures might affect crime in several different ways. First, foreclosures may lead to physical deterioration of buildings and grounds, which might signal a degree of complacency among neighborhood residents about social disorder and crime. Second, foreclosures may increase residential turnover and social disengagement, which may in turn weaken the informal social controls in a neighborhood that prevent crime. Finally, foreclosures may lead to prolonged vacancies, which change the costs of and payoff from building theft and vandalism, provide a safe haven for criminal activity, and signal that there are fewer eyes on the street to monitor criminal activity.

Although our analyses do not distinguish precisely between these different mechanisms, our detailed data will allow us to better understand whether and how foreclosures affect crime. Previous studies of the relationship between foreclosures and crime have been plagued by endogeneity, with researchers unable to determine if elevated foreclosures actually lead to higher crime rates or whether both are driven by underlying neighborhood decline. Our point-specific, longitudinal data and research design enable us to sort out the causal relationships more effectively and shed light on possible mechanisms.

[1] Mummolo and Brubaker, 2008

Specifically, our main geographic unit of analysis is the blockface – an individual street segment including properties on both sides of the street, or what is colloquially known as a block. We compare crime levels on blockfaces before and after homes on the block enter foreclosure to changes in crime on other blockfaces in the same police precinct that have experienced fewer foreclosures. Given that crime trends are likely to be the same on other blockfaces in the same precinct, such a difference-in-differences model can persuasively determine if foreclosures lead to higher crime. To bolster confidence in the direction of causality, we test whether *future* foreclosures predict crime, suggesting that crime may trigger foreclosures, rather than the reverse.

To shed light on mechanisms, we look separately at properties entering foreclosure that quickly sell to another owner (and thus likely stay occupied) and those that revert to bank ownership (and likely sit vacant), examine whether concentrated foreclosure activity on a single blockface has a disproportionate impact, and explore whether particular types of crime – violent crimes, property crimes, or public order crimes – are more sensitive to foreclosures. Finally, by estimating the relationship between foreclosure activity and crime in a larger geographic area (police precincts), we can examine whether any increase in crime on a block associated with elevated foreclosures leads to net new crime in the larger community, or whether it is roughly matched by corresponding decreases in crime on surrounding blocks.

In brief, while much of the association between foreclosures and crime is explained by both occurring in similar types of blockfaces, we find that marginal foreclosures on a blockface lead to a small number of additional violent crimes and public order crimes, such as harassment, vandalism, drug crimes, prostitution, loitering, and simple assault. Our results are robust to both OLS and negative binomial estimation. When estimating threshold-level models, we find that foreclosures typically have a significant effect on crime only after there are at least two foreclosures on the block. As for spillover effects, our precinct-level models offer some suggestive evidence that foreclosures lead to net new crime and do not simply attract crimes that would have occurred on neighboring blockfaces.

I. Existing Evidence

The Impacts of Foreclosures on Neighborhood Crime

Only a few papers have explored whether foreclosures are linked to increases in crime. Using data from Chicago, Immergluck and Smith (2006b) find that higher foreclosure rates are associated with higher levels of violent crime in a given Census tract, but not higher levels of property crime. Because their analysis is limited to a single cross-section of Census tract-level data on crime and foreclosures, however, the authors cannot tell whether foreclosures actually lead to higher crime or if they simply tend to occur in areas with higher crime.

Clark and Teasdale (2005) find that subprime mortgage foreclosures have a significant, positive association with public order crime, which they define as the sum of all larceny, burglary, drug, and disorderly conduct crimes, at the Census tract level in Akron, Ohio. Again, the authors are unable to infer causality given that the study examines the link between foreclosures during 2001-2003 and a single cross section of crimes in 2003. In a national study of counties, Goodstein and Lee (2009) determine that a one percentage point increase in the one-year lagged county Real Estate Owned (REO) rate is associated with a three percent increase in burglaries per capita, controlling for demographic characteristics, macroeconomic conditions, law enforcement, and the incidence of subprime lending. Although their data are longitudinal, counties are large, and the time-period they study is short. Thus, the authors are ultimately unable to distinguish whether elevated foreclosures lead to crime or whether some changes in unobserved conditions lead to increases in both foreclosures and crime.

In a study of foreclosures in Pittsburgh, Cui (2010) undertakes an analysis that is most similar to ours. Using point-specific data on foreclosures and crime, Cui finds that the number of violent crimes occurring within 250 feet of a foreclosed property increases once the property becomes vacant. However, she only has four years of data and the relatively small size of Pittsburgh means that her sample is considerably smaller than ours. In addition, the analysis uses rings as the primary geographic unit of analysis, which imposes the assumption that a foreclosure will have an equal impact on crime across blockfaces within the ring. Our theory of criminal activity suggests that a foreclosure will have a stronger effect on its own blockface than on nearby blockfaces.

The Impact of Physical Disorder and Turnover on Crime

Related research has investigated the relationship between physical disorder (such as litter, graffiti, and structural disrepair) and crime. Spelman (1993) studies the link between abandonment and crime by comparing crime on blocks with abandoned buildings to crime on a matched cohort of blocks without abandoned properties in one neighborhood in Austin, Texas. Brown, Perkins, and Brown (2004) study the association between physical disorder and police reports, using cross-sectional data from a surveyor assessment of the physical condition of the housing stock in randomly selected blocks within one Salt Lake City neighborhood. These studies find that there are more reported crimes on blocks with abandoned buildings or other signs of physical disorder. However, neither of the studies addresses the endogeneity concern that increased crime may lead to disinvestment and abandonment, or that both crime and physical deterioration may be caused by underlying neighborhood weakness. Also, each of the studies only focuses on a single neighborhood.

Finally, some studies examine whether heightened turnover invites crime. For example, Xie and McDowall (2008) use longitudinal data to study the effect of residential turnover on household property crime victimization and find that neighborhoods with higher turnover rates have higher rates of victimization.

The Impact of Foreclosures on Other Community Outcomes

While few researchers have studied the impact of foreclosures on local crime, several have examined other community outcomes. Most notably, a growing number of papers study the impact of foreclosures on neighboring home values (Harding, Rosenblatt, & Yao, 2009; Haughwout, Mayer, & Tracy, 2009; Immergluck & Smith, 2006a; Lin, Rosenblatt, & Yao, 2009; Rogers & Winter, 2009; Schuetz, Been, & Ellen, 2008; Wassmer, 2010; Hartley, 2010). The papers vary in their methods but several use statistical techniques to demonstrate that foreclosures actually lead to reductions in property values, rather than the reverse. However, while these papers persuasively demonstrate causality, few explore the mechanism through which foreclosures reduce property values. They can only speculate whether the declines in values result from increased supply or sales, from reductions in the physical attractiveness of the neighborhood, or from a deterioration in neighborhood services or public safety.

A few studies have explored whether and how foreclosures affect the racial composition of neighborhoods and have found conflicting evidence. Using block group level data in New Orleans, Lauria and Baxter (1999) find that foreclosures are related to a decreasing percentage of black residents on blocks between 1980 and 1990. In contrast, Li and Morrow-Jones (2010) found foreclosure sales between 1983 and 1989 in Cuyahoga County, IL, are related to increases in the black share of residents in a block group.

II. Model

We model the relationship between foreclosures and crime by focusing on the decision-making process of potential offenders, borrowing from Becker's theory of criminal behavior (Becker, 1968) and the framework of routine activity theory commonly used in criminology research (Cohen and Felson, 1979). The assumptions of routine activity theory, which are that criminal acts require potential offenders, suitable targets, and the absence of "capable guardians," provide a set of theoretical pathways through which foreclosures may affect crime. While we expect that foreclosures that result in vacancies may have the greatest effect on crime, foreclosures may still invite crime, even if the underlying homes stay occupied.

The consequences of each stage of the foreclosure process – from the initial foreclosure notification, to eviction of the foreclosed owner and eventual bank ownership – affect the costs and benefits of committing crime. First, a homeowner who receives a foreclosure notice is more likely than others to cut back on maintenance of her building or grounds, either because she needs to save money to pay back arrears or because she realizes that she may lose the property. The visible deterioration of the property that follows a foreclosure notification may signal to the potential offender that local residents are less invested in the block, and are less likely to intervene in or report crime, which decreases the perceived chances of being caught (Harcourt and Ludwig, 2006). After all, potential offenders inevitably have imperfect information about the degree to which local residents and law enforcement monitor activities in a community. They therefore look to signals of such community engagement.

An increase in foreclosure notices may affect the social fabric in a community as well. After receiving a foreclosure notice, households may withdraw from the neighborhood and decrease their participation in civic and social activities, either due to the stress of foreclosure or because they simply care less about the neighborhood once their financial investment in it is imperiled. Similarly, elevated rates of foreclosure are likely to heighten residential turnover in a neighborhood as owners sell or lose their homes, and owner-occupied properties are converted to rental units (Clark & Teasdale, 2005). High rates of turnover may impede social ties among neighbors (Taylor, 1997). As a result, crime may increase as local residents are less able to recognize outsiders and to maintain the effective social controls (such as neighborhood watch associations) that help to cut off opportunities for crime and warn potential offenders that the chance of getting caught for crime is high (Sampson, Raudenbush, & Earls, 1997). These weakened protective networks may manifest themselves to potential criminals through visible signs of social disorder, such as littering and loitering, and fewer neighbors greeting each other or spending time outside on the blockface.

The breakdown of social cohesion also suggests that foreclosures may reduce the penalty to crime if offenders are in fact caught. In an environment with high residential turnover and weak ties among neighbors, potential offenders might lose less in terms of social relationships and reputation if they commit crimes against their neighbors.

The likely effects of foreclosures on the costs and benefits of committing crime are likely to be magnified for foreclosed properties that revert to bank ownership and sit vacant for extended periods. First, such vacancies increase the number of available targets for public order crimes. Vacant buildings are easy targets for vandalism and may also provide a safe haven for prostitution and drug-related crimes that can potentially lead to more serious, violent crimes (Spelman, 1993).[2]

As for the costs of committing crime, vacant buildings clearly communicate that there are fewer "eyes on the street" to monitor behavior and fewer capable guardians to engage in local civic and social activities that protect against crime. Vacant buildings, which are often also poorly maintained, may signal to potential offenders that residents on the block are less invested in the community and that enforcement is weak. Vacant properties are also difficult to secure, and may facilitate certain types of property crime, such as theft of wires and appliances.[3]

That said, the payoff from stealing from vacant buildings may be lower than that from stealing from occupied buildings, because vacant buildings include fewer valuable and marketable items (e.g. bicycles, jewelry, laptop computers, and other electronics). In this way, a larger number of foreclosed properties on a blockface might actually reduce the payoff to property crimes relative to other types of crime (such as drug sales and prostitution) and *decrease* their number. Moreover, increased vacancy and abandonment may lead to fewer individuals and vehicles on the blockface, which make is less likely that a potential offender will encounter an "easy" target (for example, an elderly individual or an unlocked car). Vacancies might thus cause the composition of crimes to shift away from more serious property crimes, and towards public order crimes, such as vandalism.

Note that concentrated foreclosures may have a disproportionate impact on crime due to nonlinearities in the effects of vacancy and turnover on the weakening of social networks and

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[2] Indeed, vacant properties may attract more lucrative or dangerous forms of criminal activity (for example, a vacant building can house a drug lab, while a street corner can only provide a "retail" site), which might increase the seriousness of crime as well as increasing the amount of crime.
[3] Often, the departing owners are the primary suspects in these crimes (see "As Foreclosed Homes Empty, Crime Arrives", The Washington Post, April 27, 2008).

neighborhood decline. For example, if a handful of residents on the block are responsible for much of the monitoring and collective efforts, a single foreclosed property is unlikely to affect their behavior (and might even galvanize them into action). Multiple foreclosures, however, may lead residents to feel that the block is irretrievably lost and that further efforts will be futile. Moreover, if one of the key residents involved in monitoring efforts departs as a result of foreclosure (which is more likely in an environment of concentrated foreclosure), this may cause the entire social network to crumble.

To summarize, foreclosures affect the number and type of crimes on the blockface by changing the payoff to committing property crimes, facilitating certain public order and property crimes, and decreasing the perceived and actual likelihood of getting caught.

More formally, potential offenders move across blockfaces and encounter opportunities to commit crime, beginning with their own blockface and extending to the entire city.[4] Potential offenders in this model are rational agents, and commit crime if the payoff from the crime minus the cost of committing the crime, exceeds the payoff from not committing the crime. The cost of not committing the crime is assumed to be zero, and most of the cost of committing a crime is the perceived chance of being caught. Foreclosures potentially change the benefits and costs of committing a crime on a blockface by affecting both the availability of suitable targets for criminal activity and the perceived presence (or absence) of "capable guardians" against crime.

We can then model the potential offender's tradeoff as:

$$V_{ibt}(Crime) - C_{ibt}(Crime) \geq V_{ibt}(No\ crime) - C_{ibt}(No\ crime) + \varepsilon_{ibt}$$

[4] Potential offenders are assumed to move around the city as a part of their routine activities, and so the costs of searching for a criminal opportunity (relative to not committing a crime) are zero.

where $V_{ibt}(.)$ and $C_{ibt}(.)$ are the benefit and cost functions, respectively, of potential offenders i who search across blockfaces b for opportunities to commit crime during time period t, and ε_{ibt} is a random term affecting the payoff and cost of crime. The sum of all potential offenders' crimes on the blockface b at time t, which equals the sum of all instances where the payoff from the crime net of the cost of committing the crime, exceeds the payoff from not committing the crime (plus the stochastic element of individual utility),

$$y_{bt} = \sum_i \left[\mathbf{1}(V_{ibt}(Crime) - V_{ibt}(NoCrime) - C_{ibt}(Crime) \leq \varepsilon_{ibt}) \right]$$

equals the expected number of crimes on the blockface and can be modeled as following a normal distribution or a negative binomial distribution.[5] While all individuals are potential offenders, there is heterogeneity across individuals in the payoff and expected cost to committing a given crime. This implies that there are some individuals who would commit crime on a different blockface in the absence of the foreclosure, while others are drawn into committing crime by changes in the payoffs and costs due to foreclosures. In this way, the model predicts both an increase in crime on the blockface due to new crimes committed when a property enters foreclosure on the blockface, and a relocation of crime to blockfaces with more foreclosures. New crimes are committed by individuals who were previously at the margin of committing crime; while relocated crimes are committed by inframarginal offenders who would have committed crime elsewhere, but choose to commit crime on the blockface with the foreclosure. Due to this displacement effect, the predicted impact of foreclosure activity on the sum of crimes in a larger area (such as a Census tract or police precinct),

$$\mathrm{Y}_t = \sum_b \left[y_{bt} \right]$$

[5] For further details on why the expected count of crimes might be distributed according to a negative binomial distribution rather than a normal distribution, refer to the appendix.

depends on whether increases in crime on blockfaces are driven primarily by new crimes or by displacement.

The expected number of crimes on the blockface also depends on the other benefits and costs of committing crime (aside from those caused by foreclosure). By including blockface fixed effects as explanatory variables, we take into account pre-existing, time invariant, blockface-specific contributions to the payoffs and costs of committing crime, such as geographic features, proximity to commercial areas and transit, and the distribution of building and occupancy types.[6] Further, we control for the characteristics of the larger neighborhood that change over time by including police precinct-by-quarter fixed effects. Finally, we include some attributes of blockfaces that change over time and may also affect the payoffs and costs of crime, including changes in the number of residential units, building demolitions and construction, and new liquor licenses.

III. Analysis: Differences-in-Differences Model

Geographic Unit of Analysis

Our primary unit of analysis is the blockface, a street segment that is bounded by the two closest cross-streets, and which incorporates buildings on both sides of the street (see Figure 1). We believe blockfaces are preferable to the more commonly-used Census blocks (encompassing all buildings on the interior of a square city block bordered by four street segments) and foreclosure-centered rings because foreclosures are most likely to affect behavior and crime on both sides of the street segment on which they occur, and less likely to affect crime around the corner. We employed New York City street shapefiles and GIS analysis to create blockfaces, which are not captured in standard mapping shapefiles. To our knowledge, no other research has

[6] We also estimate models without blockface fixed effects that include these measures directly.

been able to generate blockfaces for such an extensive and broad analysis. We also link foreclosures and crimes to police precincts, to capture broader policing strategies that are likely to affect crime.

Baseline Model and Identification Strategy

Our core research question is whether elevated rates of foreclosure cause increases in local crime. Intuitively, our empirical strategy in answering this question is to compare changes in crime levels on blockfaces experiencing an increase in foreclosure activity to changes in crime levels on nearby blockfaces that are not experiencing an increase in foreclosures, but are within the same neighborhood (defined as a police precinct).[7] Limiting the comparison group of blockfaces to those within the same precinct ensures that trends in these nearby comparison blockfaces differ from trends in the foreclosure-affected blockfaces only in the growth of foreclosure activity, and not in other unobservable characteristics which might drive both foreclosures and crime.

Our preferred specification includes blockface fixed effects and time-varying police precinct fixed effects to allow for such a within-precinct comparison. Specifically, we estimate the following model:

$$y_{bpt} = \alpha + \beta X_{bpt-1} + Z_{bpt} + T_{pt} + B_b + \varepsilon_{bpt}$$

where y_{bpt} is the level of criminal activity on blockface b in precinct p and quarter t. We focus primarily on simple counts of crimes per quarter, rather than rates, in part because we do not have quarterly population estimates for blockfaces. Our inclusion of blockface fixed effects controls for differences in average population across blockfaces. Moreover, any bias caused by

[7] We will use Census tracts as neighborhoods in subsequent updates of this paper.

our use of crime counts will be in the direction of not finding an effect, because if foreclosures lead to reductions in the population, our estimates of the effects foreclosures have on crime will understate the true impact by not accounting for the reduction in population. That said, we include the number of units on the blockface in our regressions, to control for the effect of any changes in blockface density on both foreclosures and crime counts.

On the right hand side of the equation, X_{bpt-1} is a measure of foreclosure activity in the previous quarter on blockface *b*; Z_{bnt} represents our set of time-varying blockface characteristics (including total units) to control for other observable changes in the blockface over time that might affect the payoffs and costs to committing crime; T_{pt} is a vector of variables indicating the quarter for each police precinct, which controls for crime and policing trends in the larger neighborhood; B_b are blockface fixed effects, which control for time-invariant differences between blockfaces with more and less foreclosure activity; and ε_{bnt} is the random error term.

We estimate the relationship between crimes in quarter *t* and foreclosure activity in quarter *t-1* to ensure that we are not estimating a reverse relationship between criminal activity and the decision to default or foreclose. To further test the direction of causality, we also estimate models in which we include *future* foreclosures on the right hand side, as foreclosures two years in the future should not have any effect on criminal activity. A positive correlation between crime on a blockface in year *t* and foreclosures on a blockface in year *t+2* would suggest some degree of reverse causality – or indicate unobserved changes on a blockface that affect both crime and foreclosures.

Additional Analysis

Our paper addresses four secondary questions as well. First, what types of crime are most sensitive to foreclosures? Second, do impacts on crime vary depending on the outcomes of the foreclosures? Third, is there a threshold level of foreclosures that triggers crime? Fourth, do foreclosures draw marginal offenders into crime or do they merely attract crime from other nearby blockfaces?

To answer the first question, we simply re-estimate the above equation separately for counts of violent, property, and public order crimes. The theoretical discussion above offers less certain predictions about the impact of foreclosures on property crimes, and thus we expect larger effects on public order and violent crimes. For the second question about foreclosure outcomes, we compare results of regressions using three distinct measures of foreclosures, ranging from a simple cumulative count of foreclosure notices issued to properties on the blockface in the past 18 months, to a count of bank-owned (REO) properties. These measures are discussed in greater detail below. To address the third question about threshold effects, we model foreclosure counts using a set of interval variables to capture the intensity of foreclosure activity.

Finally, examining whether foreclosures lead to net new crimes or whether they simply attract crimes that would have occurred elsewhere is more difficult. To test whether foreclosures lead to a net increase in crimes, we estimate the relationship between lagged foreclosure activity and criminal activity in a larger area – the entire police precinct – using a linear model similar to the one above. The precinct-level model includes precinct fixed effects and time-varying fixed effects for the City's five boroughs to capture sub-city trends in crime. As we explained in the theoretical section, expanding the size of the unit of analysis will internalize some of the spillover effects – if there are any.[8]

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[8] A second way to explore whether foreclosure activity on a blockface attracts crime from surrounding blocks is to directly measure what happens to crime on surrounding blocks. We are in the process of identifying adjoining blockfaces to implement this analysis.

Statistical Extensions

The fine-grained nature of our data, while very advantageous, presents some potential pitfalls for estimation. Specifically, because blockfaces are such small geographic units, there are a substantial number of time periods when no crimes in our chosen categories occur. As shown in Figure 2, this skews the distribution of crime levels towards zero, violating the normal distribution assumption and making it likely that an ordinary least squares regression will be a poor fit for the data. We address this issue by estimating the above relationship using a negative binomial model (following Sampson, Raudenbush, and Earls (1997), and Osgood (2000) in their studies of neighborhood crime). These models, which we discuss in further detail in the appendix, estimate the relationship between foreclosure activity and crime using a different distributional assumption for the underlying empirical relationship than the standard linear model, and arguably provide a better fit for our data, as shown in Figure 2. (See Appendix for more detail on estimation.)

Due to computing constraints, it is not possible to estimate the negative binomial models with both blockface and time fixed effects. Researchers have suggested several different approaches to addressing this problem. We believe the hybrid approach suggested by Allison (2005), which algebraically transforms the independent variables matrix into a matrix of blockface-level sample means and observation-specific deviations from these means, is the best to apply to the negative binomial estimator because it does not impose any restrictions on the relationship between the dependent and independent variables, and it drastically reduces the number of coefficients that need to be directly estimated (see Appendix 1).

Data Sources

Crime Data

Under an agreement with the NYPD, we have obtained point-specific data on all crimes reported in New York City between 2004 and 2008. This detailed dataset includes the spatial coordinates of each reported crime, along with its date, time, and offense category (see Table 1 for crime categories). We used GIS procedures to assign each crime to various levels of geography, including police precincts and blockfaces.[9] Many of the X/Y coordinates of crimes are geo-coded to the middle of the street, or literally on the border of two Census blocks (and often two Census tracts). These crimes do not pose a problem for our analysis, because they clearly occur on a single blockface. We assign the 20% of crimes that take place at intersections to multiple blockfaces, as they could be shaped/encouraged by conditions on all adjoining blockfaces. Although we have the exact date of both crimes and foreclosure notices, we aggregate crimes to quarters, as sample sizes do not permit shorter time periods for blockfaces.

Mortgage Foreclosure Data

In New York State, a mortgage foreclosure is initiated when the foreclosing party files a legal document, called a *lis pendens*, in the county court.[10] We use foreclosure filing data obtained from a private vendor, the Public Data Corporation.[11] We also incorporate information about how and when the foreclosure notice is resolved. Using data from the New York City

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[9] There are 76 police precincts, 2,246 census tracts, 36,601 census blocks, and 96,933 blockfaces in New York City. We limit our sample of blockfaces to those that have at least 1 building, and that are able to be matched to the New York City Department of Finance's Real Property Assessment Database (RPAD) data about property characteristics, resulting in a sample of approximately 89,000.

[10] Beginning in 2010, mortgage servicers are required by New York State law to issue pre-foreclosure notifications to borrowers at risk of foreclosure. However, this law was not in effect during our time period of analysis.

[11] A *lis pendens* may be filed for many reasons, unrelated to a mortgage foreclosure. The Furman Center uses a variety of screening mechanisms to identify *lis pendens* related specifically to mortgage default. Details on the procedures used to identify mortgage defaults and REO transfers are available in Armstrong et.al., 2010.

Department of Finance's Automated City Register Information System (ACRIS), we identify actions that occur following the filing of *lis pendens*, including deed transfers such as arms-length sales, auction sales, and reversion to lender ownership or Real Estate Owned (REO) status.

Most researchers simply have access to foreclosure filings or notices data, but our ability to track foreclosure filings from initiation to resolution allows us to better understand how foreclosures resulting in different outcomes affect crime. Figure 3 shows the overall trend in *lis pendens* over the years in our study period, while Figure 4 shows the distribution of outcomes of those foreclosure notices three years after issuance. As the total number of *lis pendens* increases over time, so does the share that becomes REO (and that likely experience prolonged periods of vacancy).

We rely on three measures of foreclosure activity. First, and most simply, because the foreclosure process typically lasts about 18 months in New York City, we count the total number of properties on a blockface or in a neighborhood that entered foreclosure in the prior 18 months, or six quarters. We call this measure "cumulative foreclosure starts." After 18 months have passed, this measure treats a foreclosure as resolved, implicitly assuming that it will not have the same negative impact on the surrounding community. Second, we construct a measure of "active foreclosures," which captures the number of properties currently in the foreclosure process. We assume a property is in the foreclosure process if it either has received a foreclosure notice within the last 18 months or is REO, and has not been resold to a new owner.[12] Thus, the active foreclosure measure assumes that properties receiving foreclosure notices that quickly sell to another owner have no further effect on the blockface, while those that go to auction and revert

[12] If a property reverts to REO status after an auction, we assume that the property is still an active foreclosure, until the time when another party purchases the property from the lender.

to bank ownership (and thus are likely to sit vacant) affect the neighborhood until they are sold to a new private owner. While the active foreclosure metric may be a more accurate measure of the complete stock of foreclosed properties in distress than the number of cumulative foreclosure starts, the latter measure captures the potentially lasting effects that residential turnover may have on crime.

Finally, we also simply track the number of REO properties on a blockface, as these properties are almost certainly vacant and thus theoretically should have the largest impact on crime on the blockface.

Control Variables

As noted, we also control for several characteristics of blockfaces that may affect the likelihood of both foreclosures and crime occurring in that place. These include the total number of housing units on a blockface, measures of new construction or demolitions (created from permit data from the New York City Department of Buildings), and the number of active liquor licenses for a bar or alcohol purveyor on the blockface in a given quarter from the New York State Liquor Authority.[13]

For some models, we omit blockface fixed effects and include instead time-invariant blockface level variables that describe the structural composition of the blockface from the New York City Department of Finance's Real Property Assessment Database (RPAD): the number of religious buildings, educational structures, store buildings, and the number of vacant lots. We also include measures of the composition of the residential housing stock from RPAD: the number of single family, two-to-four family, and multifamily buildings with five or more units,

[13] Our measure excludes liquor licenses granted to grocery stores and drug stores.

the number of condos and co-ops, and the share of building square footage on the blockface that is of commercial use, which are unlikely to vary much over time.

Descriptive Statistics

Table 2 presents the time-invariant characteristics at the blockface level, and compares the characteristics of blockfaces with no foreclosure activity during our 5 year period to those that experienced one, two, and three or more foreclosure filings. The vast majority of blockfaces (80 percent) did not experience a foreclosure filing, which is perhaps not surprising given the small size of blockfaces. On the other hand, seven percent of the blockfaces experienced three or more foreclosure filings.

There are distinct differences in the structural characteristics of blockfaces that experienced differing levels of foreclosure activity. Blockfaces with more foreclosed properties had more buildings overall, a greater proportion of 2 to 4 family residences, and fewer large (5-plus family) and mixed-use buildings. Compared to the mean across all blockfaces (the first column in Table 1), blockfaces with any foreclosures during the period were home to more churches, fewer stores (a higher share of units were residential), and more vacant lots. Overall, there seem to be some distinct differences in the blockfaces that experienced differing levels of foreclosure activity, underscoring the importance of including blockface fixed effects in our model.

Table 3 presents the average, time-varying characteristics across blockfaces for each year in our time frame. On average, the mean number of total crime complaints decreased over time, while foreclosure activity increased dramatically across the city as the economic crisis deepened. The mean number of cumulative foreclosure starts (in the previous 6 quarters) increased in 2007 and 2008 after fluctuating between 2004 and 2006, while the mean number of active foreclosures increased starting in 2006 and actually surpassed the mean number of cumulative foreclosure starts in 2008, indicating that a substantial portion of foreclosures initiated prior to 2008 entered REO and had not been sold to a new resident or landlord by 2008.

Results

The results of our baseline regression analyses are found in Tables 4-6. Table 4 presents estimates from models using our measure of active foreclosures, Table 5 shows the results from our models using the cumulative count of foreclosure starts in the past 18 months, and Table 6 presents results from our models using a count of REO properties as a dependent variable. In all three tables, Specification 1 is our base model, simply estimating the association between the measure of foreclosure activity on a blockface and crime (controlling for the total number of units on the blockface). As the tables below show, the base specification shows a positive, statistically significant relationship between all three foreclosure measures, and all four types of neighborhood crime (total, violent, property, and public order crime). Each subsequent specification builds from this raw model.

In Specification 2, we control for the time-varying and time-invariant characteristics of blockfaces that may contribute to the level of crime on the blockface, by adding a host of blockface level control variables. These control variables (as described above) include the number of active liquor licenses, the number of new building permits issued, the number of demolition permits issued, the share of properties that are single family, 2-4 family, 5-plus family, or condo properties, the share of units that are of non-residential use and mixed use, and the number of properties used for commercial sales (stores), churches or other religious uses, and are vacant. In this specification, the magnitudes of the coefficients on our foreclosure measures decrease but remain statistically significant for all types of crime, and we see a modest increase in our ability to explain blockface-level variation in crime levels.

Next, in Specification 3 we include precinct-quarter interaction fixed effects to capture changes in policing strategy, localized housing price changes, and other factors that change over time in the larger neighborhood surrounding each blockface. The coefficients on our foreclosure variables decrease slightly, and we gain explanatory power with our models.

Given that many of the complex demographic and social characteristics that are likely related to both foreclosure activity and crime are difficult to measure at the blockface level, we omit the time-invariant blockface characteristics and replace them with blockface level fixed effects in Specification 4. In this preferred specification, the estimates of the impact of foreclosure activity on total crime and public order crime are still statistically significant but considerably smaller in magnitude compared to the previous specifications. Our models predicting total and public order crime now explain about 75 and 69 percent of the variation in blockface level crime (as compared to only around 40 percent of violent and property crimes).[14]

In this preferred specification, the coefficients on total, violent, and public order crimes remain significant, but the estimate of the impact of foreclosure on property crime is only marginally significant when using the cumulative foreclosure start measure and loses significance entirely when using the active foreclosure and REO measures. This weaker result for property crime is consistent with our theoretical predictions, as foreclosed properties – especially when they sit vacant as they change ownership or go to auction – may be less attractive targets for theft.

[14] Past research finds that patterns of more serious crimes are more difficult to explain.

As expected, the coefficients estimated when using the REO measure of foreclosure are consistently significant and considerably larger (more than twice as large) than those presented in Tables 4 and 5. In other words, foreclosure filings that result in vacancy appear to have larger effects on neighborhood crime than foreclosure filings that are resolved in other ways. Perhaps surprisingly, however, we find little difference between the estimated impact of an additional active foreclosure on crime and the impact of an additional foreclosure start in the past 18 months. As for effect sizes, the OLS results suggest that an additional active foreclosure in the prior quarter is associated with a 1.0 percent increase in total crime, a 2.1 percent increase in violent crime, and a 0.8 percent increase in public order crimes. The REO results suggest even larger effects, indicating that an additional REO property on a blockface leads to a 2.6 percent increase in total crime, a 5.7 percent increase in violent crimes, and a 2.8 percent increase in public order crimes.

To bolster confidence that our results are capturing a causal relationship between foreclosures and crimes, we run a set of regressions to test whether the results we are identifying reflect an endogenous relationship between crime and foreclosures on the blockface. Specifically, we regress future foreclosures on the blockface (a count of the number of foreclosure starts in the 18 months *following* the quarter for which we measure crime) on total crime. As presented in Table 7, the coefficient on the number of future foreclosure starts is statistically insignificant (and much smaller than the coefficient on our measure of lagged foreclosure starts). As shown, we obtain the same results when we include the number of active foreclosures 6 quarters after the quarter in which crime is measured.

Modeling crime at the micro-neighborhood level raises the concern that the dependent variable (crime) may not be normally distributed across geographic units or time. As shown in

Figure 2, we find evidence that the distribution of crime across blockfaces follows a gamma distribution. Therefore, we also estimate a negative binomial model to account for the concentration of observations on the left tail of the crime distribution. Tables 8, 9, and 10 present the results of our negative binomial models of the impact of active foreclosures, cumulative foreclosure starts, and REOs, on total crime. Specification 1 shows the unadjusted association between the foreclosure measure and total crime, Specification 2 adds precinct-quarter interaction fixed effects, and Specification 3 presents the results of the preferred "hybrid" model (discussed above). All of the models have likelihood ratios above well above the critical chi-square values, allowing us to reject the null hypothesis that the model is not explaining the variance in crime. The coefficients on the foreclosure measures (presented in the tables as deviations from the blockface mean) are all positive and statistically significant.

All these results so far assume that foreclosures have a linear effect on crime. But, as noted, there may be threshold effects such that one foreclosure occurs with little notice but several may signal that the block is unraveling. In the panels of Table 11, we estimate models with categorical variables for blockfaces with 1, 2, or 3 or more foreclosures in a given quarter by crime type. The reference category is zero foreclosures in a given quarter. We see some evidence of non-linearity in Panel A (active foreclosures). Foreclosure activity only appears to be linked to subsequent crime when there are two or three foreclosures on a blockface. Similarly, for REOs, we see that three properties in REO have a demonstrably larger impact on crime than one or two.[15] Meanwhile, the impact of foreclosure starts (Panel A) on total crime appears to be fairly linear, but foreclosure starts only appear to have a significant effect on violent and public order crimes after the second foreclosure.

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[15] Note that the average number of REO properties on a blockface with three or more REO properties is 3.44.

In order to explore whether the impacts that we are seeing result from actual increases in net crime (rather than from displacement of existing crime), we estimate similar models at the precinct level. In Table 12, the initial specification controls for the total number of housing units in the precinct, the second specification controls for precinct-level characteristics, the third specification adds borough-specific time trends, and the final specification adds precinct fixed effects.[16] In the final specification, we find positive, significant increases in total, violent, and public order crime when foreclosures increase in the precinct (as captured by all three measures of foreclosure activity). Mirroring our blockface-level results, the effect of foreclosures on property crime is weaker – in all of the models, the effect on property crime is insignificant, after controlling for borough-wide time trends and time invariant characteristics of the precinct. These results suggest that foreclosure activity on the blockface may actually generate new public order and violent crimes and not simply draw such crimes from nearby blockfaces that would have occurred anyway.

Conclusions & Policy Recommendations

Using more detailed spatial analysis than previous researchers, our examination suggests that foreclosures can lead to elevated crime on the blockfaces where they occur. Consistent with theoretical predictions, effects are least robust for property crimes and are largest when foreclosure activity is measured by the number of REO (and presumably vacant) properties on a blockface. Finally, we provide some suggestive evidence that foreclosures lead to net new crimes, rather than simply displacing existing crime.

While our results only cover New York City, we expect that they are generalizable to other cities. New York City includes a large and diverse set of neighborhoods, and many of

[16] New York City has five separate boroughs, which are also independent counties.

them are similar to other cities in the country in terms of the nature and quality of the housing stock, density, and neighborhood demographics. Indeed, most foreclosures in New York City have taken place in neighborhoods outside of Manhattan with high concentrations of single-family and two- to four-family homes. If anything, we suspect our results may understate the impact of foreclosures in other cities that have been harder hit by the foreclosure crisis and where fewer of the foreclosures are resolved through arms-length sales. While the elevated rates of turnover that result from a foreclosure start may affect neighborhood crime, our results suggest that foreclosure starts have a smaller effect on crime than do extended vacancies.

Bibliography

Allison, P. D., & Waterman, R. P. (2002). Fixed–effects negative binomial regression models. *Sociological Methodology*, 32(1), 247-265.

Allison, P. D. (2005). *Fixed effects regression methods for longitudinal data using SAS®*. Cary, NC: SAS Institute Inc.

Baltagi, B.H. and Liu, L. (2008). Testing for random effects and spatial lag dependence in panel data models. *Statistics and Probability Letters 78*, 3304-3306.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *The Journal of Political Economy, 76*(2), 169-217.

Brown, B., Perkins, D., & Brown, G. (2004). Incivilities, place attachment and crime: Block and individual effects. *Journal of Environmental Psychology, 24*(3), 359-371.

Clark, L. M., & Teasdale, B. (2005). Subprime lending, crime, and neighborhood disorganization: Beyond internal dynamics. University of Akron.

Cohen, Lawrence and Marcus Felson. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review, 44*(4), 588-608.

Cui, Lin. (2010). Foreclosure, Vacancy and Crime. Manuscript, Department of Economics, University of Pittsburgh.

Debarsy, N. and Ertur, C. (2009). Testing for Spatial Autocorrelation in a Fixed Effects Panel Data Model. Working paper no. 2009-12, Laboratoire d'Economie d'Orleans.

Dietz, R., & Haurin, D. (2003). The social and private micro-level consequences of homeownership. *Journal of Urban Economics, 54*(3), 401-450.

Dubin, R. (1998). Spatial Autocorrelation: A Primer. *Journal of Housing Economics , 7*, 304-327.

Gardner, W., Mulvey, E.P. and Shaw, E.C. (1995). Regression Analyses of Counts and Rates: Poisson, Overdispersed Poisson, and Negative Binomial Models. *Psychological Bulletin 118*(3), 392-404.

Goodstein, R., & Lee, Y. (2009). *Do foreclosures increase crime?* Paper presented at the Association of Public Policy Analysis and Management 2009 31st Annual Research Conference.

Harcourt, Bernard E. and Ludwig, Jens. 2006. Broken Windows: New Evidence from New York City and a Five-City Social Experiment. University of Chicago Law Review, Vol. 73: 271-320.

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

Hartley, Daniel. (2010). The Effect of Foreclosures on Nearby Housing Prices: Supply or Disamenity? Working Paper 10-11, Federal Reserve Bank of Cleveland.

Haughwout, A., Mayer, C., & Tracy, J. (2009). Subprime mortgage pricing: the impact of race, ethnicity, and gender on the cost of borrowing.

Immergluck, D., & Smith, G. (2006a). The external costs of foreclosure:The impact of single-family mortgage foreclosures on property values. *Housing Policy Debate, 17*(1), 57-79.

Immergluck, D., & Smith, G. (2006b). The impact of single-family mortgage foreclosures on neighborhood crime. *Housing Studies, 21*(6), 851-866.

Lauria, M., & Baxter, V. (1999). Residential mortgage foreclosure and racial transition in New Orleans. *Urban Affairs Review, 34*(6), 757.

Li, Y., & Morrow-Jones, H. (2010). The Impact of Residential Mortgage Foreclosure on Neighborhood Change and Succession.

Lin, Z., Rosenblatt, E., & Yao, V. W. (2009). Spillover Effects of Foreclosures on Neighborhood Property Values. *Journal of Real Estate Finance and Economics, Vol. 38, No. 4, May 2009*.

Mummulo, Jonathan and Bill Brubaker. (2008). As Foreclosed Homes Empty, Crime Arrives. *The Washington Post*, Sunday, April 27, 2008. Metro section.

Osgood, D. W. (2000). Poisson-based regression analysis of aggregate crime rates. *Journal of Quantitative Criminology, 16*(1), 21-43.

Rogers, W., & Winter, W. (2009). The impact of foreclosures on neighboring housing sales. *Journal of Real Estate Research, 31*(4), 455-479.

Rohe, W., McCarthy, G., & Van Zandt, S. (2002). The social benefits and costs of homeownership. In N. P. Retsinas & E. S. Belsky (Eds.), *Low-Income Homeownership: Examining the Unexamined Policy*: Brookings Institution Press.

Rohe, W., & Stewart, L. (1996). Homeownership and neighborhood stability. *Housing Policy Debate, 7*, 37-81.

Sampson, R., Raudenbush, S., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*(5328), 918.

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

Spelman, W. (1993). Abandoned buildings: Magnets for crime? *Journal of Criminal Justice, 21*, 481-481.

Taylor, R. (1997). Social order and disorder of street blocks and neighborhoods: Ecology, microecology, and the systemic model of social disorganization. *Journal of Research in Crime and Delinquency, 34*(1), 113-155.

Wassmer, R. (2010). The Recent Pervasive External Effects of Residential Home Foreclosure.

Wilson, J., & Kelling, G. (1982). The police and neighborhood safety: Broken windows. *Atlantic Monthly, 127,* 29-38.

Wilson, R., & Paulsen, D. (2010). A Theoretical Underpinning of Neighborhood Deterioration and the Onset of Long-Term Crime Problems From Foreclosures (Working Paper).

Wolf, R. V. (2010). *A full response to an empty house: Public safety strategies for addressing mortgage fraud and the foreclosure crisis.*: Center for Court Innovation. Bureau of Justice Assistance, U.S. Department of Justice.

Xie, M., & McDowall, D. (2008). The effects of residential turnover on household victimization. *Criminology, 46*(3), 539-575.

Figures

Figure 1: Blockface Geography

Figure 2: Blockface-level crime distribution versus Poisson, Negative Binomial Distributions

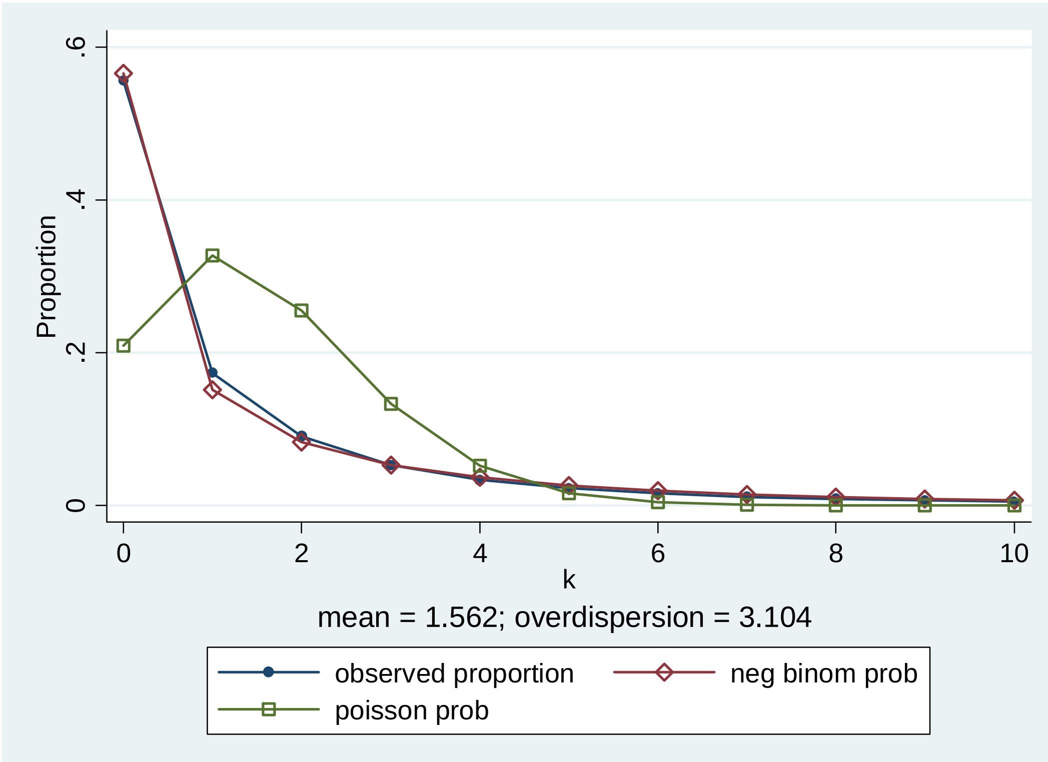


Figure 3: Lis Pendens filings in New York City (2000-2010)

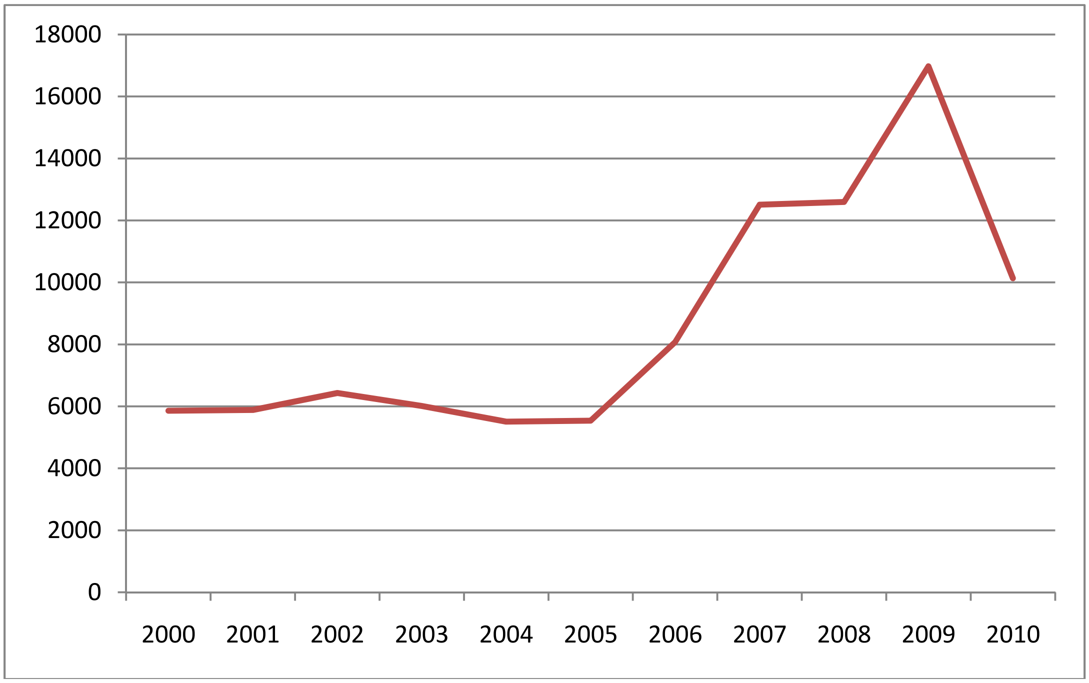
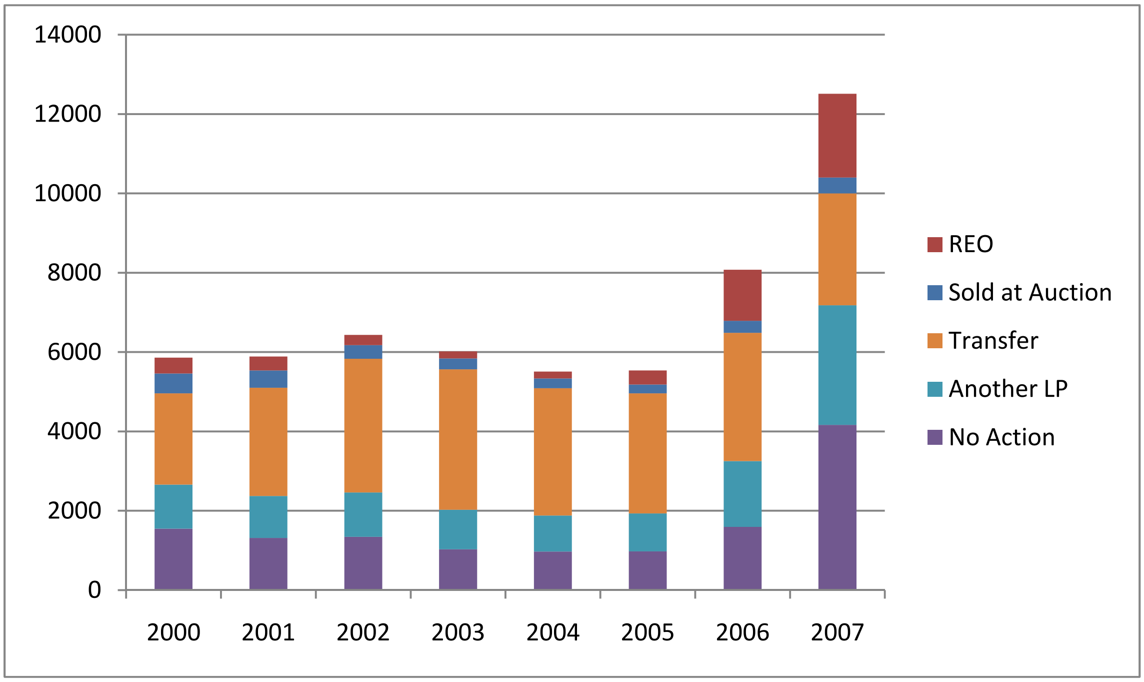


Figure 4: Outcomes of Lis Pendens, within 3 years of the lis pendens, by year of LP filing, through Q4, 2010[17]



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[17] Data through June 30, 2009. Historically, many REO properties experience dramatic lags between the transfer date and the recording date. We expect this number to rise when all the data has been recorded by the city register. Transfer category includes other deed transfer, arms length sale or deed in lieu.

Tables

Table 1: Crime Categories

UCR Part 1 Violent Crimes	N	% Total
ROBBERY	130,804	59.27%
FELONY ASSAULT	87,504	39.65%
MURDER & NON-NEGL. MANSLAUGHTER	2,021	0.92%
HOMICIDE-NEGLIGENT, NEGLIGENT-VEHICLE	361	0.16%
UCR Part 1 Property Crimes	**N**	**% Total**
PETIT LARCENY	401,217	46.72%
GRAND LARCENY	225,354	26.24%
BURGLARY	115,555	13.46%
GRAND & PETIT LARCENY OF MOTOR VEHICLE	79,730	9.28%
THEFT-FRAUD	28,278	3.29%
ARSON	8,624	1.00%
Public Order Crimes	**N**	**% Total**
HARRASSMENT 2	347,447	24.85%
CRIMINAL MISCHIEF & RELATED OFFENSES	264,071	18.88%
ASSAULT 3 & RELATED OFFENSES	262,118	18.75%
OFFENSES AGAINST PUBLIC ORDER SENSIBILITY	179,306	12.82%
DANGEROUS DRUGS	176,057	12.59%
MISCELLANEOUS PENAL LAW	54,107	3.87%
DANGEROUS WEAPONS	53,640	3.84%
CRIMINAL TRESPASS	34,747	2.48%
POSSESSION OF STOLEN PROPERTY	14,848	1.06%
OFFENSES AGAINST THE PERSON	5,681	0.41%
OTHER OFFENSES RELATED TO THEFT	3,011	0.22%
FRAUDULENT ACCOSTING	1,368	0.10%
BURGLAR'S TOOLS	772	0.06%
PROSTITUTION & RELATED OFFENSES	392	0.03%
DISORDERLY CONDUCT	326	0.02%
OFFENSES AGAINST PUBLIC SAFETY	199	0.01%
LOITERING/GAMBLING (CARDS, DICE, ETC)	216	0.01%

Table 2: Average Time-Invariant Characteristics of Blockfaces

	Total LP Activity 2004-2008				
	All Blockfaces	zero LPs	1 LP	2 LPs	3+ LPs
Mean Number of LPs	0.54	0.00	1.00	2.00	5.24
Number of Blockfaces	89,143	70,959	8,082	3,959	6,143
Time Invariant Blockface Attributes					
Number of Buildings	11.29	8.56	17.49	19.80	29.10
Share 1 Family Buildings	30%	28%	43%	42%	38%
Share 2-4 Family Buildings	29%	25%	45%	47%	53%
Share 5+ Family Buildings	12%	14%	6%	5%	5%
Share Co-ops	3%	4%	0%	0%	0%
Share Condos	2%	3%	0%	0%	0%
Share Mixed Use Buildings	7%	8%	6%	5%	3%
Number of Churches	0.08	0.07	0.09	0.10	0.16
Number of Vacant Lots	0.39	0.33	0.52	0.57	0.91
Share of Units that are Residential	77%	72%	95%	95%	97%

Source: Real Property Assessment Dataset, 2008.

Table 3: Average, Time-Varying Characteristics of Blockfaces

	2004	2005	2006	2007	2008
Crime Complaints	1.516	1.464	1.454	1.501	1.396
Violent Crimes	0.129	0.126	0.124	0.123	0.105
Property Crimes	0.504	0.478	0.463	0.465	0.449
Public Order Crimes	0.771	0.757	0.765	0.806	0.744
Cumulative Foreclosure Starts (previous 6 quarters)	0.113	0.105	0.114	0.159	0.232
Active Foreclosures	0.096	0.086	0.094	0.148	0.247
REOs	0.010	0.012	0.020	0.040	0.051
Demolition Permits	0.006	0.008	0.009	0.009	0.004
New Building Permits	0.028	0.038	0.035	0.032	0.013
Liquor Licenses	0.010	0.026	0.037	0.045	0.056
Number of Blockface-Quarters	356,972	356,152	356,080	356,308	356,572

Table 4: OLS Regression of Active Foreclosure on Crime by Type

Total Crime	**(1)**		**(2)**		**(3)**		**(4)**	
Activelag1	0.3910	***	0.3595	***	0.3182	***	0.0167	***
	(0.005)		(0.005)		(0.005)		(0.004)	
Tot_Unit	0.0057	***	0.0033	***	0.0030	***	-0.0003	***
	(3.2E-5)		(3.2E-5)		(3.1E-5)		(7.5E-5)	
BarLiqLics			0.2196	***	0.2274	***	-0.0560	**
			(0.026)		(0.026)		(0.026)	
Demo Permits			0.0224		0.1078	***	0.0043	
			(0.029)		(0.028)		(0.017)	
New Permits			0.0891	***	0.0867	***	-0.0143	**
			(0.009)		(0.009)		(0.006)	
% 1 fam			-2.0022	***	-1.0287	***		
			(0.048)		(0.048)			
% 2-4 fam			-0.6490	***	-0.3338	***		
			(0.048)		(0.047)			
% 5 fam+			3.9176	***	2.2208	***		
			(0.056)		(0.056)			
% Mixed Use			0.3633	***	0.4514	***		
			(0.045)		(0.044)			
% Condo			-0.9830	***	-0.5431	***		
			(0.131)		(0.129)			
% Non Res			-1.6277	***	-1.6713	***		
			(0.044)		(0.043)			
Churches			0.6771	***	0.4612	***		
			(0.011)		(0.011)			
Stores			0.3375	***	0.3732	***		
			(0.006)		(0.006)			
Vacant			0.0856	***	0.0541	***		
			(0.003)		(0.003)			
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.084		0.206		0.278		0.753	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Violent Crime	(1)		(2)		(3)		(4)	
Activelag1	0.0375	***	0.0355	***	0.0268	***	0.0032	***
	(0.001)		(0.001)		(0.001)		(0.001)	
Tot_Unit	0.0005	***	0.0002	***	0.0002	***	-4.9E-05	**
	(5.5E-6)		(5.7E-6)		(5.6E-6)		(2.0E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.023		0.076		0.116		0.329	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Property Crime	(1)		(2)		(3)		(4)	
Activelag1	0.0660	***	0.0595	***	0.0559	***	0.0023	
	(0.001)		(0.001)		(0.001)		(0.002)	
Tot_Unit	0.0013	***	0.0008	***	0.0006	***	0.0000	
	(9.8E-6)		(1.0E-5)		(9.8E-6)		(3.3E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.044		0.1127		0.168		0.470	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Public Order Crime	(1)		(2)		(3)		(4)	
Activelag1	0.2694	***	0.2465	***	0.2191	***	0.0085	***
	(0.003)		(0.003)		(0.003)		(0.003)	
Tot_Unit	0.0036	***	0.0021	***	0.0020	***	-0.0002	***
	(2.3E-5)		(2.3E-5)		(2.2E-5)		(5.8E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.072		0.167		0.231		0.691	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Table 5: OLS Regression of Cumulative Foreclosure Starts on Crime by Type

Total Crime	(1)		(2)		(3)		(4)	
LP6Qlag	0.2935	***	0.3000	***	0.2432	***	0.0187	***
	(0.0046)		(0.0044)		(0.0045)		(0.0039)	
TOT_UNIT	0.0153	***	0.0103	***	0.0096	***	3.04E-05	
	(0.0001)		(0.0001)		(0.0001)		(0.0001)	
Nobs	387,800		387,800		387,800		387,800	
RSquare	0.181		0.262		0.331		0.739	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Violent Crime	(1)		(2)		(3)		(4)	
LP6Qlag	0.0301	***	0.0322	***	0.0203	***	0.0030	***
	(0.0008)		(0.0008)		(0.0009)		(0.0011)	
TOT_UNIT	0.0013	***	0.0008	***	0.0007	***	-1.22E-05	
	(1.01E-05)		(1.12E-05)		(1.16E-05)		(2.27E-05)	
Nobs	387,800		387,800		387,800		387,800	
RSquare	0.048		0.090		0.127		0.319	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Property Crime	(1)		(2)		(3)		(4)	
LP6Qlag	0.0460	***	0.0467	***	0.0415	***	0.0028	*
	(0.0014)		(0.0014)		(0.0014)		(0.0017)	
TOT_UNIT	0.0036	***	0.0025	***	0.0021	***	0.0000	
	(1.7E-05)		(1.9E-05)		(1.9E-05)		(3.6E-05)	
Nobs	387,800		387,800		387,800		387,800	
RSquare	0.109		0.151		0.194		0.429	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Public Order Crime	(1)		(2)		(3)		(4)	
LP6Qlag	0.2046	***	0.2068	***	0.1688	***	0.0097	***
	(0.0033)		(0.0032)		(0.0033)		(0.0031)	
TOT_UNIT	0.0097	***	0.0065	***	0.0064	***	0.0001	
	(4.0E-05)		(4.4E-05)		(4.4E-05)		(6.6E-05)	
Nobs	387,800		387,800		387,800		387,800	
RSquare	0.147		0.210		0.277		0.674	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Table 6: OLS Regression of REOs on Crime by Type

Total Crime	(1)		(2)		(3)		(4)	
REOlag1	0.5937	***	0.5572	***	0.4991	***	0.0447	***
	(0.012)		(0.011)		(0.011)		(0.010)	
TOT_UNIT	0.0058	***	0.0033	***	0.0030	***	-0.0003	***
	(3.2E-5)		(3.2E-5)		(3.1E-5)		(7.5E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.076		0.199		0.273		0.753	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Violent Crime	(1)		(2)		(3)		(4)	
REOlag1	0.0559	***	0.0546	***	0.0446	***	0.0087	***
	(0.002)		(0.002)		(0.002)		(0.003)	
TOT_UNIT	0.0005	***	0.0002	***	0.0002	***	-4.8E-05	**
	(5.5E-6)		(5.7E-6)		(5.6E-6)		(2.0E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.020		0.074		0.115		0.329	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Property Crime	**(1)**		**(2)**		**(3)**		**(4)**	
REOlag1	0.0674	***	0.0626	***	0.0709	***	0.0039	
	(0.004)		(0.003)		(0.003)		(0.004)	
TOT_UNIT	0.0013	***	0.0008	***	0.0006	***	-2.6E-05	
	(9.8E-6)		(1.0E-5)		(9.8E-6)		(3.3E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.040		0.110		0.166		0.470	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Public Order Crime	**(1)**		**(2)**		**(3)**		**(4)**	
REOlag1	0.4441	***	0.4128	***	0.3598	***	0.0293	***
	(0.008)		(0.008)		(0.008)		(0.008)	
TOT_UNIT	0.0037	***	0.0022	***	0.0020	***	-0.0002	***
	(2.3E-5)		(2.3E-5)		(2.2E-5)		(5.8E-5)	
Nobs	434,228		434,228		434,228		434,228	
RSquare	0.065		0.161		0.227		0.691	
Covariates	N		Y		Y		N	
BlockfaceFE	N		N		N		Y	
Precinct*YRQ	N		N		Y		Y	

Table 7a: Impact of Future Foreclosure Starts on Total Crime

	OLS Estimate		Robust Check	
LP6Qlag	0.0265	***		
	(0.0050)			
FutureLP			0.0047	
			(0.0043)	
Total_Unit	0.0001		0.0001	*
	(0.0001)		(0.0001)	
Nobs	310,220		310,220	
R-Square	0.746		0.746	
Blockface FEs	Y		Y	
Precinct*YrQ FEs	Y		Y	

Table 7b: Impact of Future Active Foreclosures on Total Crime

	OLS Estimate		Robust Check
Actlag1	0.0231	***	
	(0.0049)		
FutureLP			0.0048
			(0.0043)
Total_Unit	-0.0002		-0.0002
	(0.0001)		(0.0001)
Nobs	309,894		309,894
R-Square	0.760		0.760
Blockface FEs	Y		Y
Precinct*YrQ FEs	Y		Y

Models include demolition permits, new building permits, and liquor licenses.

Table 8: Negative Binomial Regression of Active Foreclosures on Total Crime

Total Crime	**(1)**		**(2)**		**(3)**		**(4)**	
Activelag1	0.1367	***	0.1509	***	0.1327	***		
	(0.0023)		(0.0021)		(0.0022)			
Active_Dev							0.0057	**
							(0.0023)	
Tot_Unit	0.0063	***	0.0030	***	0.0022	***		
	(3.4E-5)		(3.2E-5)		(2.9E-5)			
Tot_Unit_Dev							-4.4E-05	***
							(1.7E-5)	
Nobs	434,228		434,228		434,228		434,228	
Log Likelihood	63,250		86,831		103,444			
Likelihood Ratio								
QIC							-161,612	
QICu							-161,356	
Covariates	N		Y		Y		N	
Precinct*YRQ	N		N		Y		Y	

Table 9: Negative Binomial Regression of Cumulative Foreclosure Starts on Total Crime

Total Crime	**(1)**		**(2)**		**(3)**		**(4)**	
LP6Qlag	0.1084	***	0.1264	***	0.1000	***		
	(0.0021)		(0.0020)		(0.0020)			
LP6Qlag_Dev							0.0075	***
							(0.0023)	
Tot_Unit	0.0083	***	0.0051	***	0.0045	***		
	(3.8E-5)		(3.8E-5)		(3.7E-5)			
Tot_Unit_Dev							9.5E-05	***
							(1.6E-5)	
Nobs	387,800		387,800		387,800		387,800	
Log Likelihood	60,171		79,959		95,066			
Likelihood Ratio								
QIC							-144,988	
QICu							-144,805	
Covariates	N		Y		Y		N	
Precinct*YRQ	N		N		Y		Y	

Table 10: Negative Binomial Regression of REOs on Total Crime

Total Crime	(1)		(2)		(3)		(4)	
REO	0.2186	***	0.2394	***	0.2107	***		
	(0.0055)		(0.0051)		(0.0050)			
REO_Dev							0.0117	
							(0.0074)	
Tot_Unit	0.0065	***	0.0032	***	0.0024	***		
	(3.4E-5)		(3.3E-5)		(3.0E-5)			
Tot_Unit_Dev							-2.8E-05	*
							(1.6E-5)	
Nobs	434,228		434,228		434,228		434,228	
Log Likelihood	62,146		85,335		102,416			
Likelihood Ratio								
QIC							-161390	
QICu							-161147	
Covariates	N		Y		Y		N	
Precinct*YRQ	N		N		Y		Y	

Table 11: Blockface Threshold Models

A. OLS Regression of Active Foreclosures on Crime by Type

	Total Crime		Violent Crime		Property Crime		Public Order Crime	
ACT01	0.0105		0.0028		0.0004		0.0032	
	(0.007)		(0.002)		(0.003)		(0.005)	
ACT02	0.0297	**	0.0048		0.0060		0.0143	
	(0.012)		(0.003)		(0.005)		(0.010)	
ACT3p	0.0450	***	0.0122	***	0.0058		0.0239	*
	(0.017)		(0.005)		(0.007)		(0.013)	
TOT_UNIT	-0.0003	***	-4.9E-05	**	-2.6E-05		-0.0002	***
	(7.5E-5)		(2.0E-5)		(3.3E-5)		(5.8E-5)	
Nobs	434,228		434,228		434,228		434,228	
R-Squared	0.753		0.329		0.470		0.691	
Covariates	N		N		N		N	
Blockface FE	Y		Y		Y		Y	
PrecinctYrQ FE	Y		Y		Y		Y	

B. OLS Regression of Cumulative Foreclosure Starts on Crime by Type

	Total Crime		Violent Crime		Property Crime		Public Order Crime	
LP601	0.0165	**	0.0018		0.0031		0.0072	
	(0.007)		(0.002)		(0.003)		(0.006)	
LP602	0.0421	***	0.0075	**	0.0094	*	0.0188	*
	(0.012)		(0.003)		(0.005)		(0.010)	
LP63p	0.0669	***	0.0103	**	0.0063		0.0446	***
	(0.017)		(0.005)		(0.008)		(0.014)	
TOT_UNIT	0.0000		-1.2E-05		-2.6E-05		0.0001	
	(8.4E-5)		(2.3E-5)		(3.6E-5)		(6.6E-5)	
Nobs	387,800		387,800		387,800		387,800	
R-Squared	0.739		0.319		0.429		0.674	
Covariates	N		N		N		N	
Blockface FE	Y		Y		Y		Y	
PrecinctYrQ FE	Y		Y		Y		Y	

C. OLS Regression of REOs on Crime by Type

	Total Crime		Violent Crime		Property Crime		Public Order Crime	
REO01	0.0345	**	0.0100	**	0.0075		0.0193	
	(0.015)		(0.004)		(0.007)		(0.012)	
REO02	0.0705	**	0.0124		0.0110		0.0337	
	(0.029)		(0.008)		(0.013)		(0.023)	
REO3p	0.2016	***	0.0369	***	-0.0077		0.1619	***
	(0.048)		(0.013)		(0.021)		(0.038)	
TOT_UNIT	-0.0003	***	-4.8E-05	**	-2.6E-05		-2.2E-04	***
	(7.5E-5)		(2.0E-5)		(3.3E-5)		(5.8E-5)	
Nobs	434,228		434,228		434,228		434,228	
R-Squared	0.753		0.329		0.470		0.691	
Covariates	N		N		N		N	
Blockface FE	Y		Y		Y		Y	
PrecinctYrQ FE	Y		Y		Y		Y	

Table 12: Precinct Level Models

A. Active Foreclosures (2004-2008)

	Total Crime				Violent Crime			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Actlag1	0.7040***	0.6122***	1.0669***	0.0849**	0.0948***	0.0894***	0.1313***	0.0120**
	(0.0698)	(0.0725)	(0.0789)	(0.0335)	(0.0078)	(0.0079)	(0.0085)	(0.0061)
Total Units	0.0018***	0.0017***	0.0015***	0.0000	0.0000	0.0001***	0.0001***	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Covariates	N	Y	Y	Y	N	Y	Y	Y
Boro*QuarterFE	N	N	Y	Y	N	N	Y	Y
Precinct FE	N	N	N	Y	N	N	N	Y
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.1009	0.1273	0.4000	0.9775	0.0898	0.1746	0.4337	0.9400

	Property Crime				Public Order Crime			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Actlag1	-0.0308	0.0205	0.2093***	-0.0029	0.6151***	0.4813***	0.6540***	0.0643***
	(0.0275)	(0.0259)	(0.0294)	(0.0160)	(0.0457)	(0.0460)	(0.0490)	(0.0220)
Total Units	0.0014***	0.0008***	0.0006***	0.0000	0.0003*	0.0007***	0.0007***	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Covariates	N	Y	Y	Y	N	Y	Y	Y
Boro*QuarterFE	N	N	Y	Y	N	N	Y	Y
Precinct FE	N	N	N	Y	N	N	N	Y
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.1370	0.3090	0.4825	0.9684	0.1114	0.1899	0.4652	0.9777

B. Cumulative Foreclosure Starts (2004-2008)

	Total Crime				Violent Crime			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
lp6qlag	0.7159***	0.6330***	1.0330***	0.1337***	0.1024***	0.0982***	0.1285***	0.0212***
	(0.0678)	(0.0717)	(0.0753)	(0.0425)	(0.0075)	(0.0077)	(0.0081)	(0.0077)
Total Units	0.0018***	0.0017***	0.0014***	-0.0000	0.0000	0.0001***	0.0001***	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Covariates	N	Y	Y	Y	N	Y	Y	Y
Boro*QuarterFE	N	N	Y	Y	N	N	Y	Y
Precinct FE	N	N	N	Y	N	N	N	Y
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.1063	0.1309	0.4019	0.9776	0.1102	0.1907	0.4383	0.9402

	Property Crime				Public Order Crime			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
lp6qlag	-0.0250	0.0429*	0.2085***	0.0045	0.6156***	0.4726***	0.6279***	0.0928***
	(0.0268)	(0.0257)	(0.0281)	(0.0203)	(0.0444)	(0.0457)	(0.0469)	(0.0279)
Total Units	0.0014***	0.0008***	0.0006***	0.0000	0.0003*	0.0007***	0.0007***	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Covariates	N	Y	Y	Y	N	Y	Y	Y
Boro*QuarterFE	N	N	Y	Y	N	N	Y	Y
Precinct FE	N	N	N	Y	N	N	N	Y
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.1368	0.3100	0.4840	0.9684	0.1172	0.1887	0.4657	0.9778

C. REOs (2004-2008)

	Total Crime				Violent Crime			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
REOlag1	2.2176***	1.7947***	3.3562***	0.5582***	0.2883***	0.2745***	0.4442***	0.1102***
	(0.2661)	(0.2726)	(0.3069)	(0.0991)	(0.0300)	(0.0297)	(0.0331)	(0.0180)
Total Units	0.0018***	0.0018***	0.0016***	-0.0000	0.0000	0.0001***	0.0001***	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Covariates	N	Y	Y	Y	N	Y	Y	Y
Boro*QuarterFE	N	N	Y	Y	N	N	Y	Y
Precinct FE	N	N	N	Y	N	N	N	Y
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.0824	0.1114	0.3748	0.9779	0.0584	0.1516	0.4134	0.9415

	Property Crime				Public Order Crime			
VARIABLES	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
REOlag1	-0.2170**	-0.1492	0.5368***	0.0427	2.0411***	1.5855***	2.1226***	0.3489***
	(0.1036)	(0.0965)	(0.1133)	(0.0477)	(0.1748)	(0.1728)	(0.1902)	(0.0651)
Total Units	0.0014***	0.0009***	0.0007***	0.0000	0.0003*	0.0007***	0.0008***	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Covariates	N	Y	Y	Y	N	Y	Y	Y
Boro*QuarterFE	N	N	Y	Y	N	N	Y	Y
Precinct FE	N	N	N	Y	N	N	N	Y
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.1388	0.3098	0.4722	0.9684	0.0869	0.1769	0.4464	0.9781

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A: Nonlinear Models

The geographic detail of our analysis presents some potential pitfalls when deciding on the ideal functional form. Particularly when focusing on subcategories of crime, the use of blockfaces as geographic units makes it likely that there will be a substantial number of quarters where no violent or property crime occurs. This skews the data towards zero, violating the normal distribution assumption and making it likely that a least squares regression would be a poor fit for the data. Another issue is heteroskedasticity. Regardless of the level of geography – blockface, Census tract, or police precinct – the variance of errors is likely to be dependent on the population size. Given our very small geographic units, zero crime counts are also going to be more frequent in the areas with small populations.

Criminologists have frequently used Poisson regression models to deal with each of these issues (Osgood, 2000; Sampson, Raudenbush, and Earls, 1997). Poisson models are very commonly used in research on criminal careers (for example, counts of recidivism events or the amount of time to recidivism), but these models are increasingly used for the analysis of aggregate crime rates, as in our case. The basic Poisson regression model is expressed as:

$$\lambda_i = \Sigma\beta_k x_{ik}$$

where λ_i is the expected event count and the right-hand side is the sum of the products of each explanatory variable. The key distribution assumption is that

$$P(Y_i = y_i) = e^{-\lambda i}\lambda_i^{\,yi} / y_i!$$

– the probability of any observed outcome follows the Poisson distribution. As in the linear model, we can include blockface and time-varying fixed effects as independent variables.

It is also fairly simple to account for group-specific heteroskedasticity in Poisson regressions, since the underlying model does not depend on a homoskedastic variance assumption. However, overdispersion may be a problem if the data do not fit the above distribution assumption, and the residual variance is greater than λ_i. Overdispersion can occur when crime events are not independent of each other. This is likely to be an issue at very small geographies, given that the same person could be committing several crimes. To address this problem, Osgood (2000) suggests estimating a model which allows for a more flexible specification of the variance structure, using a quasi-maximum likelihood estimation technique. This model retains the structure of the Poisson regression model, but adjusts the standard errors, which are assumed to be proportional to the mean as follows:

$$Var(Y|x) = \sigma^2 E(Y|x)$$

When $\sigma^2 = 1$, we have the standard variance assumption. When $\sigma^2 > 1$, we have overdispersion, and when $\sigma^2 < 1$, we have underdispersion (which is less common). It is relatively straightforward to compute the estimator for σ^2:

$$(\Sigma u_i^2/y_i\,)\ /\ (n\text{-}k\text{-}1)$$

where u_i represents the set of estimated residuals.

Finally, the negative binomial model is commonly used as a generalized form of the Poisson model that deals effectively with the overdispersion problem. Following Gardner et. al. (1995) and Osgood (2000), the negative binomial distribution is expressed as:

$$P(Y_i = y_i) = [\Gamma(y_i + \varphi) / y_i\ \Gamma(\varphi)] / [\varphi^{\varphi}\lambda_i^{y_i} / (\varphi + \lambda_i)^{\varphi\text{-}y_i}]$$

where Γ is the gamma function (a continuous version of the factorial function above) and φ is the reciprocal of the residual variance of the crime levels. Essentially, the negative binomial adds a random term to the variance estimator to reflect between-block differences. The negative binomial likelihood function is

$$\mathrm{Prob}(Y = \mathrm{yit}\ \ |x_{it}) = \frac{\Gamma(\theta + y_{it})}{\Gamma(y_{it}+1)\Gamma(\theta)} r_{it}^{y_{it}}(1 - r_{it})^{\theta},$$

$$\text{where } \lambda_{it} = \exp(x_{it}'\beta) \ \text{ and } r_{it} = {}^{\lambda_{it}}/_{(\theta + \lambda_{it})},$$

and the conditional mean function is

$$E[y_{it}|x_{it}] = \exp(x_{it}'\beta) = \lambda_{it}.$$

In a negative binomial model with fixed effects, the likelihood function is

$$\mathrm{Prob}\left(y_{i1}, y_{i2}, \dots y_{iT_i}, \middle| \textstyle\sum_{t=1}^{T_i} y_i\right) = \frac{\Gamma\left(1+\sum_{t=1}^{T_i} y_{it}\right)\Gamma\left(1+\sum_{t=1}^{T_i} \lambda_{it}\right)}{\Gamma\left(\sum_{t=1}^{T_i} y_{it}+\sum_{t=1}^{T_i} \lambda_{it}\right)} \Pi_{t=1}^{T_i} \frac{\Gamma(y_{it}+\lambda_{it})}{\Gamma(1+y_{it})\Gamma(\lambda_{it})},$$

with conditional mean function

$$E[y_i|x_i] = \theta_i\omega_{pt}\phi_{it} = \exp\left(\alpha_i + \delta_{pt}\right)\phi_{it} = \lambda_{ipt} = \exp\left(x_{it}'\beta + \alpha_i + \delta_{pt}\right).$$

Estimating such nonlinear models with a large set of fixed effects is challenging. As discussed in text, we opt for the hybrid approach suggested by Allison (2005), which algebraically transforms the independent variables matrix into a matrix of blockface-level sample means and observation-specific deviations from these means. Other work by Allison and Waterman (2002) suggests that this is preferred to an actual fixed effects model, because the negative binomial fixed effects model produces coefficients for the entity-specific intercepts *and* time-invariant covariate measures, and as such does not fully control for all of the time-invariant characteristics of the entity.

Specifically, to facilitate estimating this nonlinear model with our large set of fixed effects, we transform the log-linear conditional mean function into mean-deviated form. Instead of the entity dummy and time dummy variables, the X matrix now includes the independent variables in the form of deviations from the entity means ($\tilde{x}'_{it}$), and both the entity means ($\bar{x}'_i\vartheta$), and the precinct*quarter dummy variables (δ_{pt}) are entered into the model. The conditional mean function for the hybrid approach is

$$E[y_{it}|\tilde{x}_{it}] = \omega_{pt}\phi_{it} = \exp(\delta_{pt})\phi_{it} = \lambda_{ipt} = \exp\left(\tilde{x}'_{it}\beta + \bar{x}'_i\vartheta + \delta_{pt}\right),$$

where $\tilde{x}'_{it}$ is transformed according to

$$[(x_{1it} - \bar{x}_{1i})\ (x_{2it} - \bar{x}_{2i})\ (x_{3it} - \bar{x}_{3i})\ ]' \begin{bmatrix}\beta_1\\ \beta_2\\ \beta_3\end{bmatrix}.$$