Lending Next to the Courthouse: Exposure to Adverse Events and Mortgage Lending Decisions

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Abstract

Adverse market events can affect credit supply not only by hurting financial fundamentals but also by changing the risk-taking behaviors of individual decision makers. In this paper, we provide micro-level evidence of this individual decision-making channel in the U.S. mortgage market. We find that mortgage lending standards are more stringent when loan officers are more exposed to the foreclosure news, despite the same housing market fundamentals and bank characteristics. This effect is through both the extensive margin (higher rejection) and intensive margin (smaller loan size). In the aggregate, it results in significantly tighter credit supply by the affected lending branches.

1 Introduction

In the aftermath of the last foreclosure crisis, intense focus has been centered around how the negative housing market shocks lead to severe credit crunches and adverse real economic outcomes. So far, most of the discussions are concentrated on the relatively macro-level channels, e.g., how financial institutions' deteriorating fundamentals (such as the fall of capital value and the tightening of liquidity constraints) reduce credit supply.[1] Meanwhile, it has also been noted that negative financial and economic shocks could change individuals' subsequent risk-taking behaviors in the financial market by influencing their risk preferences and beliefs (e.g., Malmendier and Nagel, 2011; Guiso et al., 2018).[2] If such individual-level behavioral changes apply generally to the financial professionals who make lending decisions on behalf of the financial institutions, it is plausible that this micro-level lender-decision-making channel can significantly worsen the credit supply contraction and even lead to a recovery slower than what a rational macro-finance model predicts.

Despite the potentially important role of this micro-level lender-decision-making channel in affecting credit supply, identifying it can be empirically challenging. First, adverse events affect not only the risk preferences and subjective risk beliefs of individual loan officers who make lending decisions but also the asset prices and the objective risk prospects of borrowers. It is difficult to distinguish the individual decision-making channel from changes in fundamental credit risk and collateral value. Second, lending decisions and credit supply are jointly affected by the risk-taking behaviors of loan officers and the fundamentals of the financial institutions.

[1] For example, Gan (2007) shows that bank balance sheet losses reduce credit supply to large and small firms, which could affect investment and the real economic growth; Ivashina and Scharfstein (2010), Chava (2011), and Cornett et al. (2011) show that short-term liquidities lead to falling credit supply.

[2] Cohn et al. (2015) and Guiso et al. (2018) show that individual risk aversion is time-varying and increases substantially after an economic bust. The time-varying risk aversion could result from dynamic changes in preferences (e.g., Campbell and Cochrane, 1999; Barberis et al., 2001), subjective beliefs about the future states or the ability of making good decisions (e.g., Greenwood and Hanson, 2014; Koudijs and Voth, 2016; Anagol, Balasubramaniam, and Ramadorai, 2020), and emotional factors (e.g., Barberis et al., 2005; Baker and Wurgler, 2007; Kandasamy et al., 2014).

The tighter lending standards and credit supply after adverse market shocks can be simultaneously driven by deteriorating bank fundamentals and by lowered risk-taking incentives of individual loan officers.

In this paper, we test this lender-decision-making channel by investigating whether exposures to foreclosure-related news influence bank loan officers' mortgage lending decisions and what are the quantitative consequences on credit supply. Our identification strategy stems from a specific feature of the foreclosure process: auctions for foreclosed homes throughout a county are typically conducted live at the county courthouse. Figure A1 in the appendix shows a picture of people gathering at the county courthouse steps for the foreclosure auction. Given this setup, loan officers who work next to the county courthouse can be more aware of the county-wise foreclosure events, compared to their colleagues who are experiencing the same macroeconomic and housing market fundamentals in the same county but who work in places that are not as closely exposed to these events. Based on this within-county comparison in the extent of exposure to the whole county's adverse housing market events, we could test whether the "treated" loan officers tighten the lending standards in response to an escalation of foreclosures, relative to others within the same county and from the same bank.

By comparing mortgage lending decisions by bank loan officers who are heavily exposed to the county-wise foreclosure events with decisions made by otherwise similar loan officers *within* the same county, bank, and year, our identification design addresses the two concerns discussed earlier. First, since the county courthouse takes care of foreclosure auctions for the entire county, loan officers who work next to the courthouse are subject to the same (objective) foreclosure events and housing market fundamentals as the other loan officers in the same county, but given that loan officers next to the courthouses are particularly exposed to the county-wise foreclosure events, these loan officers' subjective risk beliefs and risk preferences would be more affected. This within-county-year comparison pin down the local housing market shocks and macroeconomic conditions that affect asset prices and the objective borrower risk, making it possible for us to focus on the channel that affects lending outcomes through individual loan officers' differential risk-taking behaviors. Second, our micro-level comparison is also made across branches within the same bank. By controlling for bank-year fixed effects, we can tease out any changes in lending outcomes that are driven by changes in the fundamentals of the financial institution and focus specifically on those driven by changes in individual loan officers' behavior.

Based on this identification strategy, we provide evidence that exposures to adverse housing market events affect mortgage lending outcomes by altering bank loan officers' lending behaviors. Using loan-level information of mortgage applications and lending decisions, we compare mortgage lending decisions made by different loan officers from the same bank within the same county and year. We first show that, controlling for loan characteristics, the probability of a mortgage loan application being rejected is on average 106 basis points higher during the foreclosure crisis and the post-crisis period if the application is processed by loan officers in a bank branch next to the county courthouse. This effect is significant not only statistically but also economically, representing an 8.2% increase in rejection rates over the sample mean. The economic magnitude of the effect is as large as if the local tract-level housing price growth rate drops by 1.9 standard deviations or if the county-level foreclosure number increases by 1.5 standard deviations.

More importantly, this "courthouse" effect is not driven by any static differences in lending standards across loan officers. Instead, we show that it comes from their differential "sensitivities" to the foreclosure events: when a county has few foreclosures going on in a given year, loan officers next to the courthouse follow the same lending standards as their other colleagues within the same county and bank; when foreclosure numbers grow and auctions are held more intensively in a county, the salience of these adverse events becomes stronger to loan officers located next to the courthouse, and thus these loan officers tighten their lending standards by more compared to their colleagues. This evidence further corroborates our hypothesis that loan officers choose to take less risk when they are more exposed to the foreclosure-related events.

We also provide more direct evidence that this greater sensitivity of lending decisions to the county-wise foreclosure results from lending decision makers' closer exposure to foreclosure auction events. Specifically, we compare counties that hold foreclosure auctions outside the county courthouse, usually at the steps or in front of the main entrance, where activities can be more easily observed by people nearby, versus counties that hold the auctions online, inside the courthouse, or somewhere else. We find that our results concentrate in the former group: lending decisions are significantly sensitive to the foreclosure events only when they are made next to courthouses in counties where foreclosure auctions are held outside the courthouse. Given that the location and type of a county's foreclosure auction are unlikely to be related to the fundamental economic and housing market conditions of the small neighborhood next to the courthouse, this finding also helps to rule out the potential alternative channels based on unobserved local conditions.

While our identification design allows us to pin down unobserved fundamentals that vary across counties and over time, a potential remaining concern might be that courthouses happen to be in neighborhoods with more vulnerable economic and housing market conditions. We address this concern from four aspects. First, it should be noted that this "courthouse" effect is only observed within a very small range around the courthouse. In fact, it quickly diminishes once the branch is out of the 500m-circle around the courthouse. Second, we show that our results remain qualitatively and quantitatively robust after further controlling for borrowers' census-tract-by-year fixed effects, which fully pin down any static and time-varying economic fundamentals of the very small local neighborhood. Third, we show that the riskiness of applications and the neighborhood economic conditions are not any worse for the next-to-courthouse branches; and more importantly, these factors are not any more sensitive to the county-wise foreclosure intensity compared to those of the control branches. Fourth, we match each treated branch with otherwise similar control branches from the same bank and show that our results continue to hold using the matched sample.

The tighter lending standards are not only observed at the extensive margin through an increase in rejection probability but also at the intensive margin through a downsizing of approved loans. We find that conditional on being approved, the size of mortgage loans also turns out to be significantly smaller if those loans are processed by loan officers working next to the county courthouses and when the county-wise foreclosure intensity is higher.

The higher rejection together with the smaller approved loan size lead to a reduction of credit supply by bank branches next to the county courthouses relative to other branches of the same bank within the same county. Controlling for average borrower characteristics, we show that the total amount of mortgage lending per year is on average 9.5% lower in a next-to-courthouse branch relative to otherwise-similar branches from the same bank and within the same county. Again, this is because the credit supply of these next-to-courthouse branches is more sensitive to the county-wise foreclosure intensity. When the county-level foreclosure rate increases from the 25th to the 75th percentile of the sample distribution, the amount of lending by a next-to-court branch drops by 25.9%, which is 47% larger than the average sensitivity to the county-wise foreclosure shock by the remaining branches of the same bank in the same county.

Since the higher rejection rate results from changes in loan officers' risk-taking behaviors, we expect the results to be stronger for riskier borrowers. This is because the screening of first-mortgage applications[3] is more like a "lemon-dropping" process in which the loan officers accept the majority of the applications but carefully investigate the high-risk ones to decide whether to drop each of them (Bartoš et al., 2016). Under this circumstance, when loan officers are more aware of and therefore more sensitive to the adverse events, they filter out more marginal applications, which are the high-risk ones.[4] We confirm this prediction by showing that the higher

[3] In this paper we focus on mortgage applications for the purpose of home purchases (the first mortgages) and exclude applications for mortgage refinance from our sample to avoid noises brought by government bailout programs through mortgage refinancing such as the Home Affordable Refinance Program (HARP). We discuss our sample construction in detail in Section 3.

[4] On the other hand, if the rejection rate is high and the screening is more like a "cherry-picking" process, then the marginal applications would likely be the relatively low-risk ones.

rejection rate and higher sensitivity to county-wise foreclosure by next-to-courthouse loan officers are most pronounced for applications with high debt-to-income (DTI) ratios and applications from census tracts that are experiencing negative house price growth.

One premise for the exposure to foreclosure events to affect lending outcomes is that lending decisions are made by individual loan officers in the local bank branches, rather than by a higher-level "mortgage center" or by an automatic underwriting system. Since a centralized or automatic system is most likely to be used by large national banks, we expect our results to mainly come from relatively smaller banks, in which local loan officers generally play a more important role in the lending decisions. This is exactly what we find in the data: among branches that locate next to the county courthouses, the higher rejection rate is mainly observed from those branches that belong to the relatively smaller banks, rather than the large national ones.

We also explore what specific screening behaviors by loan officers lead to the change in lending outcomes. When loan officers are more exposed to foreclosure events and tighten the lending standards as a result, they may do so by screening more "carefully", i.e., making more efforts to collect information from the application packages and filtering out more bad applications, or by simply becoming more "conservative", turning down more applications despite the same risk profile of the borrowers. While it is difficult to cleanly distinguish these two types of behaviors, we find suggestive evidence that supports the latter. Specifically, we analyze the denial reasons that loan officers report for each of the loan applications they reject, and find that exposures to foreclosure events increase the use of risk-related reasons such as "debt-to-income ratio", "credit/employment history", "insufficient cash", or "collateral", but not the use of information- or documentation-related reasons such as "unverifiable information" or "credit application incomplete". This suggests that loan officers increase rejection likely because they are less willing to take risk given what they can easily observe, rather than because they spend more efforts to gather information and detect risk.

While the results in this paper are based on very specific comparisons across loan officers, their implication can be much broader: taken together, our results provide micro-level evidence that adverse news can have significant impacts on credit market outcomes by changing the risk-taking behaviors of individual financial decision makers. In a larger framework, what we identify in this paper is only a very specific partial effect of this individual lender-decision-making channel; the overall financial and real consequences of this effect can be of much greater importance in terms of both the coverage and the magnitude.

Our study is part of the literature that discusses how economic and financial market dynamics affect financial outcomes by shaping individual preferences and beliefs. So far, the related studies have documented how the corresponding changes in preferences and beliefs affect individual activities such as investment (Malmendier and Nagel, 2011; Gennaioli et al., 2015; Anagol, Balasubramaniam, and Ramadorai, 2020) and consumption (Agarwal et al., 2021), corporate activities such as cash holding, leverage, and investment (e.g., Bernile et al., 2017), and even analyst forecasts (e.g., Cen et al., 2013). Our study focuses on how adverse market shocks influence bank employees' preferences and beliefs, and how this ultimately affects lending decisions and credit supply.

Our work is also closely related to the literature that explores how the dynamic changes of credit conditions are driven by behavioral factors such as experiences and beliefs. For example, Koudijs and Voth (2016) show that financiers who experience adverse market events lend with increased haircuts even without personal losses; and Chernenko et al. (2016) show that fund managers' investments in high-risk securities are affected by their personal experiences.[5] Our work contributes to these studies by investigating at the micro level how differential exposure to adverse housing market news results in different credit supply outcomes even under the same macroeconomic and financial conditions.

This paper also fits in the broad literature that investigates bank credit activities subsequent to adverse shocks. Most of the existing studies focus on the impacts of adverse shocks on bank

[5] Also, Morck et al. (2013) show that political-driven self-interests by individual bank officers who make lending decisions can also affect credit supply over the business cycle.

fundamentals and the economic and financial consequences, such as the impacts via bank balance sheet losses (e.g., Gan, 2007) and short-term liquidities (e.g., Ivashina and Scharfstein, 2010; Chava, 2011; Cornett et al., 2011). Our study, instead, focuses on the micro-level lending decisions by individual loan officers whose risk preferences or subjective risk beliefs are changed by their exposure to adverse market news.

The paper proceeds as follows. Section 2 discusses the institutional background related with the foreclosure process and our identification strategy based on that. Section 3 presents the data and the sample construction methods. Section 4 reports the empirical results. Section 5 concludes.

2 Institutional Background and Identification Strategy

2.1 Institutional Background

The collapse of the U.S. housing market during the late 2000s led to a nationwide foreclosure crisis over the subsequent few years. In 2008, 1.84% (one in 54) housing units filed foreclosure; this rate increases to 2.23% (one in 45) in 2010.[6] Altogether, about as many as 10 million mortgage borrowers lost their homes over the foreclosure crisis and the post-crisis period.[7] This housing market distress and the massive foreclosure events are believed to have important impacts on the sentiment of consumers and investors, and it could spread to non-housing markets and influence the entire financial system (Chauvet et al., 2013).

The foreclosure process can be briefly summarized in a few steps. First, when a mortgage borrower falls behind with his or her payments for over 120 days, the foreclosure process typically

[6] Source: RealtyTrac 2011 Year-End Foreclosure Report (https://www.realtytrac.com/news/2011-year-end-foreclosure-report-foreclosures-on-the-retreat/).

[7] According to the estimation by the St. Louis Fed (https://www.stlouisfed.org/publications/housing-market-perspectives/2016/the-end-is-in-sight-for-the-us-foreclosure-crisis), the national foreclosure crisis starts from late 2007 and ends in early 2017.

starts with a "breach" letter sent by the bank. If the borrower and the lender cannot reach an agreement on the missed payments, the lender files a lawsuit asking the court for the right to sell the home (in judicial states) or directly sends a notice of sale to the borrower (in non-judicial states).[8] Then the foreclosure sale will be held. The foreclosure sale typically involves a public auction of the foreclosed home, the information of which (the notice of sale) is posted in advance in a public place, usually the county courthouse. In most cases, the foreclosure auction is held live in front of the county courthouse during regular business hours on business days.[9] For example, in Tarrant County, Texas, foreclosure auctions are held every first Tuesday of the month at the base of the courthouse steps.

As the county courthouse holds auctions for foreclosed homes from all across the county, these events should reflect the housing market fundamentals of the entire local county. However, since the auction events are concentrated in one single location, they can become more salient to people who live and work in that specific neighborhood, compared to people in other places within the same county. Specifically, people who work right next to the county courthouse are likely to have greater chances to witness the foreclosure-related events. As a result, these people may increase their probability weights on future negative housing market shocks, driven by the availability bias (Tversky and Kahneman, 1973; Bordalo et al., 2012); or they may have their risk tolerance reduced, as a result of negative sentiment (Guiso et al., 2018).

All these effects would lead to heightened risk aversion, and for loan officers who work in bank branches located next to the county courthouses, this can translate to: 1) less lenient lending standard on average compared to their colleagues who work elsewhere; and 2) greater sensitivity

[8] See Agarwal et al. (2018) for other aspects of the foreclosure process.

[9] This happens even in non-judicial states where the foreclosure itself does not need to be filed to the court. For example, see the California foreclosure process at https://www.propertyshark.com/info/foreclosure-process-california/. We also confirm this by searching for the locations of forthcoming foreclosure auctions of non-judicial states on major real estate platforms such as RealtyTrac and Zillow.

to the county-wise foreclosure intensity, i.e., lending standards would be especially tight by loan officers next to the courthouse when the county is experiencing a large number of foreclosures.

2.2 Identification Strategy

This within-county concentration of foreclosure auctions and its differential impacts on different people's "subjective" exposure to the county-wise housing market shocks lead to two baseline implications. We test these two implications to identify how adverse housing market shocks affect lending outcomes and credit supply by changing individual loan officers' behaviors.

First, since greater exposure to the concentrated foreclosure events can result in heightened risk aversion, we should expect that loan officers working in branches next to the county courthouses are on average more conservative when making lending decisions during the foreclosure crisis and the post-crisis period. Based on this idea, we compare lending decisions made by those next-to-courthouse loan officers with decisions made by other loan officers within the same county and from the same bank, and we expect loan applications processed by the former to face higher probability of rejection:

$$Rejection_{ijbct} = \beta_1 \times Courthouse_{jc} + X_{it} + X_{jt} + \alpha_{ct} + \alpha_{bt} + \epsilon_{ijbct}, \tag{1}$$

where $Rejection_{ijbct}$ is the decision outcome for mortgage application i from county c in year t, which is process by the loan officer in branch j of bank b. It takes the value one if the application is rejected and zero otherwise.[10] $Courthouse_{jc}$ is a dummy variable indicating whether branch j where the loan officer works is next to the courthouse of county c.[11] X_{it} is a vector of loan-specific characteristics such as the debt-to-income ratio (DTI), the race/ethnicity of the borrower, lien of the loan, and the housing price growth of the census tract where the applicant is located.

[10] Given the large sample size and high dimensions of fixed effects in our specification, we use linear probability model for our estimation. Consistent results are found when the sample is aggregated at the branch level and the continuous rejection rate is estimated.

[11] We discuss in detail on how we define this indicator variable in Section 4.

X_{jt} is a vector of bank-branch-specific controls, including the house price and income growth of the zip code where the branch locates, the log population of the specific zip code, as well as the log deposit of the branch and an indicator whether the branch is the head branch of the bank. α_{ct} and α_{bt} are the county-year and bank-year fixed effects, which control for all static and dynamic county-specific economic conditions and bank-specific financial fundamentals. The coefficient of interest is β_1, which is expected to be positive as lending standards are tighter by loan officers who work next to the courthouse.

Furthermore, for this effect to be meaningful, loan officers need to be exposed to enough foreclosure auction events. If a county has a healthy housing market and thus not many foreclosures are going on, then neither loan officers next to the courthouse nor those who are located farther away would be concerned, and we should observe no difference in lending behaviors between them. If a county is suffering from a large number of foreclosures and a massive number of foreclosure auctions are concentratedly held in the county courthouse, people located next to the courthouse will be more exposed to these adverse events. Loan officers who work near the courthouse are thus more likely to have their risk preferences and beliefs affected.

Therefore, we should expect the lending decisions by next-to-courthouse loan officers are more sensitive to the county-wise foreclosure:

$$\begin{aligned} Rejection_{ijbct} &= \beta_1 \times Courthouse_{jc} + \beta_2 \times Foreclosure_{ct} \\ &+ \delta \times Courthouse_{jc} \times Foreclosure_{ct} + X_{it} + X_{jt} + \alpha_{ct} + \alpha_{bt} + \epsilon_{ijbct}, \end{aligned} \tag{2}$$

where $Foreclosure_{ct}$ measures the foreclosure intensity of county c in year t. Under this specification, the coefficient β_1 estimates the difference in rejection rates for the next-to-courthouse loan officers in a county with zero foreclosure. This coefficient is expected to be close to zero. Intuitively, if foreclosure auctions rarely take place in the county courthouse, then even loan officers working next to this courthouse should feel no big difference about the future housing market prospects compared to their peers within the same county. Instead, we expect the coefficient δ for the interaction term $Courthouse_{jc} \times Foreclosure_{ct}$ to be positive, because a county with higher foreclosure intensity should have more auction events in the courthouse, and exposures to these events by the next-to-courthouse loan officers should have a stronger effect on their risk-taking behaviors when making lending decisions. To put it differently, we can also say that a negative coefficient δ reflects a higher sensitivity to the county-wise foreclosures by lending decision makers who are particularly exposed to the foreclosure-related events.

We should note that the county-year fixed effect α_{ct} controls for the county where the loan applicant locates, while the foreclosure intensity $Foreclosure_{ct}$ measures foreclosures in the county where the nearest courthouse locates.[12] In most cases, the loan applicant and the nearest courthouse are in the same county and $Foreclosure_{ct}$ should be absorbed by the county-year fixed effect α_{ct}. However, there are occasions when the nearest courthouse is in a different county from the one where the loan applicant is located.[13] Given this, the coefficient for $Foreclosure_{ct}$ itself will be estimated despite that the county-year fixed effect α_{ct} is controlled for. Our results are not affected if we exclude these special cases in our sample, as we will show in the regression analysis.

Besides the rejection rate, we also use this specification to analyze other dimensions of the lending behaviors or outcomes, such as the size of approved loans and the denial reasons for loan rejections. We will also aggregate the loan-level information to estimate the overall loan volume for each branch and examine how the aggregate credit supply is affected by exposures to the foreclosure news.

3 Data and Empirical Measures

[12] The nearest courthouse is the one that has the shortest distance to the bank branch j that processes the application i.

[13] For example, the borrower may apply for the mortgage from a branch in a different (but adjacent) county; or a branch close to the county border may be closer to the adjacent county's courthouse than the local county's courthouse. The latter case happens because even for each "control" branch (i.e., a branch that is distant from a courthouse), we need to match it to the nearest courthouse (which can be many miles away) for regression purpose.

The Mortgage Application and Origination Data

In order to examine the impacts of adverse housing market shock on micro-level lending decisions, we utilize the loan-level mortgage application and origination data reported under the Home Mortgage Disclosure Act (HMDA),[14] which requires financial institutions including banks, savings associations, credit unions, and other mortgage lending institutions above certain threshold[15] to disclose basic information about each mortgage application they process. The HMDA data are the most comprehensive source of publicly available information on the U.S. mortgage lending activities. In 2016, it covers about 94% of the estimated mortgage originations of the country.

For each mortgage application, the HMDA data disclose the year of the application, the financial institution that processes it, the dollar amount of the loan, the outcome of the application (whether it is approved or rejected), as well as the basic characteristics of the borrower (such as income, race, and ethnicity) and the loan (such as whether it is a first mortgage for home purchase or a mortgage refinance). The data also specify the geographic location of the property to the census tract level, a small geographic entity that covers about an average of 4,000 people within the county.[16]

We focus on applications of conventional mortgages that are for the purpose of one-to-four family home purchases and exclude applications for mortgage refinance to avoid the influences from government bailout programs during our sample period. We also exclude observations for which borrower characteristics are missing. Additionally, we focus on applications processed by FDIC-insured depository institutions for which the location information of physical branches is

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[14] HMDA is a data collection, reporting, and disclosure statute that was enacted by the Congress in 1975 and expanded in 1988, and the data are used to help determine whether financial institutions are serving the local communities and to identify possible discriminatory lending patterns.

[15] The threshold changes over time. In 2018, depositories with more than $44 million in assets and nondepositories with assets above $10 million or originated over 100 loans in a year are required to report. More details can be found in the Consumer Financial Protection Bureau (CFPB) report: https://files.consumerfinance.gov/f/documents/bcfp_hmda_2017-mortgage-market-activity-trends_report.pdf.

[16] There are 74,134 census tracts defined according to the 2010 census in the U.S., about 25 per county on average.

available. Our sample period includes the foreclosure crisis and post-crisis years from 2008 to 2016, during which the sample includes about 3,500 to 4,000 lenders.[17]

Local Housing Market and Income Data

The county-level foreclosure intensity is measured by the average log number of foreclosure cases per 10,000 homes within the county per month in a specific calendar year.[18] This information is reported by Zillow, and it covers 541 populous counties from major metropolitan areas across 44 states. These counties account for about 1/3 of the loan records in our HMDA loan sample.

We collect house price data for each census tract where the underlying property of the mortgage is located and for each zip code where the bank branch is located. This information is from the Federal Housing Finance Agency (FHFA) House Price Index, which is a weighted, repeat-sales index for single-family homes. We also collect income data at each zip code from the SOI Tax Stats by IRS, which report the average adjusted gross income across individual income tax filers.

Location and Distance Information

In order to determine which loan applications are processed next to the county courthouses, we need to know the location for each bank branch that handles the loan application and the location for the courthouse of each county, as well as the distance between each branch-courthouse pair.

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[17] Auclert et al. (2019) show that the average county-level foreclosure rate went up substantially starting the last quarter of 2007 and remained high until 2013.

[18] Note that there is only one number reported for each county each year. We use monthly averages because Zillow reports the foreclosure data at monthly frequencies and in some years we do not observe the data for all 12 months (usually at the beginning or end of the sample period for each county). This is equivalent to using the annual foreclosure number by multiplying the average monthly number by 12. To include observations with zero foreclosures, we calculate the log foreclosure as *log(1+actual foreclosure number)*.

For the branch location, we use information from the Summary of Deposits (SOD) data provided by the Federal Deposit Insurance Corporation (FDIC). For each branch of the FDIC-insured depository institutions, the SOD data report the annual deposits and other basic information including its location, which is specified by its latitude and longitude.

For the courthouse location, we search for the location of each county courthouse as reported in Google Map. We calculate the geodesic distance between each branch and its closest courthouse using the Vincenty's formulae, which are widely used in geodesy, with accuracy to within 0.5 mm on the Earth ellipsoid. Across our sample branches, the median distance to the nearest county courthouse is 12 kilometers. About 5.3% of these branches are located within 1,000 meters from the nearest courthouse, and about 3.4% are within 500 meters.

Since the HMDA data only report which bank processes the mortgage application but not the specific branch, we assume each application is submitted to the nearest branch of the corresponding bank.[19] The nearest branch is identified by calculating the distance between the location of the branch and the location of the mortgage applicant, which is approximated by the center of the census tract to which the applicant belongs.[20]

Our ultimate sample has 1,471,410 loan records from 2008 to 2016. These are mortgage applications for home purchase purpose that are submitted to depository institutions, and they have non-missing borrower characteristics and local housing market and income information. These loans involve 42,374 branches from 3,044 institutions, and sum to an average of $50 billion per year.

Summary Statistics

[19] Recent studies such as Berger (2016) and Nguyen (2019) show that bank branches in the very local neighborhood play a predominantly important role in providing mortgage and small business credit.

[20] We exclude loans that are out of driving distance from even the nearest branch of the corresponding bank, as such loans are likely applied for remotely (e.g., through online application) and thus the loan officer who processes the loan is likely not in the nearest branch. In the current empirical analysis, we exclude loans that are over 200km (about a two-hour drive) away from the nearest branch. The results are robust to using alternative cutoffs including 100km, 50km, and 10km.

Table 1 reports the summary statistics at different aggregation levels. At the loan level, the overall rejection rate is 13%, as applications for home-purchase mortgage loans generally have a lower rejection rate than those for mortgage refinance or other purposes. Average debt-to-income ratio is about 2.5, suggesting that the loan size is about 2.5 times as large as the annual income of an average applicant. Approximately 83% applicants are white, and 6.8% are Hispanic. Average house price growth (both across census tracts of the properties and across zip codes of the branches) is close to zero due to a mix of negative and positive growth across localities and over time, and the average income growth across the branch zip codes is 2.4%.

Across the sample county-year pairs, we measure the foreclosure intensity using the log number of average monthly foreclosures per year per 10,000 homes. Its mean is 0.956, which indicates that on average about 31 out of 10,000 homes are foreclosed in a county per year. The foreclosure number varies across counties and over years, and its variation allows us to estimate the sensitivity of lending decisions to the foreclosure intensity.

[Place Table 1 about here]

4 Empirical Results

4.1 Lending Decision Outcomes

4.1.1 Baseline Analysis

Our basic hypothesis is that loan officers next to the county courthouses have a greater mortgage rejection rate during the foreclosure crisis and the post-crisis period, because these loan officers are particularly exposed to news about the county-wise foreclosure shocks, which heightens their risk aversion when they make lending decisions. To test this hypothesis, we follow the specification in Equation (1) and regress the decision outcome of each mortgage loan application on the next-to-courthouse indicator.

Before we start the regression analysis, we need to identify the mortgage applications that are processed by bank branches that are considered "next to" the county courthouses. In most of our estimations, we define the next-to-courthouse branches as the ones within 500 meters from each courthouse. That is, we draw a 500m-radius circle with the courthouse in the center, and branches that fall into this circle are considered to be next to the courthouse. These branches are typically about one to two blocks away, and people who work in these branches could easily pass by the courthouse every day when they come to work, go to lunch or coffee, and go back home. Figure 1 illustrate how this 500m-circle looks like in the map by showing the example of Miami County, FL. We also try to use alternative distance cutoff points as discussed below.

[Place Figure 1 about here]

Table 2 reports the regression results of the baseline tests. With county-year and bank-year fixed effects, which control for all time-varying macroeconomic and housing market conditions in the local county and financial fundamentals of the lending institution, a mortgage loan applied in a next-to-courthouse branch faces a 58 basis-point higher probability of being rejected (Column 1). When we further include loan-level controls (Column 2) and branch-level controls (Column3), this effect increases to 106 basis points. Note that this is an economically important magnitude, representing an 8.2% increase in rejection rates over the sample mean. The economic magnitude is as large as if the local census tract house price growth drops by 1.9 standard deviations or if the local county-level log foreclosure number increases by 1.5 standard deviations.[21]

Since the county-year fixed effects are included in the regressions, we are comparing the differential lending decisions made within the same county; this higher rejection rate by those next-to-courthouse branches is thus not driven by any differences in local macroeconomic fundamentals or housing market conditions. Furthermore, since the bank-year fixed effects are

[21] The local census tract house price growth is one of the loan-related control variables. Its coefficient in the regression (which is not reported in the table due to space limit) is 0.0622. The effect of county-level foreclosure will be tested in the next table. Its coefficient is 0.0096.

also controlled for, we are comparing across lending decisions within the same bank, so this result is not driven by the different financial fundamentals across different financial institutions.

The higher rejection rate next to the county courthouses is robust when we use a smaller cutoff for the distance measure. Column (4) reduces the range of next-to-courthouse branches to within 300 meters from the courthouses, and the results are similar. In fact, Column (5) shows that the effect on mortgage rejection is observed both within the 300m circle and among those within 300-500 meters.

On the other hand, this effect quickly vanishes when we expand the range from 500 meters to 1,000 meters. Although we still find a significantly higher rejection rate among all observations within the 1,000m circle (Column 6), this result is driven by those within 500 meters. If we split the 1,000m circle into two parts, the 500m inner circle and the 500-1,000m ring, as shown in Column 7, we find that only observations within the 500m inner circle have significantly higher rejection rate, while the rejection rate for observations in the 500-1,000m ring is not significantly different from the remaining observations that are farther away. Given that this effect is mainly identified within a narrow range around the courthouse and quickly dissipates once we expand this range, it is unlikely that our result is driven by any fundamental differences in the whole neighborhood of the courthouse.

[Place Table 2 about here]

Since this cross-sectional difference in mortgage rejection rate is driven by lending decision makers' exposures to foreclosure-related activities, we should expect to only observe it in counties that are experiencing foreclosures. The higher the foreclosure intensity is, the larger the difference in rejection rate should be. We test this finer hypothesis based on the regression specification in Equation (2), which interacts the next-to-courthouse dummy with the county-level foreclosure intensity measured by the log number of average monthly foreclosures per 10,000 homes in the year. We report these results in Table 3.

Column (1) in Table 3 shows that a higher county-level foreclosure intensity is related to a higher mortgage rejection rate. This simple positive relation suggests that the local housing market condition, especially its downside risk measured by foreclosures, is an important fundamental factor that affects mortgage lenders' objective risk assessments and their lending decisions. However, Column (2) further shows that when the application is processed in a bank branch next to the county courthouse, the county-level foreclosure intensity raises mortgage rejection rate by more than twice as much as in other branches within the same county and from the same bank. This suggests that loan officers next to the county courthouses are more "sensitive" to the foreclosure events across the entire county. Given that these next-to-courthouse loan officers are exposed to the same objective local housing market condition as their peers, the difference in their sensitivity to the county-level foreclosure intensity reflects the fact that foreclosure auctions held at the county courthouses are particularly salient to lending-decision makers nearby.

Another equally interesting way to interpret this result is that loan officers next to the courthouses only have different lending behaviors when there are a large number of foreclosure events going on, i.e., only when their exposure to the foreclosure events is intensive enough. In fact, now the coefficient for the next-to-courthouse dummy itself, which reflects the average effect in zero-foreclosure counties, is no longer significant. When the county-level log number of foreclosures increases from the 25^{th} to the 75^{th} percentile of the sample distribution, the "courthouse" effect, which is captured by the difference in mortgage rejection rate between the next-to-courthouse observations and the others within the same county and processed by the same bank, becomes 116 basis-point larger.

Again, this result is robust when we include loan-level controls (Column 3) and branch-level controls (Column 4). We also show in Column 5 that similar to what we find in the last test, the effect diminishes once we move a bit away from the courthouse: while loan officers within the 500m circle around the courthouse are significantly more sensitive to the county-wise foreclosures, loan officers within the 500-1,000m ring do not act differently compared to their colleagues farther away.

It should be noted again that in this test, the foreclosure intensity measure is based on the foreclosure number of the county where the corresponding courthouse is located, as it is used to infer the intensity of foreclosure auctions held in the courthouse. For mortgage applications, the nearest courthouse is the one that has the shortest distance to the bank branch that processed the application, and in some cases, especially those applications processed in branches that are not close to any county courthouse, the nearest courthouse can be in a different county from the one where the applicant is located (e.g., if the branch is located near the county border and is closer to the courthouse of the neighboring county than its own county). Given the existence of such cases, the county-year fixed effects, which control for each borrower's location, do not fully absorb the foreclosure measure in the courthouse county. These special cases do not affect our results, as we show that the result is both qualitatively and quantitatively similar when we only focus on applications for which the nearest courthouse and the borrower are located in the same county (Column 6).

[Place Table 3 about here]

When foreclosure-related activities are held outside the courthouse, usually at the steps or in front of the main entrance, they can be easily observed by people nearby and influence their risk perception about the mortgage market. In contrast, if foreclosure auctions are held online, then the influence on people's risk perceptions should not vary across physical locations. Similarly, if the auctions are held at the courthouse but indoor, the related activities may not be as easily observed, and thus the effect can be less clear. Since the premise of the courthouse effect is that foreclosure-related activities can be observed by people who make lending decisions, we should expect our results to mainly come from counties that hold foreclosure auctions outside the county courthouse.

To test this conjecture, we define two separate indicators, one capturing the lending decisions made next to the courthouse of a county with outdoor auctions ("*Distance to Court <500m, Outdoor Auction*") and the other capturing the lending decisions made next to the courthouse with other types of auctions (("*Distance to Court <500m, Other Types of Auction*").

Applying these two indicators in a regression similar to Equation (2), we show in Table 4 that mortgage rejection rates are significantly more sensitive to county-wise foreclosures only when the lending decisions are made next to a courthouse that hold foreclosure auctions outdoor. Taking the point estimates in Column (3) as an example, when the county-level foreclosure increases from the 25^{th} to the 75^{th} percentile of the sample distribution, the rejection rate is 293 basis points higher if the lending decision is made next to a courthouse with outdoor foreclosure auctions. In contrast, the rejection rate only increases by 71 basis points next to a courthouse with other types of foreclosure auctions, and this latter effect is not statistically significant.

The findings in Table 4 further corroborate that lending decisions next to the courthouses are more stringent because loan officers nearby are more exposed to the foreclosure events, not because areas next to the courthouses have any special features that lead to different lending decisions. Given that the location of foreclosure auctions is unlikely to be related to the fundamental characteristics of the local neighborhood next to the county courthouse, the differential effects across counties with different auction types can help us rule out the potential alternative explanations based on unobserved local conditions.

[Place Table 4 about here]

4.1.2 Heterogeneities across Borrower Risk and Bank Size

Our baseline analysis shows that loan officers next to the county courthouses are more sensitive to the county-wise foreclosures because they are particularly exposed to the foreclosure events. A further implication would be that these loan officers are especially more sensitive when they are screening the high-risk applications. In other words, we expect our results to be more pronounced for lending decisions on the high-risk applications. The rationale is as follows: the overall low rejection rate suggests that loan officers are doing a "lemon dropping" when screening the mortgage applications in our sample. This means that the majority of the applications (those without the highest risk) in the pool will be easily accepted, while loan officers focus on the high-risk applications and make effort to filter out the bad ones and reject them (Bartoš et al., 2016). When loan officers have heightened risk aversion, they will drop more marginal applications, and these marginal applications are the ones with relatively high risk. Therefore, we should expect to observe low-risk applications not much affected by loan-officers' changing risk preferences and beliefs, as these applications would always be accepted; it is the high-risk applications that will face a higher probability of rejection.

We first measure the riskiness of each mortgage application by its borrower's debt-to-income (DTI) ratio, which is commonly used to measure the borrower's credit risk by lenders, investors, and regulators. We split our sample into two subgroups, the low-DTI group with DTI ratio below the sample median and the high-DTI group with DTI ratio at or above median. We then repeat our baseline tests in Specification (2) for each of the subsample separately. These results are reported in Table 5.

We see from the estimates in Table 5 that the effect is only significant among the mortgage applications with above-sample-median DTI. The coefficients in Columns 1-3 show that when the county-level log foreclosure number increases from the 25th to the 75th percentile of the sample distribution, loan officers next to the county courthouses only increases rejection rate by 56-65 basis points more relative to their same-county, same-bank peers, and this effect is not statistically significant. In contrast, the results are strong and statistically significant among the high-risk mortgage applications with DTI ratios above the sample median. According to Columns 4-6, an increase in county foreclosure from the 25th to the 75th percentile widens the gap between the next-to-courthouse rejection rate and that for the remaining sample by 129-184 basis points.

[Place Table 5 about here]

Besides the debt-to-income ratio, we also measure the risk of the mortgage applications by looking at the housing price trend of the small neighborhood where the underlying property is located. If housing prices in a census tract decrease more significantly in a year during the foreclosure crisis or post-crisis period, it is likely that mortgage applications from this tract would be considered more risky, due to the momentum of the fundamental housing market trends and people's potential over-extrapolation (Greenwood and Shleifer, 2014). Based on this idea, we split our sample into two groups, one with positive census tract-level house price growth in a year and the other with negative growth. Since the median growth is around zero, these two subgroups each count for about half of our whole sample.

Table 6 reports the regression results for these two subsamples separately. Consistent with our hypothesis and previous findings, the results are strong and statistically significant among mortgage applications from negative-growth tracts (Columns 1-3). For an increase in county foreclosure from the 25th to the 75th percentile, loan officers next to the county courthouses increase rejection rates by 110-139 basis points more relative to their peers within the same county and bank. However, from tracts where the housing markets are not suffering (i.e., the house price growth remains positive), we see no difference in rejection rates by the next-to-courthouse loan officers and the non-close ones, no matter how high the county-wise foreclosure rate is (Columns 4-6).

[Place Table 6 about here]

Since we are exploring a mechanism that affect lending outcomes through changes in individual loan officers' risk-taking behaviors, our results should only hold when individual loan officers have discretion on the mortgage lending decisions. In addition, since our identification is based on the geographic location of bank branches that affect loan officer behaviors, our results should only hold when the decisions are made at the branch, rather than in a higher hierarchy of the institution. These two assumptions suggest that the effect should only be observed when the lending decisions are made decentralized at bank branches, and when the decisions are made by human beings, rather than by any automatic risk management system.[22] These two premises imply that our results should be mainly driven by the relatively small banks rather than the large national ones, as the latter are more likely to have centralized "mortgage centers" that process

[22] See Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2020) for discussions on the role of automatic risk management systems in mortgage underwriting.

mortgage applications from multiple localities, and these banks are also more likely to apply automated algorithms in their decision-making process.

This conjecture is confirmed in the data as reported in Table 7: by splitting our sample into two groups based on the size of the lending banks, we find our results much more pronounced in the subsample of applications processed by banks with asset size below $10 billion. Among the mortgage applications processed by branches in these relatively smaller banks, the difference between the next-to-courthouse rejection rate and the rejection rate for others increases by about 179-193 basis-point when the county foreclosure increases from the 25th to the 75th percentile of the sample distribution (Columns 1-3). On the other hand, the results are weaker and not statistically significant in the subsample of applications processed by banks with asset size above $10 billion (Columns 4-6).

[Place Table 7 about here]

It should also be noted that also the recent development of financial technologies makes the mortgage lending process more and more centralized, there still remains significant dispersions in approval standards across branches within the same bank, which suggests that local loan officers still have discretions in making lending decisions. In fact, conditional on all other observables, the average difference in rejection rate between the 25% and 75% branches within the same bank, county, and year is still as high as 20.6 percentage points.

4.1.3 Robustness Checks

Since we are comparing the differential responses to the county-wise housing market events by different lenders within each county and within each financial institution, our results should not be driven by unobservable housing market or macroeconomic conditions in the local area at the county level. One remaining concern might be that the county courthouse locations are special in a way that the immediate neighborhoods around them are different from the other parts of the same county in terms of unobserved fundamentals, which might lead to different lending outcomes driven by unobserved differences in borrower or branch characteristics.

We first argue that this is not likely because 1) we not only find a static, cross-sectional difference for lending outcomes next to the courthouses, but also show that this difference increases with the county-wise foreclosure intensity and does not exist without foreclosure shocks in the county; 2) our results are robust after controlling for borrower characteristics and neighborhood housing market and economic conditions; and 3) the "courthouse effect" quickly diminishes once the distance exceeds 500m, a very small range that is supposed to only affect people's exposure to certain events rather than leading to differences in economic fundamentals.

To further rule out this concern, we conduct a few additional analyses in this subsection to validate our identification design and confirm the robustness of our results. First, we show that our results are both qualitatively and quantitatively robust when further controlling for borrower census tract fixed effects (as shown in Table 8). In this way, we are effectively comparing borrowers from the same small neighborhood and showing that even conditional on the same neighborhood fundamentals, borrowers who apply mortgages from a next-to-courthouse branch will still face significantly higher rejection rates when the county-wise foreclosure events are intensive.

[Place Table 8 about here]

Second, we check whether borrower characteristics or neighborhood economic fundamentals are different in places close to the county courthouses and whether they are more sensitive to the county-wise foreclosures. Table 9 reports the results of these tests. Panel A shows that the number of applications, the share of Hispanic applicants, and the neighborhood house price growth are not different around the courthouses (Column 1, 4, and 5). The DTI ratio is lower (Column 2), but this should suggest a lower rejection rate next to the courthouse, not a higher one as we find in the baseline tests. Similarly, we also find the share of white applicants (Column 3) and neighborhood income growth (Column 6) to be higher, which again should lead to a lower rejection rate but not the opposite. We further show in Panel B of Table 9 that none of these factors is more sensitive to the county-wise foreclosure intensity, which suggests that the larger increase in rejection and the greater reduction in credit supply next to the courthouses in response to the foreclosure events are not due to any differential changes in borrower characteristics or neighborhood housing market or economic conditions.

[Place Table 9 about here]

Third, we repeat our main tests by focusing on a subsample of loan records processed by matched branches. For each branch next to the county courthouse, we match it with the three most similar branches from the control group based on the method of nearest neighborhood propensity score matching. The variables used in the matching include local house price and income growth (at zip-code level), as well as deposits and local zip-code population. We first do the matching across the universe of branches in each year and show robust results on rejection rate in the first two columns of Table 10. We then do a stricter matching within each financial institution (thus requiring the matched branches are from the same bank) in each year, and the results are still similar (Columns 3 and 4). In fact, the magnitudes of these coefficients are slightly larger using the matched sample.

[Place Table 10 about here]

In addition, to further address the specific concern that courthouses could be located in neighborhoods that differ in economic fundamentals compared to other locations (e.g., town centers versus rural parts of the county), we show in Table 11 that our results remain very similar when we focus on the subset of neighborhoods that have similar levels (plus or minus 10%) of economic fundamentals to those of the courthouse zip code, as measured by house price, income, or population.

[Place Table 11 about here]

4.2 Denial Reasons

We have shown that the exposures to the foreclosure-related activities can lower mortgage rejection rate by loan officers next to the county courthouses. A related question is what specific changes in their screening behaviors lead to the more stringent lending decisions. There are two potential possibilities. First, when loan officers are more exposed to foreclosure news, they become more "careful" by making more efforts in screening the applications and filtering out more bad applications. In this case, being exposed to the foreclosure news could improve the efficiency of lending decisions. Alternatively, they may simply become more "conservative", rejecting more cases despite the same risk profile of the application packages. If this is what loan officers do, then the efficiency conclusion cannot be easily made, depending on whether loan officers were over-stringent or over-lenient before the foreclosure shocks.

Since the HMDA data report the reason of denial for each rejected application, this information allows us to conduct a preliminary analysis to explore this question. Specifically, the HMDA data report for each rejected application one of the following nine denial reasons: 1) Debt-to-income ratio; 2) Employment history; 3) Credit history; 4) Collateral; 5) Insufficient; 6) Unverifiable information; 7) Credit application incomplete; 8) Mortgage insurance denied; and 9) Other. About 90% of the rejected applications have denials reasons reported, and among them, about 90% of reasons are from one of the first seven.

We can roughly categorize these first seven reasons into two groups. The first group includes the first five reasons, which are mainly related with the applicant's potential credit risk. If a loan officer rejects an additional application because one of these five reasons conditional on the same borrower characteristics (which we control for in the regressions), it is likely that the officer becomes more conservative and is more inclined to reject a loan despite the given risk profile that she can easily observe. Instead, if the additional rejection is due to reason #6 or #7, then it is likely that the loan officer now becomes more careful and works harder to go through the documents in the application package to identify weakness and omissions in documentation.

Our regression results support the conjecture that loan officers turn more "conservative" rather than more "careful". By focusing on the sample of rejected applications, we find in Table

12 that loan officers next to the county courthouses are more likely to choose the first five risk-related denial reasons relative to their non-close peers when the county-wise foreclosure rate is high, controlling for the borrower characteristics and neighborhood housing market conditions (Columns 1-3). In contrast, Columns 4-6 show that these loan officers do not increase their use of the documentation-related reasons.

[Place Table 12 about here]

4.3 Loan Size and Credit Supply

Besides the approval/denial decisions, which affect lending outcomes through the extensive margin, we also ask whether loan officers' exposure to foreclosure events affects the intensive margin by reducing the average size of approved loans. According to our hypothesis that loan officers respond to their observation of foreclosure events by reducing risk taking, it is possible that loan officers will be relatively more willing to accept applications with smaller loan size, conditional on the same applicant income and other risk characteristics.

We test this prediction by focusing on the subsample of approved loans and using the log size of these loans as the dependent variable in the regressions. Table 13 shows that the size of an approved loan is on average about 6-8% lower when it is approved by loan officers next to the county courthouses (Columns 1-3). The approved size of such a loan also drops by more when the county-wise foreclosure intensity is higher (Columns 4-6). Based on the estimates in Column 6, for example, when the log number of county-level foreclosures increases from the 25th to the 75th percentile of the sample distribution, average loan size drops by 8.46% among loans approved next to the courthouses, compared to the 5.15% reduction by the remaining of the sample.

[Place Table 13 about here]

The higher rejection rate at the extensive margin and the smaller approved loan size at the intensive margin together lead to a decline in overall credit supply by branches next to the courthouses relative to other branches of the same bank within the same county, as shown in Table 14, where we aggregate observations at the branch level. Conditional on the log number of applications, the log number of approved loans by a next-to-court branch is 1.25% less than the remaining branches (Column 1), and this number by the next-to-court branch is also almost twice as sensitive to the county-wise foreclosure compared to the non-close branches (Column 2). While these two results basically reflect the change in the approval/rejection decisions as shown in the baseline results, Column 3 shows that the quantity of credit supply is reduced by 9.46%, which reflects the combination of the extensive and intensive margin. Similarly, Column 4 shows that the quantity is 47% more sensitive (8.31% in addition to the 17.61% drop in the control group when foreclosure increases from 25% to 75% of the sample distribution) to the county-wise foreclosure shocks by the next-to-court branches. This result is also robust when using the matched sample, as shown in Table 15.

[Place Table 14 and 15 about here]

5 Conclusion

In this paper, we explore a micro-level behavioral channel through which adverse housing market shocks affect lending outcomes and credit supply. This channel suggests that individuals' exposure to adverse events in the market can affect their financial decision making by changing their risk preferences or beliefs. When this effect applies to individual loan officers who are making lending decisions on behalf of the financial institutions they work for, it could ultimately affect the lending outcomes and credit supply.

Based on a distinctive setup in the foreclosure process, we show that when exposed to foreclosure news, loan officers increase the mortgage rejection rate, and their lending decisions become more sensitive to such events. This effect is especially pronounced for high-risk applications and relatively smaller banks in which manual loan screening at the local branches is more likely. We also show that the higher rejection rate is likely driven by an increase in loan officer conservativeness during the screening process. This effect also results in a reduction in the approved loan size, which, together with the higher rejection rate, leads to a reduction in overall credit supply.

We should note that we cannot make any efficiency conclusion on this reduction in mortgage lending, as it could go either way. On the one hand, if exposures to adverse housing market events make loan officers over-pessimistic and decline too many mortgage applications, this could lead to inefficient lending outcomes and even negatively affect the real economy and the efficiency of monetary policies. On the other hand, if loan officers overall have lax lending standards previously, which is quite likely the case before the housing market collapse, then a tightening in lending standards could actually improve the lending efficiency even when it comes from a behavioral channel.

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Figure 1. Example of Branch and Courthouse Locations

This map illustrates the locations of bank branches and the county courthouse in Miami County, FL. The green dot represents the location of the county courthouse, and the red dots are the bank branches within the 500m circle around the courthouse (see the circle in the zoomed-in map). The yellow dots are the remaining bank branches in this county.

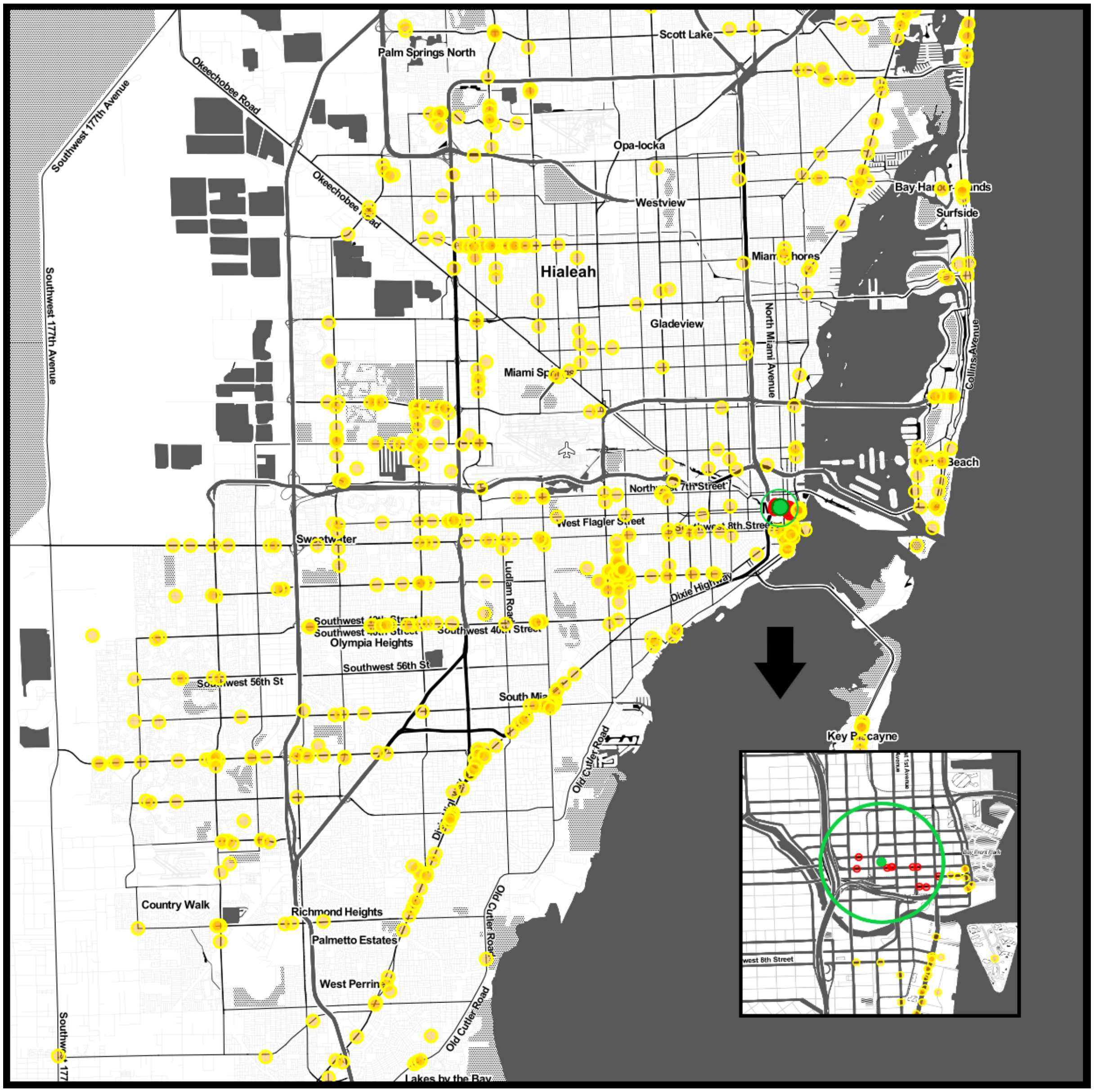

Table 1. Summary Statistics

This table reports the summary statistics of our sample at the loan level, branch level, or county level. *Rejection* is a dummy variable which equals one if the loan application is rejected and zero if the loan is accepted. *Debt-to-Income* is the ratio of loan size to the applicant's annual income reported in the HMDA data. *White* and *Hispanic* are dummy variables indicating the race/ethnicity of the applicant. *Second Lien* indicates whether the mortgage is the second lien rather than the first. *HP Growth (Property Tract)* is the annual growth rate of house prices at the census tract where the underlying property is located, while *HP Growth (Branch Zip)* and *Income Growth (Branch Zip)* are the annual house price and income growth at the zip code where the bank branch is located. *Log Foreclosure* is the log of the monthly-average number (plus one) of foreclosures per 10,000 households in the local county in each year.

	(1) N	(2) Mean	(3) S.D.	(4) P5	(5) P25	(6) P50	(7) P75	(8) P95
Loan-level								
Rejection	1,471,410	0.130	0.337	1	0	0	0	0
Debt-to-Income	1,432,604	2.515	1.536	0.478	1.506	2.362	3.311	4.893
White	1,471,410	0.830	0.376	0	1	1	1	1
Hispanic	1,471,410	0.068	0.251	0	0	0	0	1
Second Lien	1,471,410	0.032	0.175	0	0	0	0	0
HP Growth (Property Tract)	1,471,410	0.000	0.091	-0.140	-0.040	0.002	0.051	0.132
Branch-level								
HP Growth (Branch Zip)	160,082	0.000	0.074	-0.118	-0.038	-0.001	0.043	0.117
Income Growth (Branch Zip)	160,082	0.024	0.063	-0.061	0.000	0.022	0.046	0.112
County-level								
Log Foreclosure (per 10k Households)	5,520	0.956	0.736	0.000	0.325	0.894	1.447	2.279

Table 2. Distance to Courthouses and Loan Rejection

This table reports the baseline regression results that compare mortgage rejection rates by loan officers in branches with different distances to the county courthouses. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. The other distance variables are defined in a similar way. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance to Court <500m	0.0058**	0.0075***	0.0106***				0.0107***
	(0.0029)	(0.0029)	(0.0029)				(0.0029)
Distance to Court <300m				0.0085**	0.0088**		
				(0.0036)	(0.0036)		
Distance to Court <1,000m						0.0076***	
						(0.0021)	
Distance to Court 300-500m					0.0140***		
					(0.0040)		
Distance to Court 500-1,000m							0.0033
							(0.0030)
Loan-level Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Branch-level Controls	No	No	Yes	Yes	Yes	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,468,908	1,430,100	1,424,528	1,424,528	1,424,528	1,424,528	1,424,528
R-Squared	0.071	0.091	0.091	0.091	0.091	0.091	0.091

Table 3. Distance to Courthouses and Sensitivity to Foreclosures

This table test how mortgage rejection rate responds to the county-wise foreclosure intensity differently depending on loan officers' different distances to the county courthouses. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. The other distance variables are defined in a similar way. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Court <500m	0.0058**	-0.0054	-0.0035	-0.0009	-0.0008	-0.0008
	(0.0029)	(0.0048)	(0.0047)	(0.0048)	(0.0048)	(0.0063)
Log Foreclosure	0.0096**	0.0093***	0.0120***	0.0106***	0.0106***	
	(0.0026)	(0.0026)	(0.0025)	(0.0024)	(0.0024)	
Log Foreclosure × (Distance to Court <500m)		0.0103***	0.0101***	0.0104***	0.0104***	0.0108***
		(0.0032)	(0.0032)	(0.0033)	(0.0033)	(0.0038)
Dis. Court 500-1000m					0.0031	
					(0.0050)	
Log Foreclosure × (*Distance to Court 500-1,000m*)					0.0004	
					(0.0039)	
Loan-level Controls	No	No	Yes	Yes	Yes	Yes
Branch-level Controls	No	No	No	Yes	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,468,908	1,468,908	1,430,100	1,424,528	1,424,528	959,127
R-Squared	0.071	0.071	0.091	0.091	0.091	0.088

Table 4. Sensitivity to Foreclosures across Different Auction Locations

This table tests how the baseline results vary across counties with different types of foreclosure auctions. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. *Distance to Court <500m, Outdoor Auction* equals one if the loan is processed in a branch within 500m from the nearest courthouse in a county where foreclosure auctions are held outside the county courthouse. *Distance to Court <500m, Other Types of Auction* equals one if the loan is processed in a branch within 500m from the nearest courthouse in a county where foreclosure auctions are held in other forms (indoor or online). *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	(1)	(2)	(3)	(4)
Distance to Court <500m, Outdoor Auction	-0.016	-0.0153	-0.0119	-0.012
	(0.0130)	(0.0128)	(0.0128)	(0.0128)
Distance to Court <500m, Other types of Auction	0.0005	0.0013	0.0036	0.0036
	(0.0073)	(0.0071)	(0.0074)	(0.0074)
Log Foreclosure	0.0113***	0.0144***	0.0126***	
	(0.0033)	(0.0032)	(0.0030)	
Log Foreclosure, Outdoor Auction				0.0122***
				(0.0028)
Log Foreclosure, Other Types of Auction				0.0154***
				(0.0047)
Log Foreclosure × (Distance to Court <500m, Outdoor Auction)	0.0251***	0.0255***	0.0261***	0.0260***
	(0.0068)	(0.0067)	(0.0066)	(0.0066)
Log Foreclosure × (Distance to Court <500m, Other types of Auction)	0.0043	0.0057	0.0063	0.0064
	(0.0054)	(0.0053)	(0.0055)	(0.0055)
Loan-level Controls	No	Yes	Yes	Yes
Branch-level Controls	No	No	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes
Obs.	1,468,908	1,468,908	1,430,100	1,424,528
R-Squared	0.071	0.071	0.091	0.091

Table 5. Heterogeneities by Debt-to-Income (DTI) Ratio

This table compares loan applications with different debt-to-income (DTI) ratios. The regression specifications are the same as in Table 3, with Columns 1-3 reporting the regression results for the subsample of loan applications with DTI below the median and Columns 4-6 reporting for the subsample with DTI at or above the median. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Low DTI			High DTI		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Court <500m	0.0016	0.0018	0.0046	-0.0144**	-0.0100	-0.0077
	(0.0061)	(0.0058)	(0.0058)	(0.0068)	(0.0071)	(0.0073)
Log Foreclosure	0.0084***	0.0087***	0.0075***	0.0114***	0.0115***	0.0100***
	(0.0027)	(0.0025)	(0.0024)	(0.0038)	(0.0032)	(0.0031)
Log Foreclosure × (Distance to Court <500m)	0.0058	0.0053	0.0050	0.0164***	0.0115**	0.0125**
	(0.0045)	(0.0041)	(0.0041)	(0.0047)	(0.0049)	(0.005)
Loan-level Controls	No	Yes	Yes	No	Yes	Yes
Branch-level Controls	No	No	Yes	No	No	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	712,688	712,688	709,514	713,550	713,550	711,145
R-Squared	0.086	0.094	0.094	0.081	0.125	0.125

Table 6. Heterogeneities by Neighborhood House Price Growth

This table compares loan applications with different neighborhood house price growth. The regression specifications are the same as in Table 3, with Columns 1-3 reporting the regression results for the subsample of loan applications with underlying properties in census tracts that experience negative house price growth, and Columns 4-6 reporting for the subsample in tracts with positive house price growth. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Negative HP Growth (Property Tract)			Positive HP Growth (Property Tract)		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Court <500m	-0.0039	-0.0006	0.0016	0.0028	0.0052	0.0082
	(0.0064)	(0.0068)	(0.0068)	(0.0068)	(0.0069)	(0.0069)
Log Foreclosure	0.0061**	0.0072***	0.0060**	0.0131***	0.0152***	0.0147***
	(0.0030)	(0.0025)	(0.0025)	(0.0033)	(0.0031)	(0.0030)
Log Foreclosure × (Distance to Court <500m)	0.0124***	0.0098**	0.0104**	-0.0024	-0.0039	-0.0040
	(0.0035)	(0.0048)	(0.0047)	(0.0063)	(0.0063)	(0.0063)
Loan-level Controls	No	Yes	Yes	No	Yes	Yes
Branch-level Controls	No	No	Yes	No	No	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	714,514	698,333	695,512	750,731	728,113	725,367
R-Squared	0.083	0.103	0.103	0.070	0.093	0.093

Table 7. Heterogeneities by Bank Size

This table compares loan applications submitted to small versus large banks. The regression specifications are the same as in Table 3, with Columns 1-3 reporting the regression results for the subsample of loan applications submitted to small banks (with asset size below $10 billion), and Columns 4-6 reporting for the subsample submitted to large banks (with asset size equal to or above $10 billion The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Small Bank			Large Bank		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Court <500m	-0.0091	-0.0089	-0.0059	-0.0015	0.0011	0.0035
	(0.0062)	(0.0063)	(0.0063)	(0.008)	(0.0078)	(0.0081)
Log Foreclosure	0.0023	0.003	0.0027	0.0171***	0.0224***	0.0197***
	(0.002)	(0.0019)	(0.0019)	(0.0049)	(0.0047)	(0.0044)
Log Foreclosure × (Distance to Court <500m)	0.0160***	0.0177***	0.0172***	0.0063	0.0052	0.0066
	(0.0054)	(0.0055)	(0.0056)	(0.005)	(0.0045)	(0.0047)
Loan-level Controls	No	Yes	Yes	No	Yes	Yes
Branch-level Controls	No	No	Yes	No	No	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	693,509	673,898	669,388	774,324	755,105	754,043
R-Squared	0.098	0.116	0.116	0.051	0.073	0.074

Table 8. Within-census-tract Tests

This table tests the baseline results by further controlling for census-tract fixed effects. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, and the lien status of the loan. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	(1)	(2)	(3)
Distance to Court <500m	-0.0135*	-0.0143**	-0.0124*
	(0.0076)	(0.0072)	(0.0072)
Log Foreclosure	0.0061**	0.0072***	0.0068***
	(0.0024)	(0.0024)	(0.0024)
Log Foreclosure × (Distance to Court <500m)	0.0132**	0.0143***	0.0141***
	(0.0053)	(0.0052)	(0.0052)
Loan-level Controls	No	Yes	No
Branch-level Controls	No	Yes	No
FE: Bank-Year	Yes	Yes	Yes
FE: Census Tract-Year	Yes	Yes	Yes
Obs.	1,256,092	1,221,082	1,216,723
R-Squared	0.1814	0.2016	0.2019

Table 9. Differences across Branches: Loan Characteristics and Neighborhood Growth

This table tests the potential differences across branches in loan characteristics and neighborhood house price and income growth. Panel A regresses the log number of mortgage applications in each branch (Column 1), the average debt-to-income ratio of the applications (Column 2), the share of white or Hispanic applicants (Column 3 and 4), house price growth in the zip code of the branch (Column 5), and income growth in the branch zip code (Column 6) on *Distance to Court <500m*, which equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. Panel B further include the county foreclosure measure, *Log Foreclosure*, which is the log foreclosure number per 10,000 homes of the courthouse county, and its interaction with *Distance to Court <500m*. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

Panel A	(1) Ln No. Appl.	(2) DTI	(3) White	(4) Hispanic	(5) HP Growth	(6) Inc Growth
Distance to Court <500m	0.0341	-0.0678***	0.0166***	0.0052	-0.0003	0.0049***
	(0.0323)	(0.0184)	(0.0038)	(0.0046)	(0.0007)	(0.0012)
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	154,462	153,299	154,462	154,462	154,462	154,462
R-Squared	0.462	0.321	0.333	0.2829	0.829	0.388

Panel B	(1) Ln No. Appl.	(2) DTI	(3) White	(4) Hispanic	(5) HP Growth	(6) Inc Growth
Distance to Court <500m	0.0318	-0.0647**	0.0152**	-0.0005	0.0014	0.0011
	(0.0484)	(0.0326)	(0.0064)	(0.0051)	(0.0015)	(0.0023)
Log Foreclosure	-0.0763***	-0.1088***	0.0133	0.0052	-0.0055***	-0.0024**
	(0.0280)	(0.0325)	(0.0101)	(0.0100)	(0.0015)	(0.0012)
Log Foreclosure × (Distance to Court <500m)	0.0029	-0.0019	0.0012	0.0053	-0.0015	0.0036
	(0.0359)	(0.0277)	(0.0054)	(0.0060)	(0.0015)	(0.0024)
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	154,462	153,299	154,462	154,462	154,462	154,462
R-Squared	0.462	0.322	0.333	0.2829	0.829	0.388

Table 10. Rejection Rate Based on Matched Samples

This table repeats the main tests based on the subsamples with matched branches. In Columns 1-2 branches are matched within each year; in Columns 3-4 branches are matched within the same bank-year. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. The explanatory variable Distance to Court <500m equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Full-Sample Matching		Same-Bank Matching	
	(1)	(2)	(3)	(4)
Distance to Court <500m	0.0101**	-0.0055	0.0099**	-0.0066
	(0.0049)	(0.0083)	(0.0051)	(0.0095)
Log Foreclosure		0.0168***		0.0028
		(0.0057)		(0.0087)
Log Foreclosure × (Distance to Court <500m)		0.0146**		0.0152**
		(0.0061)		(0.0070)
Loan-level Controls	Yes	Yes	Yes	Yes
Branch-level Controls	Yes	Yes	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes
Obs.	181,491	181,491	88.003	88.003
R-Squared	0.130	0.130	0.119	0.119

Table 11. Tests Based on Neighborhoods with Similar Economic Fundamentals

This table tests the baseline results by focusing on the subsample of branch zip codes that have similar levels of house prices, income, or population compared to the courthouse zip code. The first column is based on the sample of zip codes whose house price level is within plus or minus 10% of that at the courthouse zip code. The samples in columns 2 and 3 are determined in a similar way based on income or population. The dependent variable is the loan-level decision outcome, which equals one if the loan is rejected and zero if the loan is accepted. *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	(1)	(2)	(3)
Distance to Court <500m	-0.0008	-0.0067	-0.0039
	(0.0074)	(0.0067)	(0.0081)
Log Foreclosure	-0.0014	0.0055	0.0003
	(0.0040)	(0.0053)	(0.0051)
Log Foreclosure × (Distance to Court <500m)	0.0139***	0.0158***	0.0120**
	(0.0049)	(0.0049)	(0.0056)
Loan-level Controls	Yes	Yes	Yes
Branch-level Controls	Yes	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes
Obs.	217,637	201,668	156,194
R-Squared	0.1194	0.1218	0.1268

Table 12. Denial Reasons

This table examines the reported denial reasons for each rejected application. The regressions are based on the subsample of loan records that are rejected. In Columns 1-3, the dependent variable is an indicator that equals one if the denial reason is one of reasons 1-5, and zero otherwise. In Columns 4-6, the dependent variable is an indicator that equals one if the denial reason is one of reasons 6-7, and zero otherwise. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Risk-related Reasons			Documentation-related reasons		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Court <500m	-0.018	-0.0162	-0.0162	-0.0013	-0.0007	-0.0015
	(0.0136)	(0.0136)	(0.0137)	(0.0100)	(0.0096)	(0.0098)
Log Foreclosure	0.0084	0.0102*	0.0091*	-0.0033	-0.0045	-0.0034
	(0.0055)	(0.0056)	(0.0055)	(0.0046)	(0.0046)	(0.0045)
Log Foreclosure × (Distance to Court <500m)	0.0174**	0.0157*	0.0177**	-0.0045	-0.0046	-0.0059
	(0.0082)	(0.0085)	(0.0084)	(0.0063)	(0.0062)	(0.0063)
Loan-level Controls	No	Yes	Yes	No	Yes	Yes
Branch-level Controls	No	No	Yes	No	No	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	187,347	180,624	180,051	187,347	180,624	180,051
R-Squared	0.355	0.370	0.369	0.277	0.286	0.286

Table 13. Loan Size

This table tests for the size of the approved loans. The regressions are based on the subsample of loans approved. The dependent variable is the log dollar size of each approved loan. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Court <500m	-0.0844***	-0.0577***	-0.0636***	-0.0391	-0.0277*	-0.0276
	(0.0173)	(0.0099)	(0.0106)	(0.0288)	(0.0156)	(0.0169)
Log Foreclosure				-0.0795***	-0.0590***	-0.0515***
				(0.0201)	(0.0117)	(0.0107)
Log Foreclosure × (Distance to Court <500m)				-0.0493*	-0.0289**	-0.0331**
				(0.0299)	(0.0140)	(0.0169)
Loan-level Controls	No	Yes	Yes	No	Yes	Yes
Branch-level Controls	No	No	Yes	No	No	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,277,185	1,245,107	1,240,097	1,277,185	1,245,107	1,240,097
R-Squared	0.393	0.698	0.699	0.393	0.698	0.699

Table 14. Branch-level Credit Supply

This table estimates the differences in aggregate credit supply by branches with different distances to the county courthouses as well as the differences in the credit supply sensitivity to the county-wise foreclosures. Each observation is a branch-year pair. The dependent variable is the log number or amount of total mortgage lending by each branch in a year. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Log Loan Number		Log Loan Amount	
	(1)	(2)	(3)	(4)
Distance to Court <500m	-0.0125***	0.0016	-0.0946***	-0.0125
	(0.0048)	(0.0087)	(0.0226)	(0.0354)
Log Foreclosure		-0.0155***		-0.1572***
		(0.0058)		(0.0383)
Log Foreclosure × (Distance to Court <500m)		-0.0129**		-0.0742**
		(0.0063)		(0.0289)
Log Number of Applications	Yes	Yes	Yes	Yes
Average Applicant Characteristics	Yes	Yes	Yes	Yes
Branch-level Controls	Yes	Yes	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes
Obs.	152,677	152,677	152,677	152,677
R-Squared	0.943	0.943	0.696	0.696

Table 15. Branch-level Credit Supply Based on the Matched Sample

This table repeats the branch-level tests based on the subsamples with matched branches. In Columns 1-4 branches are matched within each year; in Columns 5-8 branches are matched within the same bank-year. Each observation is a branch-year pair. The dependent variable is the log number or amount of total mortgage lending by each branch in a year. The explanatory variable *Distance to Court <500m* equals one if the loan is processed in a branch within 500m from the nearest courthouse, and zero otherwise. *Log Foreclosure* is the log foreclosure number per 10,000 homes of the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, race/ethnicity of the borrower, the lien status of the loan, and house price growth of the census tract where the borrower is located. Branch-level controls include house price growth and income growth of the zip code where the branch is located, log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroscedasticity-robust standard errors (clustered at the county level) are reported in the parentheses. Statistical significance is indicated by "***" at the 1% confidence level, "**" at the 5% level, and "*" at 10% level.

	Within Year				Within Bank-year			
	Log Loan Number		Log Loan Amount		Log Loan Number		Log Loan Amount	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to Court <500m	-0.0148*	0.0082	-0.1252***	0.0101	-0.0150*	0.0016	-0.0862**	0.0342
	(0.0080)	(0.0141)	(0.0348)	(0.0624)	(0.0088)	(0.0155)	(0.0382)	(0.0605)
Log Foreclosure		-0.0292**		-0.1470**		0.0176		0.0163
		(0.0129)		(0.0604)		(0.0138)		(0.0801)
Log Foreclosure × (Distance to Court <500m)		-0.0218**		-0.1285***		-0.0155		-0.1110**
		(0.0099)		(0.0486)		(0.0129)		(0.0489)
Log Number of Applications	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average Applicant Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Bank-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: County-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,764	15,764	15,764	15,764	10,846	10,846	10,846	10,846
R-Squared	0.950	0.950	0.751	0.751	0.946	0.946	0.739	0.739

Figure A1. Picture of Foreclosure at County Courthouse Steps

This figure shows people gathering at the courthouse steps for the foreclosure auction in Fulton County, GA in May 2013. The picture is a screenshot from the YouTube video https://www.youtube.com/watch?v=21jyO2hhkrY.