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Do Foreclosures Increase Crime?

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Abstract

We measure the causal impact of foreclosures on crime. Using a novel national county-level panel dataset, we find robust evidence that foreclosures increase burglary. Our baseline OLS estimate indicates that a one percentage point increase in foreclosure rates increases burglary rates by 2.1 percent. This estimate increases to roughly 10 percent when we use an IV strategy to addresses potential bias in OLS due to measurement error in foreclosure rates. Sensitive to specification, we also find positive effects of foreclosures on larceny and aggravated assault. Our estimates indicate that foreclosures do not have an effect on motor vehicle theft, robbery, rape, or murder.

Key Words: Crime, Foreclosures, Instrumental Variables

JEL Code(s): K42

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1. Introduction

Since 2005, the foreclosure rate has increased dramatically in the United States. Figure 1 shows that following a gradual secular increase from 1980 to 2005, the foreclosure start rate grew by 160 percent between 2005 and 2008.[1] This sharp increase in foreclosure activity is expected to continue given the present housing and economic crisis. Current forecasts indicate that the number of foreclosures will rise to 8 to 10 million by 2012, affecting more than 15 percent of all mortgages (Dubitsky, Yang, Stevanovic, and Suehr, 2008; Colpitts, 2009). In addition to the direct costs realized by borrowers and lenders, an increase in foreclosures may lead to decreases in area property values (Calorimis, Longhofer, and Miles, 2008; Harding, Rosenblatt, and Yao, 2009), decreases in the stigma of defaulting on a mortgage (Guiso, Sapienza, and Zingales, 2009), and substantial administrative costs and lost property tax revenue for local governments (Apgar and Duda, 2005).

Another fear is that foreclosures lead to increased crime. A March 2009 Congressional Oversight Panel report states, "Communities with high foreclosure rates suffer increased urban blight and crime rates." Anecdotally, the media frequently report increases in burglary, vandalism, and organized criminal activity associated with concentrations of foreclosure-related unoccupied homes.[2] Law enforcement has expressed concern that foreclosed properties attract

[1] The foreclosure process varies across states, but generally consists of three stages: When a borrower becomes seriously delinquent on his mortgage, a lender may start the foreclosure process by registering a legal notice of default. If the matter is not resolved, the property then goes to public auction. If the property is not sold at auction, the lender takes possession of the property; at this point the property is deemed "Real Estate Owned."

[2] See for example: Joel Millman, "Immigrants Become Hostages as Gangs Prey on Mexicans," *The Wall Street Journal*, June 10, 2009; Rusty Dornin, "Police Fight a Rash of Vacant Home Burglaries," CNN.com, July 22, 2008; Christopher B. Leinberger, "The Next Slum?", *The Atlantic Monthly*, March 2008; Jonathan Mummulo and Bill Brubaker, "As Foreclosed Homes Empty, Crime Arrives," *The Washington Post*, April 27, 2008; Les Christie, "Crime Scene: Foreclosure. Cleveland's mortgage meltdown has sparked a crime wave in the nation's hardest hit area for troubled homeowners," CNNMoney.com, November 19, 2007; J.W. Elphinstone, "After Foreclosures, Crime Moves In," *The Boston Globe*, November 18, 2007. Millman (2009) reports an increase in "drop houses," where Mexican gangs store drugs or illegally smuggled persons, in Arizona neighborhoods which have experienced substantial foreclosure activity.

“gang activity, drug dealing, prostitution, arson, rape and murder.” (Apgar and Duda, 2005). Thus, a number of public policy initiatives have been introduced to address foreclosures.[3] These programs hope to keep defaulting borrowers in their homes, or allow new residents to more quickly occupy previously foreclosed homes. Among the justifications for these programs is the assumption that keeping foreclosure-affected houses occupied will help to stem neighborhood blight and crime.

The goal of this paper is to estimate the causal effect that changes in foreclosure rates have on crime rates. That an increase in foreclosures leads to increased crime is typically presumed by public officials, the media, and even researchers.[4] However, to our knowledge only two peer-reviewed studies provide evidence in support of this presumption, both of which are limited by their cross-sectional nature and narrow geographic scope (Immergluck and Smith, 2006; Spelman, 1993).[5]

This study is the first, to our knowledge, to estimate the effect of foreclosures on crime using a nationally representative county-level panel dataset. We construct a novel dataset covering the period 2002 to 2007 using a variety of data sources. Our crime rate data are from the Federal Bureau of Investigation’s (FBI’s) Uniform Crime Report (UCR) data. We compute “real estate owned” (REO) based foreclosure rates at the county level using proprietary loan-

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[3] For example, the Obama administration’s “Making Home Affordable” loan modification and refinance program, Fannie Mae’s 2009 “Deed for Lease” program that allows residents to remain in foreclosed properties and pay rent, and the Housing and Economic Recovery Act of 2008, which in part provides local governments community development block grants to purchase foreclosed properties.

[4] Campbell, Giglio, and Pathak (2009) find larger foreclosure discounts for low-value houses and homes in poorer neighborhoods, which they conjecture is the result of higher relative fixed costs for banks to protect these homes from vandalism.

[5] Immergluck and Smith (2006) examine the effect of tract-level foreclosure rates on contemporaneous crime rates for Chicago in 2001. While they find a one standard deviation increase in foreclosure rates increases violent crime by 6.7 percent, they find a small and statistically insignificant effect on property crime. Spelman (1993) matched thirty-five blocks with abandoned buildings, some of which were foreclosed properties, to twenty-four control blocks with similar characteristics in Austin, and found that blocks with unsecured abandoned buildings had drug and property crime rates twice as high as that of control blocks. He attributes the findings to abandoned buildings creating opportunities for unsupervised “criminal hangouts.”

level data from Lender Processing Services (formerly "McDash") and LoanPerformance.[6] Drawing from the economic literature on crime, we include a comprehensive set of controls for demographic, macroeconomic, and enforcement characteristics related to the costs and benefits of committing crime. A major innovation in our analysis is that the panel nature of our data allows us to control for persistent differences in unobserved characteristics across geographies, which we show give rise to spurious correlation between foreclosure and crime rates if unaddressed. However, despite an extensive set of control variables, our ordinary least squares (OLS) estimate of the foreclosure effect on crime are likely biased downward due to error in our measurement of foreclosure rates. We pursue an instrumental variables (IV) estimation strategy to address this measurement error.

We find that foreclosures have a positive effect on burglary. This effect is statistically significant across a variety of estimation strategies and robust to a number of specification checks. Our baseline estimate, from the OLS specification that includes controls for county-level fixed effects, is that a one percentage point increase in the one-year lagged county foreclosure rate increases the burglary rate by 2.1 percent. Our IV estimates indicate that a one percentage point increase in the foreclosure rate increases burglary rates by roughly 10 percent. These effects are small, but non-trivial, in terms of economic magnitude. Based on these estimates, our back-of-the-envelope calculation is that the spike in foreclosure starts between 2005 and 2008 will generate aggregate community-wide costs of burglary ranging from $1.1 to $4.9 billion. Sensitive to specification, we also find a statistically significant effect of foreclosures on larceny, and some evidence of an effect on aggravated assault. For the

6 We include only those loans in REO status, meaning that the property is in possession of the lender as a result of foreclosure, in the numerator of our foreclosure rate computation. We feel this is the most accurate measure of foreclosures that result in the displacement of residents. Although the house may become vacant at any point during the foreclosure process, by the time a property reaches REO status, it is more likely to be vacant.

remaining FBI index crimes that we study, motor vehicle theft, robbery, rape, and murder, our estimates indicate that the foreclosure effect is not statistically different from zero.

Our results are broadly consistent with Becker's (1968) seminal economic model of crime. Becker proposes that potential criminal offenders are rational agents who respond to incentives in the form of criminal justice penalties. Within this framework, if the probability of being detected and convicted of committing crime falls as neighborhood foreclosures increase, then crime deterrence is lowered, leading to an increase in the propensity to commit crime. When a home is foreclosed upon, its residents are typically evicted from the property, leaving behind a vacant structure which remains unoccupied for months or even years.[7] Because an occupied residence is likely a much stronger deterrent to burglary than a structure vacated due to foreclosure, an increase in foreclosures should lead to an increase in burglary, which is what we find.[8] To the extent that foreclosures reduce the deterrence effect of residential "eyes on the street" (Jacobs, 1961), an increase in foreclosures may lead to increases in other types of crime.

The remainder of the paper is organized as follows: Section 2 reviews the existing empirical economic literature on crime, which we use to motivate our data elements. We also describe our foreclosure data, and detail limitations with this source data. Section 3 outlines the empirical specification. Results are presented in Section 4. Section 5 discusses the findings and provides estimates of the economic costs of crime expected to result from the recent increase in foreclosure activity. Section 6 concludes.

[7] Coulton, Mikelbank, and Schramm (2008) report that 50 percent of properties entering REO status in Cleveland and Cuyahoga County over the period 2000 to 2002 were sold to a private owner within four months. Coulton, Schramm, and Hirsch (2008) estimate that for properties entering REO in 2007, the time elapsed will be at least three times as long.

[8] From the criminal justice literature, Scarr, Pinksy, and Wyatt (1973) note that burglary incidents are more likely to occur during the hours of the day and the days of the week when a home is unoccupied, and Repetto (1974) finds that burglary victimization rates are substantially higher for homes where occupants self-report being out of the home more than 35 hours per week.

2. The Determinants of Crime

Our raw data provide suggestive evidence that foreclosures increase crime. Figure 2 illustrates trends in foreclosure and crime rates over our sample period, separately for the ten states with the highest rates of foreclosure in 2006 (solid lines) and the remaining forty states and District of Columbia (dashed lines).[9] Figure 2(a) shows that foreclosure rates in the top 10 foreclosure states doubled between 2001 and 2002, decreased slightly through 2004, and then increased again thereafter. In the other states the increase was not as dramatic; after an initial increase from 2001 to 2002, foreclosure rates subsequently declined before moderately increasing again beginning in 2004. Figures 2(b) through 2(h) show trends for each crime type, where the crime rates are indexed to their respective initial levels. With the exception of motor vehicle theft and murder, for each crime type the top foreclosure states experienced higher rates of crime growth relative to low foreclosure states. However, while the differences in crime rate trends may be caused by foreclosures, alternatively these trends may simply reflect changes in other factors. Below we review the extensive empirical economics literature on the factors hypothesized to influence crime, in order to motivate the inclusion of controls in our empirical specification. We note our data sources, as well as describe our foreclosure and crime data.

It is well-known that those involved in criminal activity are overwhelmingly young and male (Levitt, 1999, 2004; DiIulio, 1996; Freeman, 1996). In 2008, the incarceration rate of U.S. males was over 15 times that of females, while the rate for males aged 18 to 24 was 26 times that of males 65 years or older. Further, a disproportionate number of both perpetrators and victims are black (Sabol, West, and Cooper, 2009). Levitt (1999) finds that changes in age and race

[9] In 2006, the top ten states were: Michigan, Ohio, Colorado, Indiana, Georgia, Missouri, Tennessee, Texas, Kansas, and South Carolina. Note that some of the highest foreclosure states in the current crisis (for example, Florida, California, Nevada) are not on this list. Foreclosure rates in these states were still relatively low in 2006 but increased sharply thereafter. Because we investigate the effect of one-year lagged foreclosure rates, the foreclosure data used span 2001 to 2006, while the crime data cover the 2002 to 2007 period.

distribution, while not an important factor for violent crime rates, accounted for one-sixth of the decrease in property crime observed for the 1990s. Therefore, we control for the county-level share of the population which is male aged 15 to 24, and the share that is black. All of our demographic data are from county-level estimates provided by the U.S. Census Bureau.

The empirical literature investigating the influence of opportunity costs on the propensity to commit crime has primarily focused on the role of the labor market and participation in educational activities. Chiricos (1987) and Freeman (1983) survey 63 and 25 studies, respectively, and generally find a positive but modest relationship between unemployment and crime. Recent work has emphasized that because those who commit crime are predominately young and less-educated, opportunity cost measures are most relevant for those with low legitimate earnings (Freeman, 1996; Grogger 1998). Along these lines, Gould, Weinberg, and Mustard (2002) find that changes in the wage rate among low-skilled workers explain a substantial portion of the variation in crime trends over the past few decades. Following their methodology, we use Current Population Survey (CPS) data to control for the state-level wage rates of low-skilled workers; in Appendix C we detail the construction of this variable. We also control for county-level unemployment rates and per capita income using data from the Bureau of Economic Analysis.

Education and physical time spent in school should also decrease crime. In the long-term, education increases the future returns to legitimate work, or in other words, the future opportunity costs of engaging in illegal activity, and may change individuals' preferences towards criminal activity. Using state variation in compulsory schooling laws, Locher and Moretti (2004) find that education significantly reduces rates of incarceration and arrest. In the short-term, the quality of schooling may make it more worthwhile to substitute time from illegal to schooling-related activities. Jacob and Lefgren (2003) use variation in jurisdiction-level teacher in-service days to show increases in school days decreases property crime levels, while Witte and Tauchen (1994) use individual-level data to show time allocated to school decreases the probability of arrest. We control for education-related opportunity costs that may affect the crime supply decision by including state-level per capita expenditures on education, obtained from the U.S. Census Bureau State and Local Government Finances data. Following Levitt (1997), we also control for state-level welfare expenditure, using data from the same source.

Becker (1968) formalized the deterrent effect that police should have on crime. Surveying 22 empirical studies, Cameron (1988) finds that 18 show either no relationship or a positive relationship between police and crime. Given the endogenous nature of policing levels with respect to crime, where more police are assigned to high-crime areas, recent studies by Klick and Tabarrok (2005), Di Tella and Schargrodsky (2004), and Levitt (1997, 2002) devise novel identification strategies and generally find that increases in policing lead to lower rates of crime. Incarceration should also decrease crime, both by incapacitating existing criminals, and by deterring potential ones. Levitt (1996) uses prison overcrowding legislation to instrument for endogenous incarceration rates to demonstrate a negative relationship between incarceration and crime levels. Thus, formal deterrence is controlled for using state-level per capita police expenditures, the number of police officers, and the prison population. The first two controls are obtained from Criminal Justice System, Expenditure, and Employment (CJEE) data, and the latter from National Prison Statistics provided by the Bureau of Justice Statistics. Because we do not address the endogeneity of these deterrence measures, we do not attach a causal interpretation to our related coefficient estimates. However, to the extent that these factors are correlated with our parameter of interest, lagged foreclosure rates, we include them to mitigate any omitted variable concerns.[10]

In this study, we are interested in the potential influence of foreclosures on crime. We compute county-level foreclosure rates by aggregating loan-level data from LPS Applied Analytics (LPS) and LoanPerformance (LP). LPS is a database of loan-level payment records collected from the largest mortgage servicers in the U.S., covering roughly 58 percent of the total prime/near prime market and 32 percent of the subprime market (Immergluck, 2008).[11] Because LPS' coverage of subprime loans is relatively weak, and subprime loans are more likely to end in foreclosure (Gerardi, Shapiro, and Willen, 2008), we supplement our LPS data with LP data to ensure that subprime loans are well-represented. The LP data cover approximately 80 percent of the privately-securitized subprime and Alt-A mortgage loans in the U.S., and like LPS, contain loan-level payment records. To avoid double-counting, we exclude privately-securitized subprime loans from LPS and include only these loans from LP.

We limit the sample in both LPS and LP to owner-occupied, first-lien purchase or refinance mortgages on 1-4 family homes, townhouses, or condominiums. We define the foreclosure rate in county i and year t as the count of mortgage loans in real estate owned status, divided by the count of all active loans.[12] We focus on the share of loans in REO status, rather

[10] For example, property tax revenue could decrease with increased foreclosures, consequently decreasing police expenditure. Alternatively, more police could be assigned if increases in crime are expected to result from increased foreclosures. However, these scenarios seem more plausible in the period following the current financial crisis, and less so for our analysis of the pre-crisis period, with relatively low levels of foreclosure activity.
[11] See Immergluck (2008, 2009) for a detailed discussion of LPS data.
[12] Because the only geographic identifiers provided in the LPS and LP data are the state and zip codes of the property address for each loan, we aggregate to the county-level using a zip code to county crosswalk file produced by the Missouri Census Data Center MABLE program. Roughly 30% of zip codes map to more than one county. In these cases we assign the county identifier for the county that contains the highest percentage of the zip code's residents. The MABLE program is available on the web at http://mcdc2.missouri.edu/websas/geocorr2k.html.

than in any stage of the foreclosure process, because we believe this is the most accurate measure of foreclosure-related vacancies.[13]

Despite the richness of the mortgage data we use, our measure of foreclosure rates likely suffers from error for at least two reasons. First, because the true foreclosure rate is very small in magnitude over our analysis period, even our large sample of loans yields estimates of the foreclosure rate at the county and year-level that are relatively imprecise. Second, our sample is not randomly selected from the universe of mortgage loans, especially considering the relative weakness of LPS' coverage prior to 2005.[14] Thus, as discussed in greater detail in Appendices A and B, our measure of foreclosure rates suffers from selection bias, which likely results in downwardly biased estimates of the effect of foreclosures on crime. We therefore also pursue an IV strategy to address this measurement error.

Our crime data are from the Uniform Crime Reports, generated yearly by the FBI from voluntary reports collected from county, city, and state law enforcement agencies. We focus on the FBI Index crimes of larceny, burglary, motor vehicle theft, robbery, aggravated assault, rape and murder. Although there are limitations to the UCR data, no other nationally representative, geographically disaggregated source of crime data is available.[15] We include years 2002 through 2007, the most recent year available in the UCR data.[16] All crime rates are per 100,000 persons, based on population totals reported in the UCR.

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[13] Based on our sample of LPS and LP loans, only 38 percent of the loans which entered foreclosure in 2006 reached REO status within the next 24 months, suggesting a substantial share of loans in the earlier stages of foreclosure do not result in a vacancy.

[14] While LPS has expanded its coverage of the mortgage market in recent years by partnering with additional mortgage servicers, newly added servicers are not required to provide payment records in months prior to January 2005.

[15] See Levitt (1997) or Gould, Weinberg, and Mustard (2002) for a discussion of the strengths and weaknesses of the UCR data.

[16] Because we use the one-year lagged foreclosure rate in our empirical analysis, our foreclosure rate data cover the period 2001 to 2006.

Finally, we include data from a few additional sources in our analysis to address concern over other potential omitted variables. We use Home Mortgage Disclosure Act (HMDA) data to control for the share of home purchase and refinance loans within the county originated by lenders regulated by the U.S. Department of Housing and Urban Development, a proxy for subprime activity. We also control for income inequality at the state level, as measured by the ratio of the top to the bottom decile of per capita income, based on CPS data. Finally, we use in our analysis measures of house price growth based on the House Price Index (Index) published by the Federal Housing Finance Authority.[17] Because the Index is available only at the MSA level, every county within an MSA is assigned the same house price growth in a given year. For counties that are not within an MSA, we use the FHFA's state non-metropolitan house price index.

All data are merged together at the county and year-level. Of 3,139 total counties, we drop 1,353 in rural (non-MSA) areas because residences in these counties may not be spatially dense enough to form neighborhoods. Of the 10,716 remaining county-year observations, we drop 810 county-year observations with less than 75 percent of police precincts reporting UCR data, 856 county-year observations with less than 100 total active loans from LPS and LP data, and 332 county-year observations due to missing data on crime rates, unemployment rates, or per capita income. Finally, we limit the sample to counties that appear in at least four out of the six years of the sample period. Our final analysis sample consists of 8,344 county-year observations, covering 1,483 counties over the years 2002 to 2007. Summary statistics are presented in Table 1.

[17] The FHFA computes the House Price Index using a weighted, repeat sales index based on conventional, conforming mortgages purchased for securitization by Fannie Mae or Freddie Mac. We annualize the data by averaging the quarterly values in each year. We also adjust the Index for inflation using the national Consumer Price Index series less shelter for all urban consumers.

3. Empirical Specification

We model the crime rate in county *i* in year *t* as follows:

$$crime_{it} = \beta_0 + \beta_1 f^*_{it-1} + X_{it}'\beta_2 + Y_{it}'\beta_3 + P_{it}'\beta_4 + t'\lambda + i'\theta + \varepsilon_{it} \quad [2]$$

The outcome $crime_{it}$ is the log of the crime rate.[18] We estimate the model separately by type of crime to allow all coefficient estimates to vary.

The variable of interest is f^*_{it-1}, the true county-level foreclosure rate in the previous year, which we observe with error.[19] We lag foreclosure rates to ensure that the parameter β_1 represents the effect of foreclosure on crime that occur only after the foreclosure actually takes place, and to address the potential concern that causality runs in the opposite direction. Feinberg and Nickerson (2002) hypothesize that an increase in crime rates leads to an increase in default rates. While they do not find that property crime affects future default rates, they do find evidence that violent crime influences default rates three years into the future. Under the assumption that trends in crime rates are not persistent, use of the lagged foreclosure rate alleviates this issue, because the previous year's foreclosure rate is not affected by the current year crime rate.[20]

Under the null, β_1 is equal to zero. Estimates of β_1 that are positive and statistically different from zero are consistent with the alternative hypothesis that increases in foreclosure

[18] Logging the crime rates addresses concern about reporting error due to differences in reporting amongst jurisdictions; Ehrlich (1996) suggests taking logarithms since reported crime rates are likely to be proportional to true crime rates.
[19] We use the level of foreclosure rates rather than logged foreclosure rates to avoid dropping county-year observations with zero foreclosures. Estimates from a specification in which we use the log of foreclosure rates are comparable to those from the main specification.
[20] Because this assumption may be tenuous, we also estimate a specification that controls for aggregate property and violent crime rates lagged one, two, and three years relative to foreclosure rates. Results from this specification, presented in the sensitivity analysis, are quite similar to our main results.

rates increase crime rates in the following year.[21]

We include a comprehensive set of explanatory variables, as described in Section 2, in the model to control for factors that plausibly affect the relative costs and benefits of committing a crime. The vector X_{it} controls for local demographic characteristics, Y_{it} controls for local economic conditions and other measures of the opportunity costs of committing crime, and P_{it} controls for formal deterrence factors.

We also include in the model year fixed effects to control for national macroeconomic trends. Lastly, we include geographic fixed effects to control for persistent differences in unobserved characteristics across areas. Our estimates of the effect of foreclosures on crime are therefore identified by within-area deviations from mean, after netting out national time trends, rather than through level differences in foreclosure rates across geographies. We will show that identification which relies solely on cross-sectional variation is unattractive because foreclosure rates are correlated with time-invariant unobserved characteristics that also influence crime.

The error term ε_{it} contains all remaining unobserved idiosyncratic factors that affect county-level crime. Estimation of this model using OLS is valid if ε_{it} is uncorrelated with the explanatory variables. However, as discussed in Section 2, and described in greater detail in Appendix A, our data appear to systematically overstate foreclosure rates. In practice, we observe a foreclosure rate f_{it-1} that is likely a function of the true foreclosure rate, f^{*}_{it-1}. Under reasonable assumptions generated from the data, in Appendix B we show that the OLS estimate of β_1 is inconsistent and biased downward. Therefore, we also pursue an IV estimation strategy in an attempt to address this issue.

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[21] We note that while we observe the lagged completed foreclosure rate, we do not actually observe when and for how long foreclosed houses may be vacant. It is likely that any effect of foreclosure on crime is a very local phenomenon. Aggregating to the county-level captures only average effects across counties, and may conceal any heterogeneous effects that occur within counties at the neighborhood level.

4. Results

A. OLS Results

We first present our estimation results with a focus on burglary. This is the crime which we expect, *ex ante*, to be most affected by changes in the foreclosure rate. OLS estimates of the empirical model are presented in Table 2. Each column shows coefficient estimates from a separate regression, where observations are weighted by mean county population over the years in our sample, and standard errors are clustered on county in all specifications. The estimate in Column (1) shows that, when controlling only for year fixed-effects, a one percentage point increase in the lagged foreclosure rate is associated with a statistically significant, 25.9 percent increase in the burglary rate.[22] In Columns (2) through (5), the magnitude of this estimate monotonically decreases as demographic, macroeconomic, education and welfare expenditure, and formal deterrence measures are sequentially added to the specification.[23] The estimate in Column (5), the specification that includes a "standard" list of control variables based on previous literature, indicates that a one percentage point increase in lagged foreclosures is associated with an 8.9 percent increase in burglary.

In Column (6) we add to the specification three additional variables to control for factors plausibly correlated with both foreclosure rates and crime rates, which if omitted may lead to biased OLS estimates. The first is a proxy for the share of loan originations in the previous year that are subprime. Gerardi, Shapiro, and Willen (2008) show that subprime borrowers are more likely to default than prime borrowers, and institutions that specialize in subprime loans may disproportionately originate loans in areas with higher rates of crime. Second, some criminologists have advanced the notion of "strain" as an explanation for crime, following

[22] All significance tests discussed in the text are at the five percent level, unless otherwise noted.
[23] With the exception of the lagged foreclosure rate and demographic controls, the explanatory variables are in logs.

Merton's (1938) argument that crime results from frustration amongst low-status individuals regarding their relative status. Consistent with this premise, Kelly (2000) shows a relationship between income inequality and violent crime. Because foreclosures may be positively correlated with such social tensions, we include in the model income inequality as a proxy. Finally, it is possible that expectations over future economic conditions may influence a potential offender's decision to commit a crime in the current period. To the extent that expectations over future job market conditions are reflected in demand and supply shifts in the housing market, recent changes in home prices should act as a reasonable proxy for economic expectations. Thus, we include in the model a control for changes in house prices at the MSA level over the past year.

The specification in Column (6) therefore incorporates a comprehensive set of control variables. The coefficient estimate on the lagged foreclosure rate, 8.6, is very similar to the previous column. As we have noted, however, there may be persistent unobservable differences across geographic areas that are correlated with both foreclosure rates and crime rates, leading to previous estimates of the foreclosure effect potentially being driven by spurious correlation. Therefore, in Columns (7) and (8) we present estimates from specifications that include MSA (city-level) and county-level geographic fixed effects, respectively. When the foreclosure effect is identified by within-MSA variation, we estimate that a one percentage point increase in lagged foreclosure rates leads to a 5.4 percent increase in burglary. And when the foreclosure effect is identified solely by within-county variation, the point estimate falls further to 2.1. Both estimates are statistically different from zero. These estimates suggest that the foreclosure effect is small in magnitude, given that a one percentage point increase is almost a 150 percent increase in the sample mean foreclosure rate.

We next present our estimates of the foreclosure effect on the other crime types. Each cell of Table 3 shows the coefficient estimate on the lagged foreclosure rate from a separate regression, where the dependent variable varies by crime type across rows, and the econometric specification varies across columns as in Table 2. Panel A presents coefficients for property crimes and Panel B for violent crimes.[24] We do not find robust evidence of a foreclosure effect on any of the other crimes. From the specification which incorporates the full set of controls but excludes geographic fixed effects, Column (6) shows an increase in lagged foreclosures is associated with a statistically insignificant increase in larceny, and a statistically significant decrease in robbery and an increase in rape. However, when we include county-level fixed effects in the specification, Column (8) shows that we find a small but statistically significant effect of foreclosures on larceny, while for both robbery and rape the estimate becomes statistically insignificant. The estimated foreclosure effects for the remaining crime types are also not statistically different from zero.

The estimates in Columns (7) and (8) are generally substantially smaller in magnitude than the estimate from Column (6).[25] We take this as evidence that spurious correlation in the level of foreclosures and crime rates across geographic areas is an issue. Thus, our ability to control for persistent unobservable geographic differences is an important improvement over previous work in accurately measuring the causal relationship between foreclosures and crime. Over the remainder of this paper we refer to the estimation that includes county fixed-effects as our baseline OLS specification. However, we note that this specification likely yields

[24] To avoid dropping county-year observations with zero assaults, rapes, or murders, we add a one to all observations of each of these crime rates before taking logs. This transformation has little effect on our results; our estimates are quite similar if we use as the dependent variable the log of the observed crime rate, dropping all observations with crime rates equal to zero.

[25] For aggregate property crime, burglary, robbery, and rape, the differences in coefficient estimates on lagged foreclosures between Columns (6) and (8) are statistically significant. Here, and throughout the paper, standard errors on differences of coefficients across separate regressions are computed using bootstrapping, with 100 replications.

conservative estimates of the foreclosure effect on crime, because the inclusion of county fixed effects strips out any potentially important variation in levels across counties useful for identification of this effect.

We present a brief sensitivity analysis of our OLS results in Table 4. To facilitate comparison, we repeat in Column (1) our baseline results from Table 3, Column (8). The first two specification checks address the shortcoming in our data that a number of control variables are measured at the state level, and thus in our data sample values for these variables are the same for all counties within a state. In Column (2), we show estimates when standard errors are clustered on state rather than county.[26] And in Column (3), we use a more flexible specification that includes state-year fixed effects (and all control variables measured at the state-year level are dropped). Both sets of estimates show the magnitude and significance of the foreclosure effect on burglary remains essentially unchanged. For larceny, however, the point estimate loses significance, and decreases in magnitude with the second alternative specification. In this second robustness check, we also find a significant positive effect of foreclosures on aggravated assault, with a point estimate of 3.0 percent.

We also explore whether our results are sensitive to the use of an alternative foreclosure measure. As described in Appendix A, subprime loans are over-represented in earlier years of our analysis data. Following Immergluck (2009), we compute an alternative REO-based measure of foreclosures incorporating weights to the LPS and LP data based on the state-year share of loans that are subprime in the Mortgage Bankers Association's nationally representative National Delinquency Survey (NDS).[27] Estimates using this "weighted" foreclosure rate, rather than the foreclosure rate we computed on the "unweighted" sample, are presented in Column (4).

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[26] Because the foreclosure rate, our explanatory variable of interest, varies at the county level, we prefer to cluster standard errors on county in our baseline specification.
[27] See Appendix A for more detail on the NDS.

These estimates are generally similar to our baseline results, except that we surprisingly find a positive effect of foreclosures on rape, significant at the 10 percent level.[28]

Lastly, we attempt to confirm that controlling for persistence in crime rates does not affect our main results. This is necessary if foreclosures are endogenous to crime, specifically, if foreclosures are correlated with recent growth in crime rates as well as with current crime. The specification in Column (5) controls for aggregate property crime rates and aggregate violent crime rates lagged one, two, and three years relative to foreclosure rates. Results from this specification are similar to our baseline estimates.

B. IV Analysis

We consider our OLS estimates of the foreclosure effect on crime to be a substantial improvement over previous work in this area. However, as we have noted, our OLS estimates are potentially biased downward due to error in our measure of foreclosure rates. In this section we present results from an IV estimation strategy that addresses this issue.

We use two instruments for foreclosure rates: the five-year growth rate in metropolitan area house prices, and this house price growth interacted with the county unemployment rate. Our choice of instruments is motivated by recent theoretical and empirical work on mortgage default.

Standard models depicting the option to default include house values as a key state variable (for example, Foster and Van Order, 1984, and Deng, Quigley, and Van Order, 2000). In these models, a necessary condition for borrower default is that the value of the home is less

[28] The estimate in Table 4 Column (4) implies that, evaluating at the sample means, the elasticity of burglary with respect to foreclosures is 0.014. This is equivalent to the elasticity implied by the coefficient estimate on burglary from the baseline OLS specification.

than the remaining mortgage balance, in other words, that the homeowner is “underwater.”[29] However, in the absence of cash flow problems, an underwater borrower also has the option of continuing to make mortgage payments, perhaps in anticipation of future house price increases. Recent theoretical and empirical work explores the impact of “trigger events,” temporary shocks to income such as an unemployment spell, where the underwater borrower who suffers a negative income shock is unable to continue paying the mortgage or to refinance, providing a sufficient condition for default (for example, Gerardi, Shapiro, Willen, 2008 and 2009; Foote et al. 2009). The practical implication of these models is that house price growth, and its interaction with the unemployment rate, ought to have strong negative correlation with mortgage defaults and ultimately with foreclosures. Our first stage IV estimates, discussed in Appendix D, show exactly that.[30]

The validity of our IV approach rests on the assumption that the instruments are strongly correlated with local area foreclosure rates, and are not related to crime rates through another unobserved channel. We emphasize that, in addition to controlling for all time-invariant differences across counties in observable and unobservable factors, we control for macroeconomic factors such as the unemployment rate, per capita income, and the wage rate of low-skilled workers. Importantly, we also explicitly control for the one-year house price growth

[29] Rather than defaulting, a homeowner with positive home equity can instead opt to sell the home and prepay the mortgage, thereby receiving a positive cash payoff at settlement and maintaining his credit rating.
[30] In all of the IV specifications we estimate, we include the full set of control variables listed on Table 2, Column (8). In every case, the F-statistic on a test of the null hypothesis that the instrument(s) can be omitted from the first stage exceeds the critical value benchmarks for weak identification (Stock and Yogo, 2005). Our choice of a five year window over which to compute house price growth is somewhat arbitrary. Our goal is to best approximate the change in home equity from time of purchase experienced by the “average” homeowner in a particular area and year, so that our instruments provide sufficiently strong predictive power of the foreclosure rate in the first stage. Based on American Housing Survey data, Ferreira, Gyourko, and Tracy (2010) report that average homeowner tenure over the period 1985 to 2007 was 8 years. However, many homeowners refinance their mortgages at least once. Data from Freddie Mac’s Cash Out Refinance report (3Q 2010) indicate that among all refinancings over the 2002 to 2007 period, the median age of the previously held mortgage was roughly three years. Our IV results do not appear to be sensitive to using alternative house price growth windows as the instrument. Estimates were qualitatively similar using an eight year window.

in our crime equation. To the extent that short run movements in house prices proxy for expectations over future economic conditions or other unobserved factors that may also be correlated with crime, the inclusion of the one-year house price growth rate effectively strips out these undesired sources of variation in the longer-term measure of house price growth used as our instrument. Overall, the comprehensiveness of our controls helps to provide confidence that our instruments are valid.

We present our IV estimates of the foreclosure effect on crime in Table 5. Each cell shows the coefficient on the lagged foreclosure rate from a separate regression of the dependent crime outcome on the instrumented foreclosure rate and the full set of control variables. In Column (1) the instrument is the five-year growth rate in house prices. In Column (2) and (3) the instruments are the five year change in house prices, and this house price growth interacted with the logged county-level unemployment rate. Column (3) differs from Column (2) in that the specification includes additional controls for aggregate property and aggregate violent crime, lagged one, two, and three years relative to foreclosure rates. Controlling for lagged crime addresses the potential concern that longer-term house price growth may be influenced by past crime, and this past crime is correlated with current crime.

The IV estimates are generally larger in magnitude than the OLS estimates, giving credence to our concern that the OLS estimates are biased downward due to measurement error.[31] Our IV estimates vary little across the three alternative specifications. We find a one percentage point increase in the lagged foreclosure rate leads to an increase in burglary of roughly 10 percent, and an increase in larceny of over 4 percent. We also find evidence of a

[31] The differences in the estimated foreclosure effects from the IV specification of Table 5, Column (2), and the OLS specification of Table 3, Column (8), are statistically significant for the following crimes: aggregate property crime, larceny, burglary, aggregate violent crime, and aggravated assault.

foreclosure effect on aggravated assault, statistically significant at the 10 percent level. For all other crime types, our estimates of the foreclosure effect are not statistically different from zero.

Because the latter two specifications are over-identified, we are able to conduct a Sargen-Hansen test of over-identifying restrictions. For all property crime types, the p-values from such tests are over 0.10, and thus we fail to reject the joint null hypothesis that the instruments are not correlated with the error term in the crime equation. For violent crimes, our over-identification test results are mixed. For aggregate violent crime, aggravated assault, and murder, we fail to reject the null that the instruments are valid. But we reject the null for robbery and rape, because the p-values from the over-ID tests are less than 0.10. Overall, the over-identification test results lend support to our belief that our IV strategy is valid, particularly for property crimes.[32]

5. Discussion

Becker (1968) theorized that potential criminals are rational agents who take into account the probability and severity of punishment in their decision to "supply" crime. An increase in foreclosures may reduce the presence of local residents monitoring criminal activity, thereby reducing the probability of detection. In particular, because an occupied residence is likely a much stronger deterrent to burglary than a structure vacated due to foreclosure, we expect a

[32] Our over-identification test results are consistent with existing evidence on the relationship between crime and house prices. Our reading of the literature is that property crime rates are unlikely to have an important effect on house prices. Earlier studies typically find a negative relationship between crime and house prices, but these studies suffer from obvious omitted variable problems (Thaler, 1978; Hellman and Naroff, 1979; Rizzo, 1979; Naroff, Hellman, and Skinner, 1980; Dubin and Goodman, 1982; Buck and Hakim, 1989). An exception is Kain and Quigley (1970), who incorporate a comprehensive set of 39 house quality variables and other controls for neighborhood amenities, and find that crime has an insignificant effect on property values. More recent evidence suggests that increased property crime is actually associated with increased property values (Case and Mayer, 1996; Lynch and Rasmussen, 2001; Tita, Petras, and Greenbaum, 2006). Recognizing the potentially endogenous relationship between property crime and house prices, Gibbons (2004) uses an IV estimation strategy and finds that the burglary effect on house prices is statistically insignificant. For violent crime, we know of two studies that show such crime may decrease house prices (Lynch and Rasmussen, 2001; Tita, Petras, and Greenbaum, 2006). Lynch and Rasmussen (2001) find an economically trivial effect. Tita, Petras, and Greenbaum (2006) use the tract-level murder rate to instrument for other violent crime rates and correct for measurement error in reporting; however, the strength of this instrument is questionable given that homicide is a relatively low-frequency event.

priori that foreclosures should have a pronounced effect on burglary. To the extent that residential "eyes on the street" deter other types of crime, increased foreclosures could also lead to increases in other property or violent crime.

Consistent with this framework, we find robust evidence that foreclosures lead to increased burglary.[33] Our baseline OLS and IV estimates indicate that foreclosures have a smaller but statistically significant effect on larceny. Although in some specifications we find an effect of foreclosures on aggravated assault (significant at the 10 percent level), for all other violent crime types we find that foreclosures have little, if any, effect.[34] The latter finding is perhaps unsurprising. Violent crimes typically occur between non-strangers (Bureau of Justice Statistics, 2010; U.S. Census, 2006). The pre-existing relationship between offender and victim suggests that these crimes are motivated by non-pecuniary benefits, and such motivation likely outweighs the marginal impact that an increase in foreclosures may have on the probability of apprehension.[35]

Although we have established that foreclosures increase burglary, the magnitude of this effect appears to be small relative to other determinants of crime. For example, our baseline OLS estimates (Table 2 Column 8) indicate that, evaluated at the mean, the elasticity of the burglary rate with respect to the lagged foreclosure rate is 0.014. In comparison, the elasticity of burglary with respect to unemployment is 0.165, larger than the foreclosure effect by over a factor of ten.

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[33] While we use the Becker framework to motivate our priors, we do not dismiss the possibility that foreclosures may increase crime through other sociological phenomenon, such as strain (Merton, 1938) or social disorganization (Shaw and McKay, 1942). However, our finding that the foreclosure effect is most pronounced for burglary, the crime for which deterrence is likely to be most affected, seems to most closely align with the Becker model.

[34] Reports by Millman and Spelman (see Footnotes 2 and 5) provide a possible explanation for any potential foreclosure effect on aggravated assault: a community that reaches a threshold of vacant foreclosed properties may attract unmonitored organized criminal activity.

[35] Gould, Weinberg, and Mustard (2002) describe this as the "interdependence of utility" between offender and victim.

To obtain a sense of the economic magnitude of the foreclosure effect on crime, we use our results to calculate back-of-the-envelope estimates of the crime-related social costs associated with the recent spike in U.S. foreclosures shown in Figure 1. Table 6 Column (1) lists community-based costs of crime estimates for burglary and for each type of violent crime, produced by Cohen, Rust, Steen, and Tidd (2004) using a "contingent valuation," or willingness-to-pay, methodology.[36] We project that the increase in U.S. foreclosure starts between 2005 and 2008 will raise the foreclosure rate by 1.03 percentage points in the 24 months after 2008, other things equal.[37] Based on our baseline OLS estimates (Table 3, Column 8), we list in Column (2) the expected percentage changes for each crime type associated with a 1.03 percentage point increase in foreclosure rates. The estimated changes in crime per 100,000 residents, which is the product of Column (2) and mean crime rates, are shown on Column (3). Column (4) lists the estimated cost for the mean county in our sample, which is the product of Columns (1) and (3), multiplied by the mean county population of 1.8 (expressed in 100,000s of residents). Column (5) presents the estimated aggregate costs by multiplying the costs per county by the 1,483 counties in our analysis sample. Columns (6) through (9) repeat the exercise using the IV estimates from Table 5, Column (3).

[36] We prefer the contingent valuation methodology because it captures the costs of crime as perceived by the community-at-large, and therefore provides a more accurate assessment of the externalities that crime-related foreclosures may generate. An alternative cost-of-crime measure is based on ex-post victim based losses (for example, Miller, Cohen, and Wiersema, 1996). Critics point out that victim-based estimates do not capture the costs of crime to family members, potential victims, and society-at-large (Nagin, 2001; Anderson, 1999). Cohen et al. (2004) do not provide cost estimates for larceny and motor vehicle theft.

[37] The rate of foreclosure starts in the U.S. grew from 1.6 percent to 4.3 percent between 2005 and 2008, an increase of 2.7 percentage points. Based on our sample of loans from LP and LPS, 38 percent loans which entered foreclosure in 2006 reached REO status within 24 months of the start of the foreclosure process. Thus we expect that the 2.7 percentage point increase in foreclosure starts will increase the share of loans in REO status by approximately 1.03 percentage points over the next 24 months. We note this may be an overstatement of the future increase in REO rates, to the extent that recently introduced foreclosure mitigation programs successfully reduce the number of borrowers displaced by foreclosure actions. However, to date these programs have been relatively small in scope and do not appear to have had a substantial impact (see for example, Mulligan (2010), and Adelino, Gerardi, and Willen (2009)).

Based on this methodology, we estimate the collective willingness-to-pay of the analysis counties to prevent the increase in burglary incidents due to foreclosures to range from $1.1 billion to $4.9 billion, based on our OLS and IV results respectively.[38] Aggregating across the crime categories for which we have cost estimates, the total willingness-to-pay to avoid foreclosure-related increases in crime is as high as $11.9 billion. While these cost estimates may be small relative to the potential cost of government foreclosure mitigation programs, they are nonetheless non-trivial.

We note two important caveats to our analysis. First, criminal activity may be under-reported in areas with high growth in foreclosure rates. In the case of an unoccupied home that is burglarized, there is no longer an active resident to report the incident, and neighboring residents may not notice a crime has occurred. Second, we recognize that our period of analysis precedes the current foreclosure crisis. It seems plausible that the effect of foreclosures on crime is non-linear, for example if it increases sharply when foreclosures in an area exceed some critical mass.[39] To the extent that these issues are relevant, the estimates presented in this paper likely understate the impact foreclosures will have on crime during the current foreclosure crisis.

6. Conclusion

[38] We note that these cost estimates may be understated, because burglaries on foreclosed homes may result in property damage uncommon in typical burglaries. Dornin (2008) notes instances where the cost of a burglary incident at a foreclosed home significantly exceeds the cost of the typical burglary, and where the costs of the damage inflicted during these burglary incidents far outweigh the value of the stolen items. For example, he reports that a burglary in Atlanta of about $40 worth of copper wire resulted in damage to the property estimated at $15,000 to $20,000.

[39] We find suggestive evidence that the foreclosure effect on burglary is non-linear. Using OLS estimation, we regressed burglary rates on a set of dummy variables indicating whether the lagged county-year foreclosure rate was in the 2nd, 3rd, or 4th quartile of all observed foreclosure rates. The specification also included all other control variables that are listed on Table 2, Column (8). The coefficient estimates indicate that county-year observations in the 4th, or highest, quartile of lagged foreclosure rates are associated with the highest rates of burglary. And this effect decreases monotonically for county-year observations in the 3rd, 2nd, and 1st quartiles, respectively.

This paper estimates the causal effect of foreclosures on crime rates. We exploit a rich county-level panel dataset, which includes a comprehensive set of controls guided by the existing literature on the determinants of crime. The panel nature of our data, importantly, allows us to control for time-invariant observed and unobserved factors at the county level that might give rise to spurious correlation between foreclosures and crime rates. In addition to OLS estimates, we present results from an IV strategy that addresses potential measurement error in foreclosure rates. We find robust evidence that an increase in foreclosures leads to a modest increase in burglary. We estimate that a one percentage point increase in the foreclosure rate in the previous year leads to an increase in burglary of 2.1 to about 10 percent, based on our OLS and IV results, respectively. Sensitive to specification, we also find positive effects of foreclosures on larceny and on aggravated assault. For the other types of crime that we study, the foreclosure effect is not statistically different from zero. Based on our estimates, we calculate that the spike in foreclosure starts between 2005 and 2008 will result in community-wide economic losses ranging from $1.1 to $4.9 billion due to increased burglary rates. While it is beyond the scope of this paper to evaluate the cost-effectiveness of foreclosure prevention programs, which are motivated by more than concern over crime, our findings indicate that intervention is at least partially justified by its potential to stem the crime-related social costs that arise from foreclosures.

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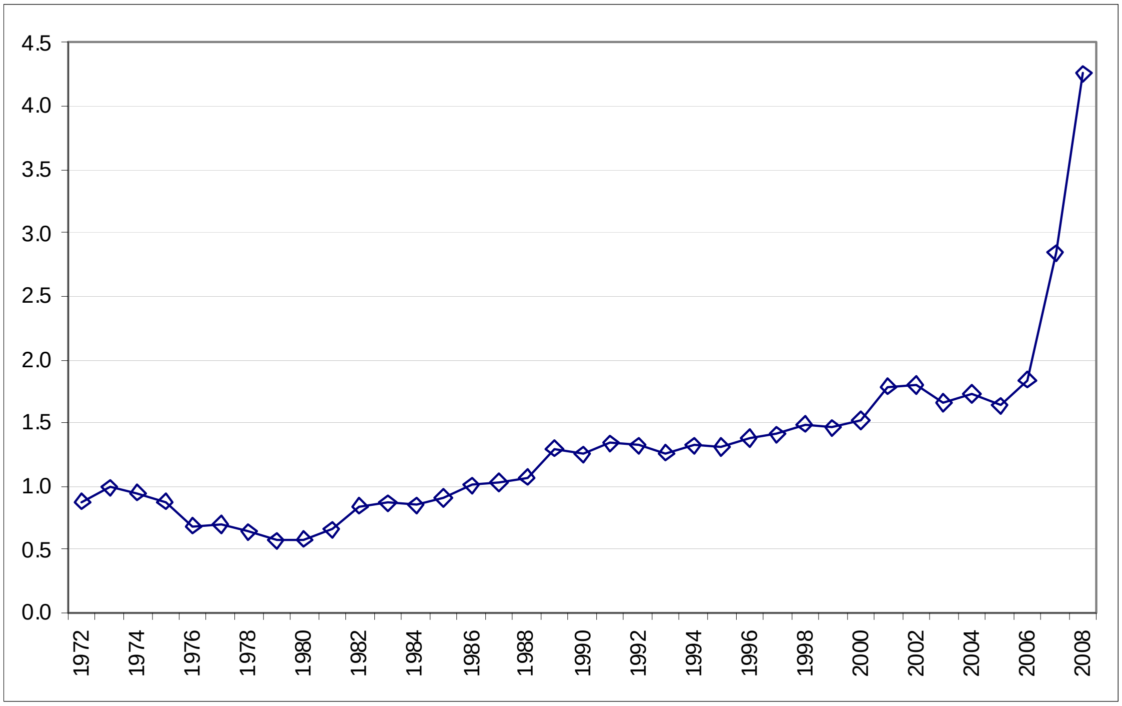
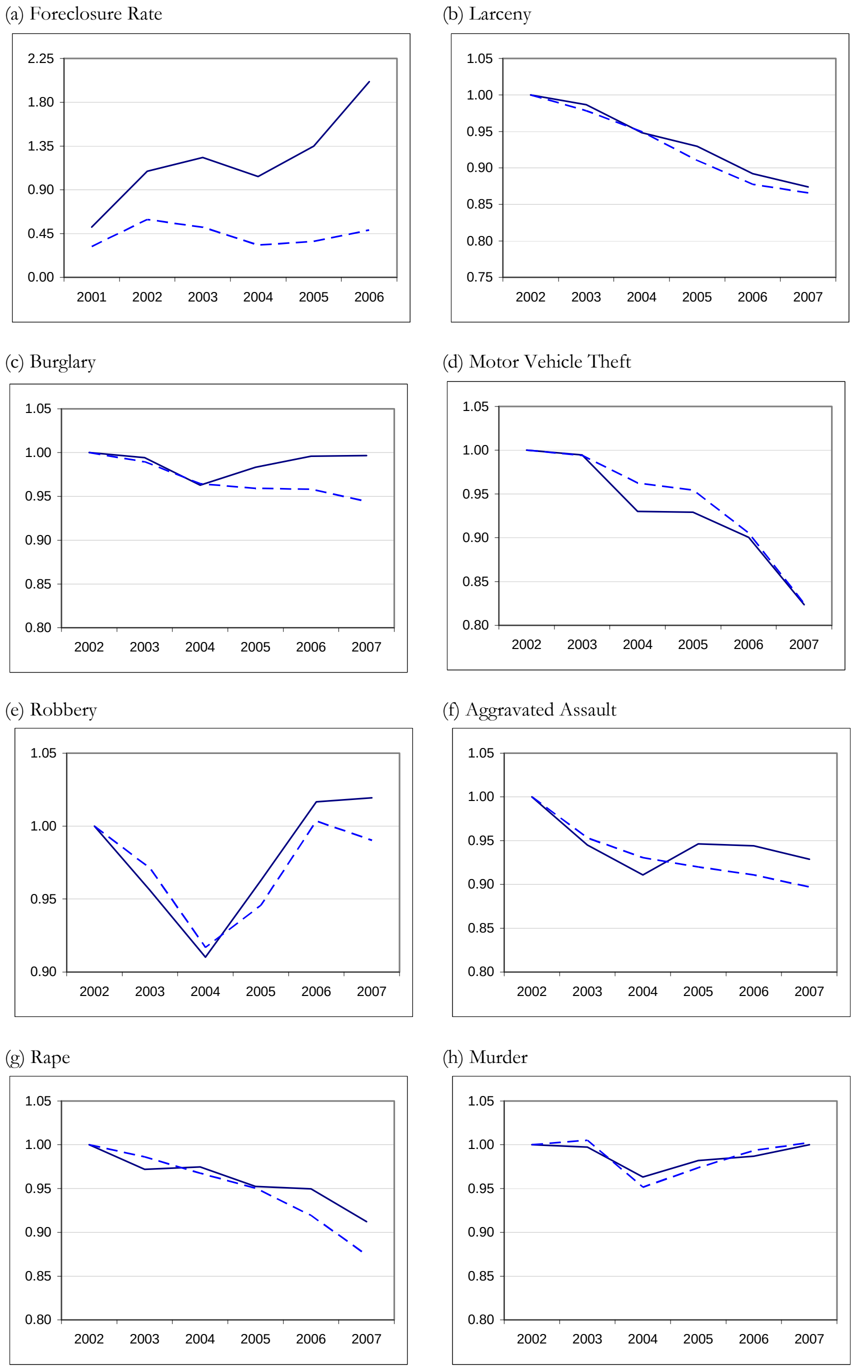
Figure 1: U.S. Foreclosure Start Rate, 1972 to 2008



Notes: Data are from the Mortgage Bankers Association's National Delinquency Survey (NDS). As of 2008, the NDS covered includes about 45.4 million first-lien mortgages on 1-to-4 unit residential properties, or over 80 percent of outstanding first-liens in the United States.

Figure 2: Per Capita Crime Rates by Year, High versus Low Foreclosure States



Notes: Solid line is the mean value over counties in the ten states with the highest foreclosure rates in 2006, weighted by mean county population. Dashed line is the weighted mean value across the remaining 40 states and the District of Columbia. The top ten foreclosure states in 2006 are MI, OH, CO, IN, GA, MS, TN, TX, KS, and SC. Foreclosure rates cover the 2001 to 2006 period. The foreclosure rate is defined as the share of active loans in REO status in each year, expressed in percentage points. Crime rates cover the 2002 to 2007 period. For Figures (b) through (h) the crime rate data presented in each line are indexed to their respective 2002 values.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Year	2005	1.7	2002	2007
Property Crime (per 100k)	3,670.4	1,497.6	92.0	21,610.2
Larceny	2,450.6	986.9	29.9	15,847.5
Burglary	767.1	373.2	4.5	4,399.8
Motor Vehicle Theft	452.7	343.3	3.5	3,516.8
Violent Crime (per 100k)	517.1	325.5	0.0	4,830.5
Robbery	164.3	142.9	0.0	907.2
Aggravated Assault	314.8	203.2	0.0	4,364.4
Rape	31.9	18.2	0.0	340.5
Murder	6.1	6.0	0.0	94.7
Lagged Foreclosure Rate (%)	0.7	0.7	0.0	8.7
Black (%)	13.8	13.0	0.1	74.5
Male and Aged 15 to 24 (%)	7.3	1.3	4.0	19.9
Unemployment (%)	5.3	1.5	1.5	19.6
Income per Capita ($)	35	6	16	49
Log State Unskilled Wage ($)	6.3	0.1	6.1	6.5
State Expenditures on Education per Capita ($1000)	2.5	0.3	1.8	4.0
State Expenditures on Welfare per Capita ($1000)	1.3	0.4	0.8	3.6
State and Local Expenditures on Police per Capita ($)	255.3	73.9	112.9	1,463.4
State Sworn Police Officers (per 1k)	2.3	0.6	1.5	12.5
State Prison Population (per 1k)	648.8	582.1	11.1	1,755.1
HUD Regulated Entity Loan Share (%)	3.8	4.8	0.0	39.8
State Income Inequality (90th Pct/10th Pct)	15.3	2.7	8.0	28.6
MSA One-Year House Price Change (%)	5.3	6.4	-14.3	29.4
Lagged MSA Five-Year House Price Change (%)	30.0	25.4	-12.0	114.4

Notes: Cells defined by county and year, and weighted by mean county population. 8,344 observations. Variables are at the county-level unless noted otherwise. Crime figures are measured per 100,000 persons. Lagged Foreclosure Rate is the percentage of mortgage loans in REO status in the previous year. Log State Unskilled Wage is the predicted log wage from regressing individual wages of non-college educated men from the CPS on education, experience, experience squared, and controls for race and marital status. HUD Regulated Entity Loan Share is the percent of loans originated or purchased by an institution regulated by HUD, the primary regulator of non-bank mortgage companies. State Income Inequality is the ratio of the 90th to 10th percentile in per capita income. Lagged MSA Five-Year House Price Change is the growth rate in the MSA-level house price index between years (t -6) and (t -1). All monetary figures are in 2005 dollars.

Table 2: OLS Estimates, Burglary

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Foreclosure Rate	0.259***	0.214***	0.155***	0.090***	0.089***	0.086***	0.054***	0.021***
	(0.027)	(0.034)	(0.028)	(0.019)	(0.019)	(0.019)	(0.013)	(0.007)
Black		0.012***	0.013***	0.013***	0.014***	0.014***	0.025***	0.015
		(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.012)
Male and Aged 15 to 24		0.038***	-0.009	0.007	0.001	0.003	-0.012	0.041**
		(0.012)	(0.010)	(0.008)	(0.008)	(0.008)	(0.013)	(0.018)
Unemployment Rate			0.139	0.326***	0.348***	0.332***	0.240***	0.165***
			(0.090)	(0.069)	(0.067)	(0.069)	(0.077)	(0.047)
Income			-1.026***	-0.580***	-0.535***	-0.546***	0.414*	-0.078
			(0.134)	(0.110)	(0.113)	(0.114)	(0.231)	(0.176)
Unskilled Wage			-2.127***	-1.586***	-2.256***	-1.976***	0.109	0.041
			(0.364)	(0.302)	(0.382)	(0.392)	(0.344)	(0.249)
Education Expenditures				-1.056***	-1.025***	-1.008***	-0.216	-0.247*
				(0.132)	(0.131)	(0.130)	(0.224)	(0.145)
Welfare Expenditures				-0.404***	-0.242***	-0.200**	-0.531**	-0.021
				(0.086)	(0.080)	(0.082)	(0.223)	(0.093)
Police Expenditures					-0.030	-0.020	0.253*	0.230**
					(0.102)	(0.101)	(0.152)	(0.091)
Sworn Police Officers					-0.302***	-0.311***	-0.182	-0.168**
					(0.117)	(0.114)	(0.167)	(0.077)
Prison Population					-0.063***	-0.065***	-0.096	0.355***
					(0.019)	(0.019)	(0.087)	(0.090)
HUD Regulated Loan Share						0.004**	-0.000	-0.002**
						(0.002)	(0.003)	(0.001)
Income Inequality						-0.006	-0.000	-0.001
						(0.005)	(0.002)	(0.002)
One-Year House Price Growth						-0.003	0.001	0.001*
						(0.002)	(0.001)	(0.001)
Constant	6.458***	6.040***	23.268***	18.921***	23.731***	21.958***	3.378	2.814
	(0.031)	(0.102)	(2.584)	(2.066)	(2.713)	(2.763)	(2.437)	(1.793)
Geographic FE	-	-	-	-	-	-	MSA	County
R-sq	0.123	0.217	0.396	0.485	0.507	0.511	0.821	0.951

Notes: Burglary outcome is logged. All explanatory variables are in logs except Lagged Foreclosure Rate, Black, Male Aged 15 to 24, Income Inequality, HUD Regulated Loan Share, and One-Year House Price Growth. All specifications include year fixed effects. Standard errors clustered on county are in parentheses. * indicates the estimate is significantly different than zero at the 10 percent level; ** five percent; *** one percent. See Table 1 for additional notes.

Table 3: OLS Estimates, Effect of Foreclosure on Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Property	0.163***	0.121***	0.094***	0.034**	0.038***	0.034**	0.018	0.014**
	(0.021)	(0.025)	(0.021)	(0.015)	(0.015)	(0.015)	(0.011)	(0.006)
Larceny	0.146***	0.115***	0.075***	0.017	0.017	0.011	0.007	0.014**
	(0.027)	(0.030)	(0.026)	(0.020)	(0.019)	(0.019)	(0.010)	(0.006)
Burglary	0.259***	0.214***	0.155***	0.090***	0.089***	0.086***	0.054***	0.021***
	(0.027)	(0.034)	(0.028)	(0.019)	(0.019)	(0.019)	(0.013)	(0.007)
MV Theft	0.057	-0.041	0.070	-0.008	0.021	0.026	0.009	-0.004
	(0.071)	(0.059)	(0.045)	(0.043)	(0.032)	(0.027)	(0.019)	(0.011)
B. Violent	0.090*	-0.029	-0.001	-0.024	-0.006	0.001	0.003	0.001
	(0.048)	(0.034)	(0.023)	(0.026)	(0.023)	(0.021)	(0.017)	(0.009)
Robbery	-0.050	-0.258***	-0.140***	-0.144***	-0.127***	-0.127***	-0.047*	-0.010
	(0.081)	(0.054)	(0.038)	(0.040)	(0.033)	(0.030)	(0.026)	(0.009)
Aggravated Assault	0.098**	0.002	0.024	-0.005	0.014	0.026	0.013	0.002
	(0.046)	(0.034)	(0.026)	(0.030)	(0.028)	(0.026)	(0.018)	(0.012)
Rape	0.211***	0.209***	0.125***	0.136**	0.121***	0.122**	-0.015	-0.004
	(0.028)	(0.028)	(0.030)	(0.067)	(0.047)	(0.048)	(0.015)	(0.013)
Murder	0.124**	-0.019	0.002	-0.016	-0.005	0.001	0.016	0.006
	(0.060)	(0.043)	(0.030)	(0.030)	(0.026)	(0.024)	(0.018)	(0.014)
Geographic FE	-	-	-	-	-	-	MSA	County

Notes: Each entry is the coefficient estimate on the lagged foreclosure rate from a separate regression of the crime outcome. Each column corresponds to the specification of the same column on Table 2. All crimes are in logs. To avoid dropping county-year observations with zero robberies, aggravated assaults, rapes, or murders, we add one to all observations of each of these crime rates before taking logs. See Table 2 for additional notes.

Table 4: OLS Estimates, Robustness of Foreclosure Effect on Crime

	Baseline OLS (1)	Cluster on State (2)	State X Year (3)	Weighted FC Rate (4)	+Lagged Crime (5)
A. Property	0.014**	0.014*	0.014**	0.023**	0.015***
	(0.006)	(0.008)	(0.006)	(0.009)	(0.006)
Larceny	0.014**	0.014*	0.009	0.021**	0.015**
	(0.006)	(0.008)	(0.006)	(0.009)	(0.006)
Burglary	0.021***	0.021***	0.025***	0.042***	0.022***
	(0.007)	(0.007)	(0.008)	(0.011)	(0.007)
MV Theft	-0.004	-0.004	0.017	0.007	-0.002
	(0.011)	(0.012)	(0.012)	(0.017)	(0.011)
B. Violent	0.001	0.001	0.021**	0.009	0.000
	(0.009)	(0.010)	(0.010)	(0.014)	(0.008)
Robbery	-0.010	-0.010	0.001	-0.018	-0.010
	(0.009)	(0.010)	(0.012)	(0.015)	(0.009)
Aggravated Assault	0.002	0.002	0.030**	0.010	0.001
	(0.012)	(0.012)	(0.013)	(0.019)	(0.011)
Rape	-0.004	-0.004	0.010	0.050*	-0.004
	(0.013)	(0.015)	(0.022)	(0.028)	(0.012)
Murder	0.006	0.006	0.013	0.008	0.006
	(0.014)	(0.016)	(0.018)	(0.022)	(0.014)
Year FE	Y	Y	-	Y	Y
State X Year FE	-	-	Y	-	-
Cluster on	County	State	County	County	County

Notes: Each entry is the coefficient estimate on the lagged foreclosure rate from a separate regression of the crime outcome. Except for the specification of Column (3), each estimation includes the full set of controls shown on Table 2, and year and county fixed effects. Estimates from Table 3, Column (8), are repeated for comparison with the baseline OLS results. Column (2) shows coefficients when standard errors are clustered on state. The specification of Column (3) instead includes state X year fixed effects. In Column (4), an alternative foreclosure rate is used which is weighted by the state-year share of subprime loans. Column (5) shows estimates when aggregate property and aggregate violent crime rates lagged one, two, and three years relative to foreclosure rates are included as additional controls. See Table 2 for additional notes.

Table 5: IV Estimates, Effect of Foreclosure on Crime

Instrument(s):			
HPI	Y	Y	Y
HPI*Unemployment Rate	-	Y	Y
	(1)	(2)	(3)
A. Property	0.058***	0.055**	0.055***
	(0.021)	(0.021)	(0.021)
		0.6313	0.5343
Larceny	0.045**	0.043**	0.043**
	(0.018)	(0.018)	(0.018)
		0.988	0.8338
Burglary	0.110***	0.097***	0.098***
	(0.028)	(0.028)	(0.028)
		0.6479	0.5653
MV Theft	0.032	0.032	0.035
	(0.049)	(0.053)	(0.050)
		0.1403	0.2239
B. Violent	0.071*	0.071*	0.070*
	(0.042)	(0.043)	(0.041)
		0.2101	0.2212
Robbery	-0.003	0.003	0.002
	(0.030)	(0.031)	(0.031)
		0.075	0.0906
Aggravated Assault	0.109*	0.110*	0.107*
	(0.064)	(0.065)	(0.062)
		0.993	0.9458
Rape	0.013	0.003	0.001
	(0.035)	(0.037)	(0.038)
		0.0735	0.0477
Murder	0.030	0.012	0.011
	(0.038)	(0.038)	(0.037)
		0.9672	0.8747
Control for Lagged Crime	-	-	Y

Notes: Each cell shows the IV coefficient estimate on the lagged foreclosure rate from a separate regression of the crime outcome. Also listed are the standard error (in parentheses), and if applicable the p-value from a Sargen-Hansen test of over-identifying restrictions. Each estimation includes the full set of controls shown on Table 2, and year and county fixed effects. In Column (1) the foreclosure rate is instrumented with the five-year growth rate in the MSA-level real house price index (HPI). In Columns (2) and (3) the foreclosure rate is instrumented with both HPI and HPI*log unemployment. The specification of Column (3) also controls for aggregate property and aggregate violent crime rates lagged one, two, and three years relative to foreclosure rates. See Table 2 for additional notes.

Table 6: Estimated Costs of Crime Resulting from Increase in Foreclosure Starts between 2005 and 2008

		OLS				IV			
	Costs Per Crime (1)	Percentage Change in Crime Rates (2)	Change in Crimes per 100k (3)	Mean Cost Per County (4)	Aggregate Cost for Analysis Counties (Mill $) (5)	Percentage Change in Crime Rates (6)	Change in Crimes per 100k (7)	Mean Cost Per County (8)	Aggregate Cost for Analysis Counties (Mill $) (9)
A. Property Crime									
Larceny		1.4	31.8			4.4	97.6		
Burglary	$25,773	2.2	15.4	$712,770	$1,057	10.0	71.0	$3,292,320	$4,883
MV Theft		-0.4	-1.0			3.3	8.0		
B. Violent Crime									
Robbery	$239,175	-1.0	-0.7	-$310,478	-$460	0.3	0.2	$93,143	$138
Aggravated Assault	$72,165	0.2	0.5	$66,987	$99	11.3	28.4	$3,684,261	$5,464
Rape	$244,330	-0.4	-0.1	-$58,216	-$86	0.3	0.1	$43,662	$65
Murder	$10,000,000	0.6	0.0	$443,525	$658	1.2	0.0	$887,050	$1,315
Total					$1,267				$11,865

Notes: Column (1) displays estimates of the community-wide willingness-to-pay to avert one crime provided by Cohen, Rust, Steen, and Tidd (2004). Column (2) shows the OLS estimates presented on Table 3, Column (8), inflated by a factor of 1.03, the estimated percentage point increase in the REO-based mean foreclosure rate implied by the increase in foreclosure starts between 2005 and 2008 (*100). See text for more discussion. Column (3) shows the product of the estimated percent change in crime rates and the mean crime rates presented on Table 1. Column (4) is the product of Columns (1) and (3), multiplied by the mean sample county population of 1.8, expressed in units of 100k persons. Column (5) aggregates the per county costs across the 1,483 counties of the analysis sample. Columns (6) through (9) repeat the exercise, but instead use the IV estimates of Table 5, Column (2). All monetary amounts are in 2005 dollars.

Appendix

A. Measurement Error in Foreclosure Rates

To assess the quality of our sample of loans and the accuracy of our foreclosure rate measure, we compare our data with national summary data from the Mortgage Bankers Association's National Delinquency Survey (NDS). The NDS is a widely utilized dataset based on surveys of approximately 120 lenders and servicers covering over 80 percent of outstanding 1 to 4 unit first-liens in the U.S., providing a reliable summary of the size and composition of the U.S. mortgage market (Immergluck, 2009). Appendix Table 1 indicates that our concern regarding sample selection is warranted. Nearly 45 percent of the loans in the composite data are from LP, and therefore subprime, in 2001. This figure far exceeds the 3 percent share of loans in the NDS that are subprime. By 2006, 14 percent of loans in our sample are from LP, comparable with the subprime share in the NDS.

Because the NDS does not publish REO-based foreclosure rates, we are unable to directly compare our measure to the NDS. However, the NDS does publish data on the *overall* foreclosure rate, defined as the number of loans in any stage of the foreclosure process divided by the number of all active loans. For comparison we compute an alternative "weighted" measure of the overall foreclosure rate. Based on the methodology of Immergluck (2009), we use the share of loans in the NDS that are subprime by state and year to weight our composite LPS and LP data. In Appendix Figure 1 we present overall foreclosure rates by year from NDS data, using our "unweighted" LPS and LP data, and applying the alternative weighting scheme to our composite data. Relative to the NDS, the unweighted measure is consistently larger in magnitude over all years of the analysis period, suggesting our REO-based measure of the foreclosure rate is overstated. However, this measure captures the national time trend in mortgage defaults with reasonable accuracy.[41] In contrast, the weighted foreclosure measure is closer in level to NDS, but does not follow the time trend well. As we show in our sensitivity analysis, our results are robust to the choice of weighting. However, we prefer the unweighted measure for our main specification because it more closely follows the time trend of NDS. Based on Appendix Figure 1, we assume our unweighted foreclosure rate exhibits positive-mean measurement error.

B. Inconsistency and Bias

Above, we present evidence of positive-mean error in our measurement of foreclosure rates. Here, we formally show the implications of this error for our OLS estimates of the effect of foreclosures on crime, under reasonable assumptions that arise from the analysis of the data.

In practice, we observe a foreclosure rate, f_{it-1}, that can be expressed as follows:

$$f_{it-1} = f^*_{it-1} + u_{it-1} + \mu_{it-1} \quad \text{[A.1].}$$

We assume that the true foreclosure rate, f^*_{it-1}, has mean $\bar{f}^*$ and variance $\sigma^2_{f^*}$. We assume that we have classical measurement error u_{it-1} with mean zero and variance σ^2_u, that is independent of the error term ε_{it} of the crime equation and of the true foreclosure rate, f^*_{it-1}. We also assume that there is a positive-mean error component, μ_{it-1}, with mean $\bar{\mu}$ greater than zero and variance σ^2_μ, that is independent of ε_{it}. We allow the positive-mean error to have covariance $\sigma_{f^*\mu}$ with f^*_{it-1}.

[41] Since subprime loans are more likely to end in foreclosure and are over-represented in our sample, we expected to see an upward bias in our measure of foreclosure rates in earlier years and no bias in the later years of our sample. However, we do not observe this, perhaps because over this period of "easy credit" and rising property values subprime borrowers were able to refinance out of problematic loans before defaulting.

Rearranging [A.1] and substituting the true foreclosure rate, f^*_{it-1}, into equation [2] of Section 3 yields:

$$crime_{it} = \beta_0 + \beta_1 f_{it-1} + X_{it}'\beta_2 + Y_{it}'\beta_3 + P_{it}'\beta_4 + t'\lambda + i'\theta + \upsilon_{it} \quad \text{[A.2]},$$

where $\upsilon_{it} = \varepsilon_{it} - \beta_1(u_{it-1} + \mu_{it-1})$. Both the observed foreclosure rate f_{it-1} and υ_{it} depend on the measurement errors, u_{it-1} and μ_{it-1}, therefore, if the true β_1 is positive, then there is negative covariance between f_{it-1} and υ_{it}. Specifically, under our assumptions about the characteristics of the component measurement errors, the probability limit of the OLS estimate of β_1 is:

$$\beta_1\left[1 - \frac{\sigma_{f^*\mu} + \sigma_u^2 + \sigma_\mu^2 + \bar{\mu}\bar{f}^* + \bar{\mu}^2}{\sigma_{f^*\mu} + \sigma_u^2 + \sigma_\mu^2 + \sigma_{f^*}^2}\right]$$

While we allow the positive-mean error μ_{it-1} to have covariance $\sigma_{f^*\mu}$ with the true foreclosure rate, f^*_{it-1}, we believe this covariance is small. Our analysis of the data indicates that there is likely a level difference between our foreclosure rate measure and the "true" foreclosure rate as measured by NDS, but not much difference in the time trend. Further, the population mean of the true foreclosure rate, $\bar{f}^*$, must be positive, and by assumption the population mean $\bar{\mu}$ is positive. Therefore, the last term of the expression is very likely positive. This implies that OLS estimates of β_1 are inconsistent, and if the true β_1 is positive, are biased downward. In particular, the larger the population mean of the positive mean error, the larger is the negative bias.

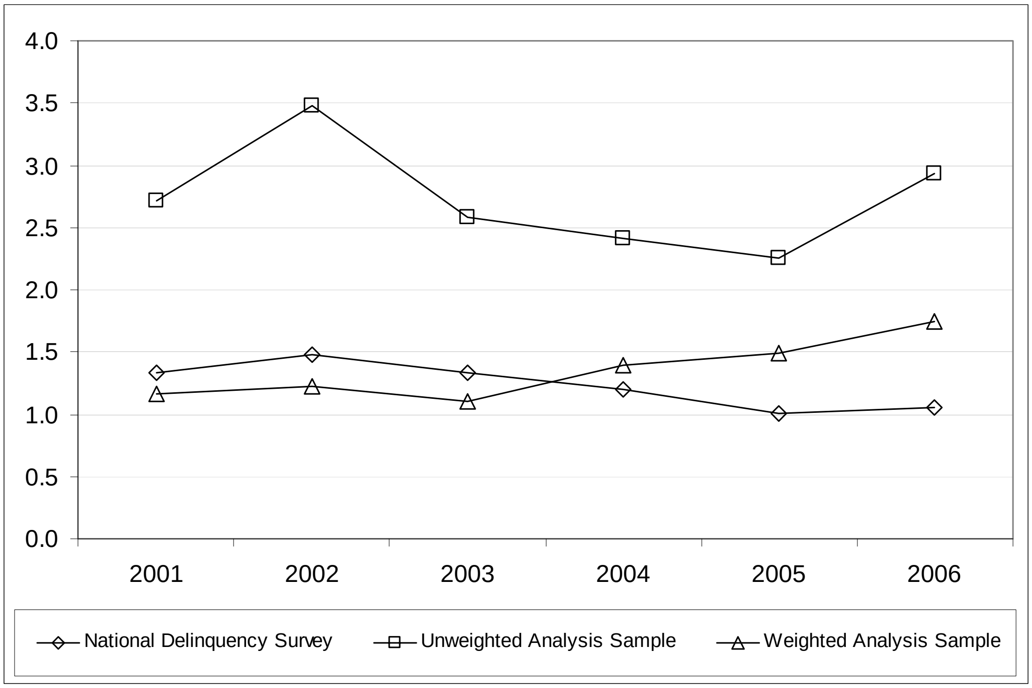
C. Wages of Low-Skilled Men

We estimate weekly log wage rates of low-skilled men by state using a methodology similar to the approach of Gould, Weinberg, and Mustard (2002) Appendix B. Our estimates are based on a sample of men aged 18 to 65 with no college education from outgoing rotation groups of the Current Population Survey (CPS) between 2002 and 2006. Self-employed men are dropped from the sample, as are men who usually work less than 35 hours per week. We make no correction for self-selection of men into the workforce. The wage measure we use is the predicted log weekly wage rate from a regression of wages on education, experience, experience squared, and controls for race and marital status. Years of experience is not directly reported in the CPS, so we define experience equal to age less years of schooling less six. As in Gould, Weinberg, and Mustard (2002), those with top-coded weekly earnings are assumed to have earnings equal to 1.5 times the top-coded value. The estimates are done separately by year. Because county-level geographic information in the CPS is sparsely populated, we compute the mean predicted log wage by state and year. All counties within a state are assigned the same predicted wage rate for each year. For ease of interpretation of our estimates, unlike Gould, Weinberg, and Mustard (2002), we include the predicted log wage directly in our empirical analysis rather than the mean state residuals from the wage regressions. Our results are quite similar if we use the state mean residual wage instead.

D. First-Stage Estimates

Consistent with the theoretical and empirical literature on mortgage default, Appendix Table 2 shows that our instruments are strongly correlated with foreclosure rates. In Column (1) the excluded instrument is the five-year growth rate in the MSA-level real house price index (HPI). The coefficient is negative as expected, verifying that a decrease in HPI is correlated with increased foreclosures. The F-statistic on a test of the null hypothesis that the instrument does not predict foreclosure rates is 90.7. In Column (2) the interaction between HPI and the logged county-level unemployment rate is added as a second instrument. The instruments are jointly significant in the first stage with an F-statistic of 40.4. The estimates in Column (3) are from an alternative specification that additionally includes controls for lagged crime rates. The first stage estimates shown on Columns (2) and (3) are the same. Evaluated at the mean level of log unemployment, the coefficient estimates on the instruments indicate that a one percentage point increase in the HPI is correlated with a decrease in the foreclosure rate of 0.013 percentage points, which is the same as the estimate shown on Column (1) when using only HPI as an instrument. In every case, the F-statistic on a test of the null hypothesis that the instrument(s) can be omitted from the first stage exceeds the critical value benchmarks for weak identification provided by Stock and Yogo (2005). In summary, the power of our instruments in predicting foreclosure rates indicates that our IV estimates do not suffer from a weak instruments problem.

Appendix Figure 1: Share of Loans in Any Stage of Foreclosure, by Data Source



Notes: Share of loans in any stage of foreclosure is equal to the total number of loans in the legal process of foreclosure divided by the total number of active loans; only first-lien mortgages on one-to-four unit residential properties are included in the calculation. "National Delinquency Survey" data are based on annual averages of quarterly national summary data published by the Mortgage Bankers Association. "Analysis Sample" data are national aggregates of our unweighted measure of foreclosure rates, computed using our composite sample of LPS and LP loans. "Weighted Analysis Sample" data are national aggregates of our weighted measure of foreclosure rates, computed using our sample of LPS and LP loans weighted as in Immergluck (2009). See Figure 1 for notes on the NDS.

Appendix Table 1: Active Loans by Type and by Data Source

	Aggregated Loan-Level LPS and LP				National Delinquency Survey				
Year	LPS	LP	Total	Share of Total from LP (%)	Non-Subprime	Subprime	Total	Share of Total from Subprime (%)	Total LPS + LP as Share of Total NDS (%)
2001	1.0	0.8	1.7	44.9	31.8	0.9	32.7	2.7	5.3
2002	1.7	1.3	3.1	43.6	32.6	1.3	33.9	3.8	9.0
2003	5.4	2.1	7.5	28.3	34.1	3.1	37.2	8.4	20.2
2004	10.4	3.1	13.5	22.7	34.5	4.9	39.3	12.3	34.3
2005	20.1	3.1	23.3	13.5	35.7	5.5	41.2	13.4	56.4
2006	20.9	3.4	24.3	14.0	37.5	6.0	43.5	13.7	55.9

Notes: All counts are in millions of loans. The first two columns show the count of owner-occupied, first-lien purchase or refinance mortgages on one-to-four unit residential properties from LPS and LP data, respectively. LPS data include only loans that are not privately-securitized subprime; LP data includes only loans of this type. See Figure 1 for notes on the NDS.

Appendix Table 2: First Stage Estimates, Predicting Lagged Foreclosure Rates

Instrument(s)	(1)	(2)	(3)
HPI	-0.013***	-0.006	-0.006
	(0.001)	(0.004)	(0.004)
HPI * Log Unemployment		-0.004	-0.004
		(0.003)	(0.003)
Control for Lagged Crime	N	N	Y
F-Statistic on Excluded Instruments	90.7	40.4	40.3

Entries in each column are the coefficient estimates from separate first stage regressions of the lagged foreclosure rate on the instruments. HPI is the five-year change in the MSA-level house price index, and HPI * log unemployment is the interaction of HPI and the log county-level unemployment rate, where both HPI and log unemployment are lagged one year. All specifications include the full set of controls shown on Table 2, and year and county fixed effects. In Column (3) the specification also includes aggregate property and violent crime rates lagged one, two, and three years relative to foreclosure rates. Cells weighted by mean county population and standard errors clustered on county. 8,433 observations. At the mean level of log unemployment, the coefficients in specifications (2) and (3) imply that a 1 percentage point increase in HPI is correlated with a decrease in the foreclosure rate of 0.013 percentage points. Standard errors are in parentheses. See Table 2 for additional notes.