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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. We provide micro-level evidence of this individual decision-making channel in the U.S. mortgage market. We find that mortgage application rejection rates are more sensitive to foreclosure intensity when loan officers are more exposed to foreclosure news, despite the same housing market and bank fundamentals. Loans originated from the affected branches have lower ex post default rates, consistent with higher lending standards being applied. In the aggregate, this effect results in tighter credit supply during housing market downturns.

I. Introduction

In the aftermath of the 2008 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, for example, how financial institutions' deteriorating fundamentals (such as the fall of capital value and the tightening

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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, Sapienza, and Zingales (2018)).[2] If such changes in risk-taking apply to the financial professionals who make lending decisions on behalf of the financial institutions, it is plausible that this micro-level risk-taking-behavior channel can significantly worsen the credit crunch and even lead to a recovery slower than what a rational macro-finance model predicts.

Despite the potentially important role of this micro-level risk-taking-behavior channel in affecting credit supply, identifying such an effect can be empirically challenging. First, adverse events driven by market fundamentals affect not only the risk preferences and subjective risk beliefs of lending decision-makers, but also the asset prices and the objective risk prospects of borrowers. It is difficult to distinguish lenders' risk-taking behaviors from changes in borrowers' fundamental credit risk and collateral value. Second, lending decisions and credit supply are jointly affected by the risk-taking behaviors of individual lending decision-makers (e.g., loan officers) and the fundamentals of the financial institutions. 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 those individual decision-makers.

In this article, we test this micro-level risk-taking-behavior channel by investigating how exposures to foreclosure-related news influence mortgage lending decisions, the quantitative consequences on ex ante credit supply, and the real impact on ex post loan performance. 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 IA1 in the Supplementary Material shows a picture of people gathering at the county courthouse steps for the foreclosure auction. Given this practice, we conjecture that loan officers who work next to the county courthouse can be more aware of the county-wide foreclosure events, compared with 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 saliently exposed to these events. Based on this within-county comparison in the different extent of *subjective* exposure to the same *objective* county-wide adverse housing market events, we could test

[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 and Purnanandam (2011), and Cornett, McNutt, Strahan, and Tehranian (2011) show that short-term liquidities lead to falling credit supply. In addition, Agarwal, Deng, Luo, and Qian (2016) show that the fundamentals of housing investors can trigger subsequent crashes of the local housing and mortgage markets.

[2]Cohn, Engelmann, Fehr, and Maréchal (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, Huang, and Santos (2001)), subjective beliefs about the future states or the ability of making good decisions (e.g., Greenwood and Hanson (2015), Koudijs and Voth (2016)), and emotional factors (e.g., Barberis, Shleifer, and Wurgler (2005), Baker and Wurgler (2007), and Kandasamy, Hardy, Page, Schaffner, Graggaber, Powlson, Fletcher, Gurnell, and Coates (2014)).

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whether lending decisions made in the exposed branches follow tighter standards in response to an escalation of foreclosures, relative to those made in otherwise similar branches within the same county and from the same bank.

Our empirical analysis examines more than 1.2 million mortgage loan applications using the confidential version of the Home Mortgage Disclosure Act (CHMDA) data from the Board of Governors of the Federal Reserve System. Based on this sample, we provide evidence that exposures to adverse housing market events affect mortgage lending outcomes by altering lending decision-makers' behaviors. Controlling for county-month and bank-month fixed effects which pin down the dynamic local economic conditions and bank fundamentals, the probability of a mortgage loan application being rejected is on average 75 basis points (BPS) higher during the foreclosure crisis and the post-crisis period if the processing branch (i.e., the originating bank's nearest branch) is next to the county courthouse. This effect is significant not only statistically but also economically, representing a 5.7% increase in rejection rates over the sample mean. The economic magnitude of the effect is as large as if the local housing price growth rate drops by 1.12 standard deviations or if the county-level foreclosure increases by 1.05 standard deviations.

More importantly, this "courthouse effect" is not driven by any static differences in lending standards across processing branches. Instead, we show that it comes from their differential "sensitivities" to the foreclosure events: When a county has few foreclosure sales going on in a given month, branches next to the courthouse follow the same lending standards as others within the same county and bank; when foreclosure numbers grow and auctions are held more intensively in a county, these adverse events become particularly salient to lending decision-makers working next to the courthouse, and thus those next-to-courthouse branches tighten lending standards by more. This evidence further corroborates our hypothesis that lending decision-makers choose to take less risk when they are more subjectively exposed to the adverse housing market events. Moreover, we also show that this effect is mostly pronounced in 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 working nearby.

In addition, we find that the higher rejection sensitivity to county-wide foreclosure next to courthouses is most pronounced for marginally riskier applications with high debt-to-income (DTI) ratios or from neighborhoods experiencing negative house price growth. Meanwhile, the effect is more pronounced for jumbo loans that are more likely to be kept on bank balance sheets compared with conforming loans that can be easily securitized and sold. This "courthouse effect" is also stronger for relatively smaller banks, for which local loan officers generally play a more important role in the lending decisions.

We also explore what specific screening behaviors by loan officers lead to the change in lending outcomes. When loan officers tighten lending standards as a result of their exposure to foreclosure events, they may do so by screening more "carefully," that is, making more efforts to collect information and detect risk, or by simply becoming more "conservative," turning down more marginal applications given the information that can be easily observed. By examining the denial reasons reported by loan officers, we find suggestive evidence that supports the latter.

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 loan size also turns out to be significantly smaller if those loans are processed by branches next to the county courthouses and when the county-wide foreclosure intensity is higher.

The higher rejection together with the smaller approved loan size leads to a reduction of credit supply by bank branches next to the county courthouses relative to that within the same county but from a different branch of the same bank. Controlling for average borrower characteristics, we show that the total number and amount of mortgage lending in a next-to-courthouse branch are more sensitive to the county-wide foreclosure intensity.

Lastly, using the Black Knight McDash data on loan performance, we find lower probabilities of bad loan performance when the processing branch is close to the courthouse of a county that has experienced intensive foreclosure sales at the time of approval, a pattern especially pronounced for loans with low documentation or high loan-to-value (LTV) ratios. This result is consistent with the idea that more stringent credit standards are being applied by lenders who are more exposed to salient adverse events such as foreclosure auctions, pointing to a scarring effect that can be self-perpetuating. It also helps to alleviate concerns that the higher rejection rates in those branches are due to unobserved credit quality differences.

Using the mortgage market as a laboratory, our results provide evidence that heightened risk avoidance in the face of a crisis can exacerbate credit contraction and potentially intensify the severity of credit crunches. The confluence of our results is consistent with the notion that the salience of adverse housing market news can magnify risk avoidance that deters credit provision. While a number of existing studies have discussed how time-varying risk aversion by investors can affect investment decisions and amplify asset price volatilities (e.g., Malmendier and Nagel (2011), Cohn et al. (2015), Gennaioli, Shleifer, and Vishny (2015), Chernenko, Hanson, and Sunderam (2016), Koudijs and Voth (2016), Guiso et al. (2018), and Agarwal, Choi, He, and Sing (2019)),[3] our results augment these discussions by presenting the first micro-level evidence on how a scarring effect on lending decision-makers could potentially prolong a credit crunch and delay recovery, highlighting an overlooked amplification mechanism on the credit market that is particularly prominent during economic downturns.

The 2008–2009 crisis was characterized by an unprecedented increase in foreclosures and persistent declines in credit supply, with feedback loops between foreclosures and credit contractions contributing to the severity and duration of the crisis. Against this backdrop, our analysis examines the role of foreclosure externalities: their effect on credit supply, and the extent to which they constitute an amplification mechanism that inhibits recovery. Changes in subjective risk beliefs and aversion driven by exposures to foreclosure news could create a downward

[3]Other studies have examined how idiosyncratic factors that shape preferences and beliefs affect individual activities, including Cen, Hilary, and Wei (2013), Morck, Yavuz, and Yeung (2013), Bernile, Bhagwat, and Rau (2017), Dessaint and Matray (2017), Gu, He, and Qian (2021), and Liao, Wang, Xiang, Yan, and Yang, (2021), among others.

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spiral in credit provision that disproportionally hurts the disadvantaged borrowers. To that end, our article contributes to existing studies on the local effects of foreclosures. Many of these papers examine the price impacts of foreclosures, including Harding, Rosenblatt, and Yao (2009), Campbell, Giglio, and Pathak (2011), Anenberg and Kung (2014), and Gerardi, Rosenblatt, Willen, and Yao (2015), emphasizing the role of foreclosures in aggravating housing downturns through fire-sale dynamics. We add to the literature by presenting a new, behavioral-based channel through which foreclosures affect nearby access to credit.

Our article is also closely related to Cortés, Duchin, and Sosyura (2016), which studies the role of sentiment in mortgage approvals. Whereas Cortés et al. (2016) use local weather as an instrument for sentiment, our article uses exposure to public foreclosure auctions. Distinct from weather, which is related to sentiment more generally and is idiosyncratic to fundamental economic and financial conditions, our article explores sentiment directly related to the housing market, and our novel empirical design allows us to examine the credit consequences by subjective exposures to economic events (i.e., foreclosure auctions) that are endogenous to underlying economic conditions. Our findings uncover an important self-perpetuating mechanism of sentiment that can operate prominently during economic downturns and can exacerbate credit contraction and intensify the severity of credit crunches, thus potentially prolonging economic recovery.

Finally, this article 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 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 and Purnanandam (2011), and Cornett et al. (2011)). Our study, instead, focuses on the micro-level lending decisions when individual decision-makers' risk preferences or subjective risk beliefs are changed by their exposure to adverse market news. What we identify is only a very specific partial effect of this risk-taking-behavior channel; the overall financial and real consequences of its effect can be of much greater importance in terms of both the coverage and the magnitude.

The article proceeds as follows: Section II discusses the institutional background related to the foreclosure process and our identification strategy based on that. Section III presents the data and the sample construction methods. Section IV reports the empirical results. Section V concludes.

II. Institutional Background and Identification Strategy

A. 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% (1 in 54) housing units filed foreclosure; this rate increased to 2.23% (1 in 45) in 2010 (source: RealtyTrac 2011 Year-End Foreclosure Report (https://www.realtytrac.com/news/2011-year-end-foreclosure-report-foreclosures-on-the-retreat/). Altogether, about as many as 10 million mortgage borrowers lost their homes

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over the foreclosure crisis and the post-crisis period.[4] 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 nonhousing markets and influence the entire financial system (Chauvet, Gabriel, and Lutz (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 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 nonjudicial states). 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.[5] For example, in Kings County, NY, foreclosure auctions are held every Thursday morning on the steps of the courthouse.

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 with 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, Gennaioli, and Shleifer (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/or more pessimistic risk beliefs. For loan officers who work in bank branches located next to the county courthouses, this can translate to i) less lenient lending standard on average compared with their colleagues who work elsewhere and ii) greater sensitivity to the county-wide foreclosure intensity, that is, lending standards would be especially tight by loan officers next to the courthouse when the county is experiencing a large number of foreclosures.

B. Identification Strategy

This within-county concentration of foreclosure auctions and its differential impacts on different people's subjective exposure to the county-wide housing

[4]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.

[5]This happens even in nonjudicial 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 nonjudicial states on major real estate platforms such as RealtyTrac and Zillow.

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 lower risk-taking, 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:

$$\text{(1)} \qquad \text{REJECT}_{ijbct} = \beta_1 \times \text{COURTHOUSE\_K}_{jc} + \mathbf{X}_{it} + \mathbf{X}_{jt} + \alpha_{ct} + \alpha_{bt} + \epsilon_{ijbct},$$

where REJECT_{ijbct} is the decision outcome for mortgage application i from county c in month t, which is processed by the loan officer in branch j of bank b. It takes the value 1 if the application is rejected, and 0 otherwise.[6] COURTHOUSE_K_{jc} is a dummy variable indicating whether branch j where the loan officer works is next to (within a distance of K meters) the courthouse of county c.[7] $\mathbf{X}_{it}$ is a vector of loan-specific characteristics such as the DTI ratio, the race/ethnicity of the borrower, the lien of the loan, and the housing price growth of the census tract where the applicant is located. $\mathbf{X}_{jt}$ 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, and the log deposit of the branch and an indicator of whether the branch is the head branch of the bank. α_{ct} and α_{bt} are the county-month and bank-month 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 that the lending decisions by next-to-courthouse loan officers are more sensitive to the county-wide foreclosure:

[6]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.

[7]We discuss in detail how we define this indicator variable in Section III.C.

$$\text{(2)}\quad \text{REJECT}_{ijbct} = \beta_1 \times \text{COURTHOUSE\_K}_{jc} + \beta_2 \times \text{FORECLOSURE}_{ct} + \delta \times \text{COURTHOUSE\_K}_{jc} \times \text{FORECLOSURE}_{ct} + \mathbf{X}_{it} + \mathbf{X}_{jt} + \alpha_{ct} + \alpha_{bt} + \epsilon_{ijbct},$$

where FORECLOSURE_{ct} measures the foreclosure intensity of county c in month 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 0. 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 $\text{COURTHOUSE\_K}_{jc} \times \text{FORECLOSURE}_{ct}$ 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 positive coefficient δ reflects a higher sensitivity to the county-wide foreclosures by lending decision-makers who are particularly exposed to the foreclosure-related events.

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, the denial reasons for loan rejections, and the ex post performance of the approved loans. We 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.

III. Data and Empirical Measures

A. The Mortgage Application and Origination Data

In order to examine the impacts of adverse housing market shock on micro-level lending decisions, we use the confidential data by Federal Financial Institutions Examination Council (U.S.) Home Mortgage Disclosure Act (hereafter CHMDA). The Home Mortgage Disclosure Act requires financial institutions, including banks, savings associations, credit unions, and other mortgage lending institutions above a certain threshold to disclose basic information about each mortgage application they process.[8] The CHMDA data are the most comprehensive source of 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, CHMDA discloses the location 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), and the decision-

[8]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 report at https://files.consumerfinance.gov/f/documents/bcfp_hmda_2017-mortgage-market-activity-trends_report.pdf.

making date (the "action" date), 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 a home purchase or a mortgage refinance). The geographic location of the property is specified at the census tract level, a small geographic entity that covers about an average of 4,000 people within the county.[9] The CHMDA data have been used by related studies that investigate mortgage lending decisions under high-frequency settings (e.g., Cortés et al. (2016), Giacoletti, Heimer, and Yu (2021)).

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 available. Our sample period includes the foreclosure crisis and post-crisis years from 2008 to 2016.[10]

B. Foreclosure Data

Our empirical design is based on monthly variations regarding the intensity of county-wide foreclosure auctions, the timing of which can be inferred from the foreclosure sales records in the housing deeds registry.[11] We measure the monthly intensity of foreclosure using the average log number of foreclosure sales per 10,000 homes in each county between 2008 and 2016.[12] This information is reported by Zillow, and it covers 541 populous counties from major metropolitan areas across 44 states. These counties account for about one-third of the loan records in our CHMDA loan sample.

C. Location and Distance Information

In order to determine which loan applications are processed next to the county courthouses, we need to know the location of each bank branch that handles the loan application and the location of the courthouse of each county, as well as the distance between each branch–courthouse pair. However, the CHMDA data only report which bank processes the mortgage application but not the specific branch. To overcome this data limitation, a key assumption that we make in the article is that each mortgage application is submitted to and processed by the nearest branch of

[9]There are 74,134 census tracts defined according to the 2010 census in the United States, about 25 per county on average.

[10]Auclert, Dobbie, and Goldsmith-Pinkham (2019) show that the average county-level foreclosure rate went up substantially starting in the last quarter of 2007 and remained high until 2013.

[11]It should be noted that the foreclosure process generally takes several months or even years. Thus, the timing of foreclosure filing could be very different from that of foreclosure sales, and the former should not be used for the purpose of our analyses.

[12]Zillow stopped reporting the county-level foreclosure information in recent years. In the data file we obtained from Zillow, it covers the years from 2008 to 2016.

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the corresponding bank (the "processing branch").[13] To identify the nearest branch of each application, we first estimate the distance between the location of the application and the location of each branch of the processing bank, and then find the branch with the shortest distance. For the mortgage application's location, we proxy for it using the center of the census tract at which the property is located.[14] For the branch location, we use information from the Summary of Deposits (SOD) data provided by the 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. Distances are computed using Vincenty's formulae, which are widely used in geodesy, with accuracy to within 0.5 mm on the Earth ellipsoid.

To determine which branches are located next to the county courthouses, we further identify the location of each county courthouse by searching Google Maps. We then compute the distance between each branch–courthouse pair and identify the courthouse with the shortest distance to each branch. Across our sample branches, the median distance between a branch to its nearest county courthouse is 12 km. About 4.6% of our sample branches are located within 1,000 meters from the nearest courthouse, and about 2.9% are within 500 meters.

Our ultimate sample has 1,272,596 loan records from 2008 to 2016. These are mortgage applications for home purchase purposes that are submitted to depository institutions, and they have nonmissing borrower characteristics and local housing market and income information. These loans involve 36,236 branches from 2,534 institutions, and sum to an average of over $40 billion per year.

D. Loan Performance Data

We also measure the performance of each originated mortgage loan using the Black Knight McDash (McDash) data. Similar to Cortés et al. (2016), we measure the ex post loan performance using an indicator that equals 1 if the loan ever experienced bad performance (delinquent, foreclosure, real estate owned (REO), or involuntary liquidation) within the first 2 years since origination. We merge loan observations in the McDash data to those in CHMDA using information such as loan origination date, loan amount, zip code, lien type, loan type, loan purpose, and occupancy type. The merged sample includes the performance records of 461,756 loans, and about 3.7% of them experienced bad performance during the first 2 years of origination. The McDash data also report additional loan characteristics, such as the FICO score, the LTV ratio, and the documentation type.

[13]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.

[14]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 our empirical analysis, we exclude loans that are over 200 km (about a 2-hour drive) away from the nearest branch. The results are robust to using alternative cutoffs such as 50 km or 10 km as reported in Table IA1 in the Supplementary Material.

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E. Local Housing Market and Income Data

We collect annual 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 House Price Index, which is a weighted, repeat-sales index for single-family homes. We also collect annual 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.

F. Summary Statistics

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 a mortgage refinance or other purposes. The average monthly DTI ratio is about 18%.[15] Approximately 82% of applicants are white, and 7% are Hispanic. Average house price growth is close to 0 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-month pairs, we measure the foreclosure intensity using the log number of monthly foreclosure sales per 10,000 homes. Its mean is 0.961, which indicates that on average about 2.6 out of 10,000 homes went to foreclosure sale in a county per month. The number of foreclosure sales varies across counties and over time, and its variation allows us to estimate the sensitivity of lending decisions to the intensity of salient foreclosure news.

TABLE 1

Summary Statistics

Table 1 reports the summary statistics of our sample at the loan level, branch-year level, or county-month level. REJECT is a dummy variable which equals 1 if the loan application is rejected and 0 if the loan is accepted. DTI is the ratio of loan size to the applicant's annual income reported in the confidential version of the Home Mortgage Disclosure Act data. WHITE, HISPANIC, and FEMALE are dummy variables indicating the race/ethnicity/gender of the applicant. SECOND_LIEN indicates whether the mortgage is the second lien rather than the first. BAD_PERFORMANCE is a dummy variable which equals 1 if the loan ever experienced bad performance (delinquent, foreclosure, REO, or involuntary liquidation) within the first 2 years since origination. HP_GROWTH and INC_GROWTH are the house price and income growth at the zip code where the bank branch is located. FORECLOSURE is the foreclosure intensity, measured as the logarithm of the monthly average number (plus 1) of foreclosure sales per 10,000 households in the local county in each month.

	No. of Obs.	Mean	Std. Dev.	*P*5	*P*25	*P*50	*P*75	*P*95
Loan level								
REJECT	1,272,596	0.132	0.338	0.000	0.000	0.000	0.000	1.000
DTI	1,272,596	0.175	0.092	0.021	0.105	0.170	0.240	0.354
WHITE	1,272,596	0.821	0.383	0.000	1.000	1.000	1.000	1.000
HISPANIC	1,272,596	0.071	0.257	0.000	0.000	0.000	0.000	1.000
FEMALE	1,272,596	0.276	0.447	0.000	0.000	0.000	1.000	1.000
SECOND_LIEN	1,272,596	0.031	0.174	0.000	0.000	0.000	0.000	0.000
BAD_PERFORMANCE	461,756	0.037	0.189	0.000	0.000	0.000	0.000	1.000
Branch-year level								
HP_GROWTH	137,847	0.001	0.076	−0.122	−0.038	0.000	0.045	0.120
INC_GROWTH	137,847	0.024	0.064	−0.064	0.000	0.023	0.046	0.112
County-month level								
FORECLOSURE	33,374	0.961	0.808	0.000	0.166	0.904	1.535	2.378

[15]To compute the monthly DTI ratio, we estimate the monthly mortgage payments by assuming that it is a 30-year fixed-rate mortgage with interest rate equal to the sample years' average.

IV. Empirical Results

A. Lending Decision Outcomes

1. Baseline Analysis

We start our empirical analyses with the specification in equation (1) to show that mortgage loan applications processed next to the county courthouses face a higher rejection rate during the foreclosure crisis and the post-crisis period. In most of our estimations, we define the next-to-courthouse branches as the ones within the 500-m-radius circle, which are typically about one-to-two blocks away, around each courthouse. Figure 1 illustrates how this 500-m circle looks like on the map by showing the example of Miami County, FL.

FIGURE 1

Example of Branch and Courthouse Locations

Figure 1 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 500-m circle around the courthouse (see the circle in the zoomed-in map). The yellow dots are the remaining bank branches in this county.

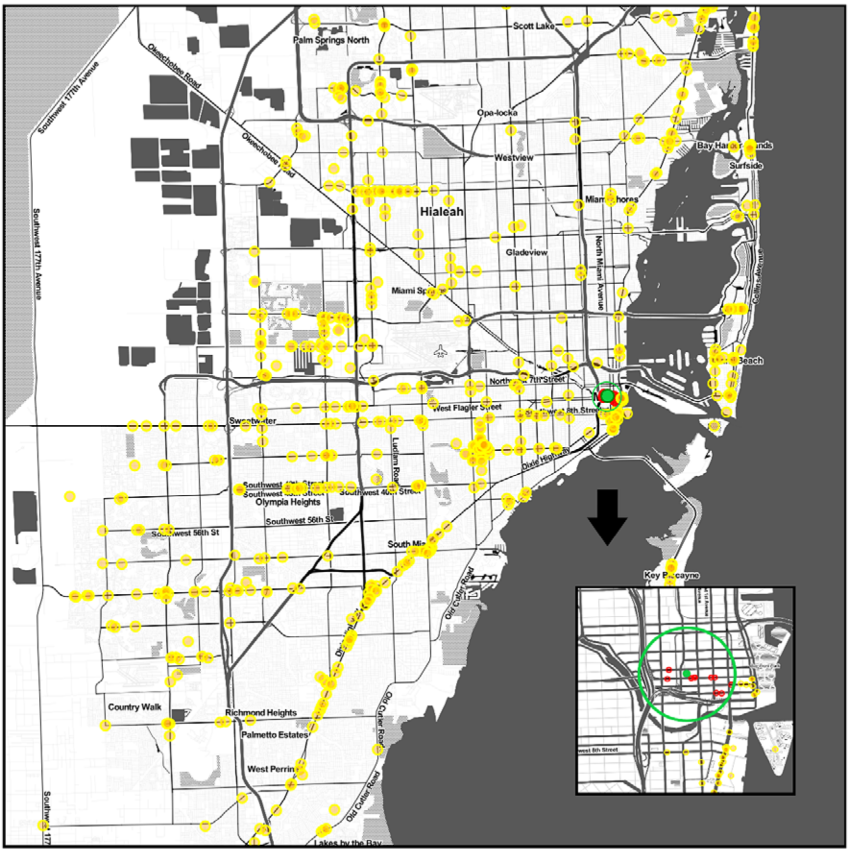

TABLE 2

Foreclosure Exposure and Mortgage Lending Decisions

Table 2 tests how mortgage rejection probability responds to the county-wide foreclosure intensity differently depending on loan officers' different distances to the county courthouses. The dependent variable is the loan-level decision outcome, which equals 1 if the loan is rejected and 0 if the loan is accepted. The explanatory variable COURTHOUSE_500 equals 1 if the processing branch is within 500 m from the nearest courthouse, and 0 otherwise. COURTHOUSE_500_1000 equals 1 if the processing branch is within 1,000 m but beyond 500 m from the nearest courthouse. FORECLOSURE is the foreclosure intensity measured by the monthly log number of foreclosure sales per 10,000 homes in the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, the race/ethnicity/gender of the borrower, the lien status of the loan, and the house price growth of the census tract where the borrower is located. Branch-level controls include the house price growth and income growth of the zip code where the branch is located, the log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
COURTHOUSE_500	0.0073**	0.0075**	0.0076**	−0.0022	−0.0017	−0.0014
	(0.0037)	(0.0037)	(0.0037)	(0.0063)	(0.0062)	(0.0062)
FORECLOSURE				0.0059**	0.0088***	0.0089***
				(0.0026)	(0.0027)	(0.0027)
FORECLOSURE × COURTHOUSE_500				0.0093**	0.0089**	0.0087**
				(0.0042)	(0.0041)	(0.0041)
COURTHOUSE_500_1000			0.0026			0.0082
			(0.0038)			(0.0074)
FORECLOSURE × COURTHOUSE_500_1000						−0.0051
						(0.0055)
Loan-level controls	No	Yes	Yes	No	Yes	Yes
Branch-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	1,227,469	1,227,469	1,227,469	1,227,469	1,227,469	1,227,469
R^2	0.1286	0.1367	0.1367	0.1286	0.1367	0.1367

Columns 1–3 of Table 2 report the regression results of the baseline tests. With county-month and bank-month fixed effects, which control for time-varying macroeconomic and housing market conditions in the local county and financial fundamentals of the lending institution, a mortgage loan application processed by a next-to-courthouse branch faces a 73 BPS higher probability of being rejected (column 1). This effect remains similar at 75 BPS when we further include loan-level controls and branch-level controls (column 2). The economic magnitude is as large as if the local house price growth drops by 1.12 standard deviations or if the local county-level log foreclosure number increases by 1.05 standard deviations.[16] Column 3 further reports that the difference in rejection rates quickly vanishes when we expand the range from 500 to 1,000 m. Thus, it is unlikely that our result is driven by any fundamental differences in the whole neighborhood of the courthouse.

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 intensive foreclosure sales. The higher the foreclosure intensity is, the larger the difference in rejection rate should be. In another word, loan officers next to the county courthouses are

[16]The local house price growth is one of the control variables. Its coefficient in the regression (which is not reported in the table due to brevity) is 0.0881. The effect of county-level log foreclosure is 0.0088, as shown in column 5 of Table 2.

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more "sensitive" to the foreclosure events across the entire county. We test this finer hypothesis based on the regression specification in equation (2), which interacts with the next-to-courthouse dummy with the county-level foreclosure intensity measured by the log number of average monthly foreclosures per 10,000 homes.

We report these results in columns 4–6 of Table 2. When the county-level intensity of foreclosures increases from the 25th to the 75th percentile of the sample distribution, the baseline "courthouse effect" becomes 122 BPS larger. Given that these next-to-courthouse loan officers are facing the same objective housing market fundamentals 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 subjectively more salient to lending decision-makers nearby.[17] We further report in column 6 that the effect diminishes once we move a bit away from the courthouse: While rejection rates in processing branches within the 500-m circle around the courthouse are significantly more sensitive to the county-wide foreclosures, rejection rates within the 500–1,000 m ring do not respond differently from those farther away.

It is worth pointing out that in this test, we look at the intensity of foreclosure sales in the county where the courthouse (the one closest to the processing branch) is located, as it is used to infer the intensity of foreclosure auctions held in the corresponding courthouse. For a small share of mortgage applications, the processing bank's nearest branch (which we assume to be the processing branch) and the courthouse closest to the branch could be in a county different from the one where the property is located.[18] As a result, the county-month fixed effects do not fully absorb the effect of foreclosures in the courthouse county. We also report in Table IA3 in the Supplementary Material that our results are consistent when looking separately at two subsamples of mortgage applications based on whether the property is located in the same or different county as the courthouse.

We note that a higher foreclosure intensity in the courthouse county is related to a higher mortgage rejection rate on average. There are two possible explanations for this. First, this measure of foreclosure reflects the housing market fundamentals of the county near the processing branch, which may influence the branch's general risk management criteria. Second, when lending decision-makers work in a county with deteriorating housing market fundamentals, their subjective risk-taking could be affected (although on average not as saliently as those next to the courthouse) due to the behavioral mechanism we discuss in this article.

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 indoor or online, the effect can be less clear. Since the premise of the courthouse effect is that foreclosure-related activities can be

[17]In Table IA2 in the Supplementary Material, we show that including the county-month and bank-month fixed effects in our estimation is important: without fully controlling for the dynamic county- and bank-level fundamentals, there could be many correlated confounding factors that can bias our estimates.

[18]For example, the processing bank may have no branch in the applicant's county, and its nearest branch (which we identify as the processing branch) and the courthouse closest to the branch are in a neighboring county.

TABLE 3

Sensitivity to Foreclosures Across Different Auction Locations

Table 3 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 1 if the loan is rejected and 0 if the loan is accepted. COURTHOUSE_500_OUTDOOR equals 1 if the loan is processed in a branch within 500 m from the nearest courthouse of a county where foreclosure auctions are held outside the county courthouse. COURTHOUSE_500_OTHER equals 1 if the loan is processed in a branch within 500 m from the nearest courthouse of a county where foreclosure auctions are held in other forms (indoor or online). FORECLOSURE is the foreclosure intensity measured by the monthly log number of foreclosure sales per 10,000 homes in the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, the race/ethnicity/gender of the borrower, the lien status of the loan, and the house price growth of the census tract where the borrower is located. Branch-level controls include the house price growth and income growth of the zip code where the branch is located, the log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
COURTHOUSE_500_OUTDOOR	−0.0161	−0.0114	−0.0116
	(0.0146)	(0.0148)	(0.0147)
COURTHOUSE_500_OTHER	−0.0013	0.0011	0.0017
	(0.0066)	(0.0070)	(0.0067)
FORECLOSURE	0.0085***	0.0060**	0.0088***
	(0.0030)	(0.0026)	(0.0027)
FORECLOSURE × COURTHOUSE_500_OUTDOOR	0.0200***	0.0211***	0.0204***
	(0.0074)	(0.0076)	(0.0074)
FORECLOSURE × COURTHOUSE_500_OTHER	0.0037	0.0045	0.0043
	(0.0045)	(0.0047)	(0.0047)
Loan-level controls	No	No	Yes
Branch-level controls	No	Yes	Yes
Bank-month FEs	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes
Diff (OUTDOOR vs. OTHER)	0.0163*	0.0166*	0.0161*
(*p*-value)	(0.0599)	(0.0601)	(0.0652)
No. of obs.	1,231,783	1,227,469	1,227,469
R^2	0.1281	0.1286	0.1367

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 (COURTHOUSE_500_OUTDOOR) and the other capturing the lending decisions made next to the courthouse with other types of auctions (COURTHOUSE_500_OTHER). Applying these two indicators in a regression similar to equation (2), we report in Table 3 that mortgage rejection rates are significantly sensitive to county-wide foreclosures only when the lending decisions are made next to a courthouse that holds foreclosure auctions outdoor. Taking the point estimates in column 3 as an example, when the county-level foreclosure increases from the 25th to the 75th percentile of the sample distribution, the rejection rate is 279 BPS higher if the lending decision is made next to a courthouse with outdoor foreclosure auctions. In contrast, the rejection rate is not significantly changed with other types of foreclosure auctions. 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 further rule out the potential alternative explanations based on unobserved local conditions.

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2. Heterogeneities Across Borrower Risk and Bank Size

Our baseline analysis shows that mortgage lending decisions next to the county courthouses are more sensitive to the county-wide foreclosures because decision-makers are particularly exposed to the foreclosure events. A further implication would be that these lending decision-makers are especially more sensitive when they are screening the marginal applications. As the overall low rejection rate suggests that the screening process is "lemon dropping" (Bartoš, Bauer, Chytilová, and Matějka (2016)), it suggests that the marginal applications that would be rejected when loan officer risk aversion heightens are likely the high-risk ones.

We first measure the riskiness of each mortgage application by its borrower's DTI ratio, which is commonly used to measure the borrower's credit risk by lenders, investors, and regulators. According to the guidelines by regulators and practitioners, a monthly mortgage DTI ratio of around 28% is likely to be the marginal case.[19] Based on this, we use 28% as the cutoff and focus on the subsample of "marginal" loan applications with a DTI ratio between 20% and 36% (±8% around 28%), comparing the rejection sensitivity for applications with DTI below and above 28% in column 1 of Table 4. By interacting the key variable of interest, FORECLOSURE × COURTHOUSE_500, further with an indicator of (DTI > 28%), we find that the increase in rejection rates is significantly greater for loan applications with DTI between 28% and 36% than those with DTI between 20% and 28%. We also report in Table IA4 in the Supplementary Material that this difference remains robust if we compare loans with DTI below and above 28% using the full sample (column 1 of Table IA4) or using a subsample with an even narrower bandwidth of DTI between 26% and 30% (column 2 of Table IA4). In addition, we consider an alternative specification (column 3 of Table IA4) that compares marginal cases (DTI between 26% and 30%) with all remaining applications (that are more likely to be "clear approvals" or "clear rejections") and find that the results are significantly stronger for the marginal cases.

Second, we measure the risk of the mortgage applications by looking at the housing price trend of the local neighborhood. If local housing prices decrease during the foreclosure crisis or post-crisis period, it is likely that mortgage applications from this neighborhood would be considered more risky, due to the momentum of the fundamental housing market trends and people's potential overextrapolation (Greenwood and Shleifer (2014)). Based on this idea, we compare in column 2 of Table 4 the "courthouse effect" on mortgage applications at neighborhoods with positive versus negative house price growth, and show that our results are significantly stronger in neighborhoods where house price growth is negative.

Since we are exploring a mechanism that affects lending outcomes through the effect of local salient events on individual loan officers' risk-taking behaviors, our results should only hold when the local branches have discretion on the mortgage lending decisions. This implies that we are more likely to identify this micro-level risk-taking-behavior channel from the relatively small banks which rely on human loan officers in the local branches to make mortgage lending decisions, rather than

[19]This is according to the so-called 28/36 rule of thumb, which says that monthly debt on housing should not exceed 28% of household gross income, and monthly total debt should not exceed 36% of household income (e.g., https://www.law.cornell.edu/wex/debt-to-income_ratio).

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TABLE 4

Heterogeneities by Application Types

Table 4 compares loan applications with different debt-to-income (DTI) ratios, neighborhood house price growth, bank types, or loan types. The dependent variable is the loan-level decision outcome, which equals 1 if the loan is rejected and 0 if the loan is accepted. The explanatory variables COURTHOUSE_500 and FORECLOSURE are defined the same way as in Table 2. (DTI > 28%) indicates that the monthly DTI ratio is above 28%. (ΔHP < 0) indicates that the house price growth in the branch zip code is negative. SMALL_BANK indicates that the bank operates in fewer than 10 states, and LARGE_BANK indicates those operating in more than 10 states. JUMBO_LOAN indicates that the loan size is above the jumbo loan threshold, and CONFORMING_LOAN below the threshold. The corresponding indicator itself and its interactions with FORECLOSURE and COURTHOUSE_500 are included although not reported for brevity. Column 1 focuses on the subsample of applications with DTI between 20% and 36%. Columns 2 and 3 use the full sample. Column 4 compares jumbo loan applications with conforming loan applications with income overlapped with jumbo loan applicants' income distribution. Other loan-level and branch-level controls are the same as in Table 2. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	By DTI	By ΔHP	By Bank Type	By Loan Type
	1	2	3	4
FORECLOSURE × COURTHOUSE_500 × (DTI > 28%)	0.0472***			
	(0.0150)			
FORECLOSURE × COURTHOUSE_500 × (DTI < 28%)	−0.0071			
	(0.0096)			
FORECLOSURE × COURTHOUSE_500 × (ΔHP < 0)		0.0144***		
		(0.0044)		
FORECLOSURE × COURTHOUSE_500 × (ΔHP > 0)		−0.0064		
		(0.0076)		
FORECLOSURE × COURTHOUSE_500 × SMALL_BANK			0.0120**	
			(0.0057)	
FORECLOSURE × COURTHOUSE_500 × LARGE_BANK			0.0064	
			(0.0062)	
FORECLOSURE × COURTHOUSE_500 × JUMBO_LOAN				0.0307**
				(0.0153)
FORECLOSURE × COURTHOUSE_500 × CONFORMING_LOAN				−0.0003
				(0.0069)
Corresponding type indicator	Yes	Yes	Yes	Yes
Type indicator × FORECLOSURE	Yes	Yes	Yes	Yes
Type indicator × COURTHOUSE_500	Yes	Yes	Yes	Yes
Loan-level controls	Yes	Yes	Yes	Yes
Branch-level controls	Yes	Yes	Yes	Yes
Bank-month FEs	Yes	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes	Yes
Diff.	0.0543***	0.0208**	0.0056	0.0310**
(*p*-value)	(0.0006)	(0.0141)	(0.5214)	(0.0389)
No. of obs.	395,348	1,227,469	1,227,469	584,697
R^2	0.1621	0.1367	0.1367	0.1391

from the large national ones which more likely have centralized "mortgage centers" that apply automated algorithms to process mortgage applications from all over the country. This conjecture is consistent with our findings in column 3 of Table 4: By comparing small banks operating in fewer than 10 states versus larger banks, we find that the effect is twice as large for the smaller banks and statistically significant only for those banks.

It should also be noted that although the recent development of financial technologies makes the mortgage lending process more and more centralized, there remains a significant dispersion 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 25th and 75th percentile branches within the same bank, county, and year is still as high as 21.2 percentage points.

Furthermore, banks are likely to care more about the risks of mortgage loans that they keep in balance sheets than those they securitize and sell. This suggests that the rejection rates for jumbo loans, which are less likely to be securitized and sold in the secondary market compared with conforming loans, are expected to be more sensitive to loan officers' exposure to adverse housing market events. In column 4 of Table 4, we compare the rejection sensitivity of jumbo loan applications versus conforming loan applications with similar borrower income,[20] and show that exposures to foreclosure news have a significantly stronger effect on the rejection rates for jumbo loans.

Moreover, according to Giacoletti et al. (2021), loan officers face monthly volume quotas and are pressured to originate more loans at month-end. This quota pressure suggests that loan officers' subjectivity in lending decision-making is lower at the end of the month, and thus loan officers' risk-taking behaviors are expected to be less sensitive to their subjective exposure to the adverse housing market news at the month-end. We find evidence consistent with this hypothesis: As reported in Table IA5 in the Supplementary Material, lending decisions made in the last week of the month are not significantly sensitive to the monthly foreclosure sales intensity, but lending decisions made in the earlier days of the same month are strongly impacted.

3. Robustness Checks

Since we are comparing the differential responses to the county-wide housing market events within each county and 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 i) 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-wide foreclosure intensity and does not exist without foreclosure shocks in the county; ii) our results are robust after controlling for borrower characteristics and neighborhood housing market and economic conditions; and iii) the "courthouse effect" quickly diminishes once the distance exceeds 500 m, 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 the Supplementary Material 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 controlling for census-tract-year fixed effects

[20]Since jumbo loan borrowers generally have a much higher income than conforming loan borrowers, the full sample of these two borrower groups are not very comparable. Thus, in this test, we restrict the sample of conforming loan borrowers to those whose income overlaps with the income distribution of jumbo loan borrowers. In particular, we limit the sample to include borrowers whose income is within the 5% and 95% of jumbo loan borrowers' sample distribution.

(Table IA6 in the Supplementary Material). Second, we show that neither borrower characteristics nor neighborhood economic fundamentals are more sensitive to the county-wide foreclosure intensity (Table IA7 in the Supplementary Material). Third, we show that our results remain very similar when we compare within the subset of neighborhoods that have similar levels of economic fundamentals (Table IA8 in the Supplementary Material). Fourth, our result also remains robust when we focus on matched branches that are selected based on the method of nearest neighborhood propensity score matching (Table IA9 in the Supplementary Material).

B. Denial Reasons

We have shown that the exposures to the foreclosure-related activities can lower mortgage rejection rates 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. Alternatively, they may simply become more "conservative," rejecting more cases despite the same risk profile that can be easily observed from the application packages.

The denial reason reported by CHMDA enables us to conduct a preliminary analysis to explore this question. Specifically, the data report for each rejected application one of the following nine denial reasons: i) DTI ratio, ii) employment history, iii) credit history, iv) collateral, v) insufficient cash, vi) unverifiable information, vii) credit application incomplete, viii) mortgage insurance denied, and ix) others. 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 categorize the first seven reasons into two groups. The first group includes the first five reasons, which are mainly related to the applicant's potential credit risk. If a loan officer rejects an additional application because of 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 works harder to go through the documents in the application package to identify weaknesses and omissions in the documentation. Our regression results in Table 5 support the conjecture that loan officers turn more "conservative" rather than more "careful," as only the first group of denial reasons significantly increases.

C. 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

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TABLE 5
Denial Reasons

Table 5 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 1 if the denial reason is risk-related (one of reasons 1–5), and 0 otherwise. In columns 4–6, the dependent variable is an indicator that equals 1 if the denial reason is documentation-related (one of reasons 6 and 7), and 0 otherwise. The explanatory variable COURTHOUSE_500 equals 1 if the loan is processed in a branch within 500 m from the nearest courthouse, and 0 otherwise. FORECLOSURE is the foreclosure intensity measured by the monthly log number of foreclosure sales per 10,000 homes in the county where the nearest courthouse is located. Loan-level controls include the debt-to-income ratio, the race/ethnicity/gender of the borrower, the lien status of the loan, and the house price growth of the census tract where the borrower is located. Branch-level controls include the house price growth and income growth of the zip code where the branch is located, the log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	REASON_RISK_RELATED			REASON_DOC_RELATED		
	1	2	3	4	5	6
COURTHOUSE_500	−0.0232	−0.0183	−0.0139	−0.0193	−0.0223	−0.0233
	(0.0222)	(0.0225)	(0.0217)	(0.0152)	(0.0150)	(0.0149)
FORECLOSURE	0.0041	0.0022	0.0079	0.0005	0.0028	−0.0002
	(0.0069)	(0.0068)	(0.0066)	(0.0066)	(0.0065)	(0.0065)
FORECLOSURE × COURTHOUSE_500	0.0324**	0.0346**	0.0306**	0.0032	0.0010	0.0024
	(0.0140)	(0.0139)	(0.0137)	(0.0116)	(0.0116)	(0.0119)
Loan-level controls	No	No	Yes	No	No	Yes
Branch-level controls	No	Yes	Yes	No	Yes	Yes
Bank-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	141,496	141,171	141,171	141,496	141,171	141,171
R^2	0.2961	0.2961	0.3068	0.3524	0.3525	0.3565

relatively more willing to accept applications with smaller loan sizes, 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 6 reports that the size of an approved loan on average drops by more when the county-wide foreclosure intensity is higher. Based on the estimates in column 3, for example, when the log number of county-level foreclosures increases from the 25th to the 75th percentile of the sample distribution, the decline in average loan size is 5 percentage-point greater among loans approved next to the courthouses.

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 reported in Table 7, where we aggregate observations at the branch level. Conditional on the log number of applications, both the log number and amount of approved loans by a next-to-court branch are significantly more sensitive to the county-wide foreclosure compared with the nonclose branches, suggesting that the quantity of credit supply is also a lot more sensitive to the county-wide foreclosure shocks by the next-to-court branches.

D. Ex Post Loan Performance

Lastly, we also examine the subsequent performance of loans originated under different exposures to salient foreclosure events. If the lower mortgage approval

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TABLE 6

Loan Size

Table 6 tests 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 COURTHOUSE_500 equals 1 if the loan is processed in a branch within 500 m from the nearest courthouse, and 0 otherwise. FORECLOSURE is the foreclosure intensity measured by the monthly log number of foreclosure sales per 10,000 homes in the county where the nearest courthouse is located. Loan-level controls include the race/ethnicity/gender of the borrower, the lien status of the loan, and the house price growth of the census tract where the borrower is located. Branch-level controls include the house price growth and income growth of the zip code where the branch is located, the log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
COURTHOUSE_500	−0.0631***	−0.0642***	−0.0577**
	(0.0235)	(0.0244)	(0.0236)
FORECLOSURE	−0.0772***	−0.0550***	−0.0597***
	(0.0233)	(0.0191)	(0.0184)
FORECLOSURE × COURTHOUSE_500	−0.0180	−0.0347**	−0.0359**
	(0.0167)	(0.0175)	(0.0170)
Loan-level controls	No	No	Yes
Branch-level controls	No	Yes	Yes
Bank-month FEs	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes
No. of obs.	1,064,694	1,060,790	1,060,790
R^2	0.4565	0.4643	0.5342

TABLE 7

Branch-Level Credit Supply

Table 7 looks at the aggregate credit supply by branches with different distances to the county courthouses and estimates their differential sensitivity to the county-wide foreclosures. Each observation is a branch–month pair. The dependent variable is the log number or amount of total mortgage lending by each branch in each month. The explanatory variable COURTHOUSE_500 equals 1 if the loan is processed in a branch within 500 m from the nearest courthouse, and 0 otherwise. FORECLOSURE is the foreclosure intensity measured by the monthly log number of foreclosure sales per 10,000 homes in the county where the nearest courthouse is located. Branch-level controls include the average loan characteristics, the house price growth and income growth of the zip code where the branch is located, the log population of the zip code, and an indicator of whether the branch is the head branch of the bank. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ln(LOAN_NUMBER)		ln(LOAN_AMOUNT)	
	1	2	4	5
COURTHOUSE_500	0.0066	0.0043	0.0323	0.0152
	(0.0058)	(0.0058)	(0.0347)	(0.0350)
FORECLOSURE	−0.0059*	−0.0057*	−0.0236	−0.0230
	(0.0034)	(0.0033)	(0.0173)	(0.0172)
FORECLOSURE × COURTHOUSE_500	−0.0068*	−0.0062*	−0.0419*	−0.0387*
	(0.0037)	(0.0038)	(0.0225)	(0.0228)
Log number/amount of applications	Yes	Yes	Yes	Yes
Average applicant characteristics	Yes	Yes	Yes	Yes
Branch-level controls	No	Yes	No	Yes
Bank-month FEs	Yes	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes	Yes
No. of obs.	566,287	564,412	566,287	564,412
R^2	0.7875	0.7874	0.4787	0.4787

rates that we document are due to more stringent lending standards applied by lending decision-makers who are more subjectively exposed to the adverse housing market events, we should expect a loan, conditional on approval, to perform better subsequently if the processing branch is close to the courthouse of a county that experienced intensive foreclosure sales at the time of approval.

TABLE 8

Subsequent Loan Performance

Table 8 tests how exposure to the county-wide foreclosure intensity relates to the subsequent loan performance of loans originated in branches with different distances to the county courthouses. The dependent variable is the loan-level loan performance, which equals 1 if the loan ever experienced bad performance (delinquent, foreclosure, REO, or involuntary liquidation) within the first 2 years since origination. The explanatory variable COURTHOUSE_500 equals 1 if the loan is processed in a branch within 500 m from the nearest courthouse, and 0 otherwise. FORECLOSURE is the foreclosure intensity at the month of loan origination, measured by the monthly log number of foreclosure sales per 10,000 homes in the county where the nearest courthouse is located. Columns 1 and 2 use the full sample of originated loans. Columns 3 and 4 focus on the subsample of loans with low documentations. Columns 5 and 6 focus on the subsample of loans with loan-to-value (LTV) ratio above 80% (which is also the 75th percentile of the sample distribution). Loan-level controls include the debt-to-income ratio, the race/ethnicity/gender of the borrower, the lien status of the loan, and the house price growth of the census tract where the borrower is located, as well as the FICO score, the LTV ratio, and the document type. Branch-level controls include the house price growth and income growth of the zip code where the branch is located, the log population of the zip code, and an indicator of whether the branch is the head branch of the bank, as well as the local house price growth and foreclosure intensity during the corresponding performance measurement period. Heteroskedasticity-robust standard errors (clustered at the county level) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample		Low Docs		LTV > 80%	
	1	2	3	4	5	6
COURTHOUSE_500	−0.0049	−0.0047	−0.0115	−0.0121	−0.0536***	−0.0530***
	(0.0081)	(0.0079)	(0.0225)	(0.0221)	(0.0161)	(0.0159)
FORECLOSURE	0.0071**	0.0054**	−0.0025	−0.0083	0.0111***	−0.0099***
	(0.0031)	(0.0021)	(0.0077)	(0.0073)	(0.0041)	(0.0037)
FORECLOSURE × COURTHOUSE_500	−0.0115**	−0.0103*	−0.0948**	−0.0949**	−0.0271**	−0.0255**
	(0.0058)	(0.0056)	(0.0402)	(0.0403)	(0.0127)	(0.0127)
Loan-level controls	No	Yes	No	Yes	No	Yes
Branch-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
County-month FEs	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	415,295	415,295	48,301	48,301	87,160	87,160
R^2	0.1074	0.1114	0.1535	0.1562	0.2210	0.2237

Using the McDash data, we measure the ex post mortgage loan performance using an indicator that equals 1 if the loan experiences any bad performance (delinquent, foreclosure, REO, or involuntary liquidation) within the first 2 years since origination. Using the bad performance indicator as the outcome variable, we report in Table 8 that loans originated in more exposed branches indeed experience lower probabilities of bad performance subsequently. When the county-level foreclosure intensity at the time of origination increases from the 25th to the 75th percentile of the sample distribution, loans originated near the courthouse have a 1.4 percentage-point lower probability of having bad performance compared with other loans originated in the same county by the same bank. This effect is also economically significant given that the sample mean for the probability of bad performance is 3.7%. We also find that this performance difference is particularly pronounced for loans with low documentations or high LTV ratios, the performance of which are likely sensitive to the stringency of the ex ante lending standards. The better ex post performance of loans originated at exposed branches also helps to further alleviate the concern that the higher rejection rates in those branches are due to loan officers' information advantages or borrowers' unobserved credit quality differences.

V. Conclusion

In this article, we explore a micro-level behavioral channel through which adverse housing market shocks affect lending outcomes and credit supply. This channel suggests that lending decision-makers' 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 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 practice 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, jumbo loans, and relatively smaller banks in which manual loan screening at the local branches is more likely. In addition, we 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. Moreover, we find that loans originated in the exposed branches have a lower probability of bad performance ex post, which is consistent with higher lending standards being applied at those branches.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000388.

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