THE UNIVERSITY OF CHICAGO

DO DELAYS IN BANKS' LOAN LOSS PROVISIONING AFFECT ECONOMIC DOWNTURNS? EVIDENCE FROM THE U.S. HOUSING MARKET

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Abstract

I study whether banks' loan loss provisioning contributed to economic downturns by examining the U.S. housing market. Specifically, I examine the influence of delayed loan loss recognition (DLR) on bank lending and risk-taking in the U.S. mortgage market and the aggregate effects of DLR on house prices and household consumption during the Great Recession. I first examine the effects of DLR on individual banks' behavior. Then I construct ZIP code-level exposure to banks' DLR to examine the aggregate effects of banks' DLR on the housing market. I find high DLR banks reduced mortgage supply, leading high exposure ZIP codes to experience larger decreases in mortgage supply during the crisis. Mortgages from high DLR banks were also more likely to become distressed, leading to more foreclosures and short sales in high exposure ZIP codes during the crisis. Consequently, banks' DLR negatively affected house prices during the crisis, implying a significant decrease in household consumption. These findings suggest banks' loan loss provisioning affected loan supply and risk-taking, exacerbating the economic downturn via the household channel.

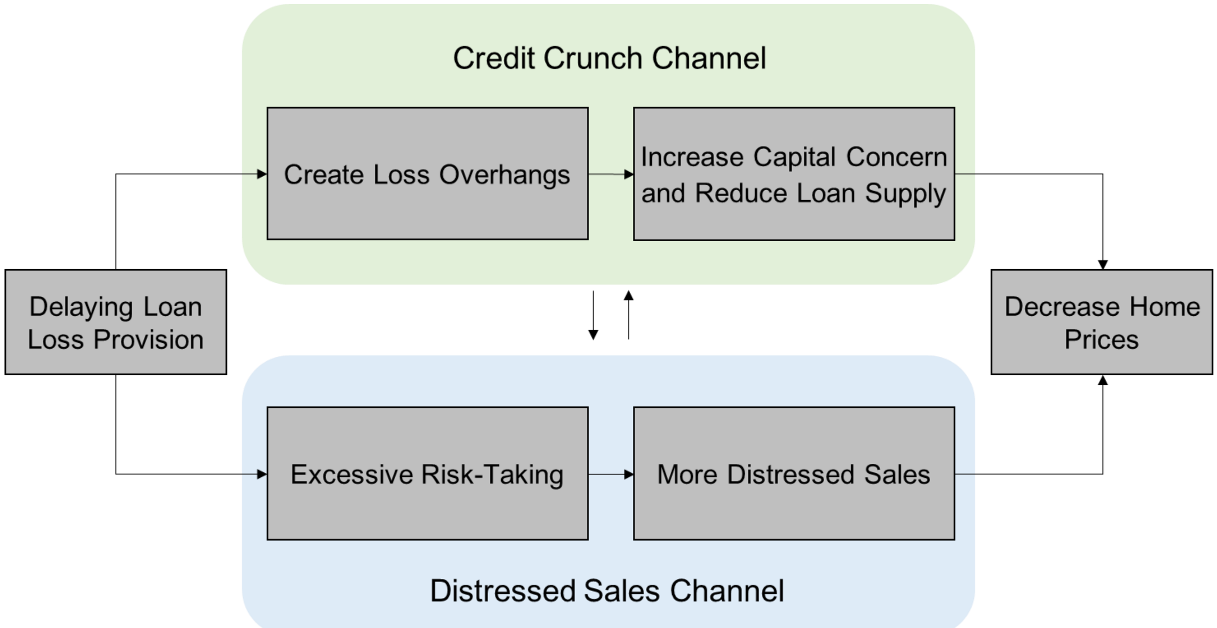
1. Introduction

The Great Recession of 2007-2009 sparked debate about accounting's role in financial stability and economic cycles. The timeliness of banks' loan loss provisioning is one of the most important issues in the debate, and its potential real effects have received great attention by bank regulators and central bankers for several reasons. Loan loss provisioning is the largest accrual in bank accounting and estimating the amount and timing of loan loss provisioning can involve significant managerial discretion (Wahlen, 1994; Liu and Ryan, 1995, 2006; Ahmed et al., 1999; Jayaraman et al., 2017). In addition, delays in loan loss provisioning may reinforce pro-cyclicality in banks' lending and weaken market discipline over banks' risk-taking (Laeven and Majnoni, 2003; Dugan, 2009; Beatty and Liao, 2011; Bushman and Williams, 2012, 2015; Acharya and Ryan, 2016). Despite the centrality of the issue, however, whether loan loss provisioning had economy-wide effects during the crisis and channels through which this happened remain open questions. In this paper, I examine whether banks' delayed loan loss recognition (DLR) influenced their lending and risk-taking in the U.S. mortgage market and the resulting aggregate effects on house prices and household consumption during the Great Recession.

To answer whether banks' DLR contributed to economic downturns, I examine the U.S. housing market for several reasons. Households are major economic agents: their consumption expenditures were 65.3% of the U.S. GDP in 2006 (FRED Economic Data). On top of this, mortgage lending is the most important business for commercial banks, accounting for about 70% of lending on bank balance sheets. Given the importance of households and mortgage lending, the housing market is likely to be an important way in which bank accounting ripples through the real economy. In addition, households amplify economic cycles. Studies suggest that falling household wealth during the Great Recession, as a result of the collapse of the housing market, reduced

Figure 1. Diagram of Two Potential Channels for the Effects of Loan Loss Provisioning on House Prices

This figure describes the underlying reasoning for the two potential channels (*the Credit Crunch Channel* and *the Distressed Sales Channel*) on how banks' delayed loan loss recognition affects house prices.



household consumption and aggravated the crisis (Mian et al., 2013; Mian and Sufi, 2014). For these reasons, examining the effects of banks' DLR on house prices can generate and implication about whether bank accounting affects economic downturns by affecting household consumption.

Banks' loan loss provisioning could affect house prices by influencing mortgage lending (which I call *the credit crunch channel*), risk-taking (which I call *the distressed sales channel*) or both. Figure 1 portrays these two channels, which are not mutually exclusive but instead likely mutually reinforcing. The credit crunch channel suggests that banks with delayed loan loss provisioning ("high DLR banks") reduced lending during the crisis and thus pushed down house prices. As banks delayed loss recognition, it created loss overhangs. Once the downturn started, they became concerned about future capital inadequacy and thus might forgo profitable lending opportunities (Van den Heuvel, 2009; Beatty and Liao, 2011). The distressed sales channel suggests that mortgages originated by high DLR banks defaulted more frequently and ended up as distressed sales during the crisis because these banks engaged in more risky lending beforehand. These banks took more risk because DLR weakens discipline by depositors, investors, and regulators, due to less transparent financial reporting or a higher threshold for liquidation of the loan portfolio (Barth and Landsman, 2010; Bushman and Williams, 2012, 2015; Bertomeu et al., 2017; Gallemore, 2018). Consequently, homes with mortgages from high DLR banks were more likely to default and be sold at distressed prices via foreclosures or short sales, putting further pressure on house prices (Campbell et al., 2011).

My analysis focuses on establishing a link from loan loss provisioning to household consumption via three major steps. I first examine the effects of banks' DLR on loan supply (the credit crunch channel) and risk-taking (the distressed sales channel) at the bank level. Investigating the effects of DLR on banks' behavior presents several empirical challenges, which have been pointed out by Beatty and Liao (2014) and Acharya and Ryan (2016). As banks can operate in many areas, their decisions on lending and risk-taking are influenced by varying local economic conditions. Distinguishing these conditions (demand side) from banks' behavior (supply side) is difficult. In addition, unobservable bank characteristics such as business models, risk-taking incentives, and management skill may affect both financial reporting and decisions in the mortgage market. Therefore, disentangling financial reporting effects from other confounding factors is critical in examining the effects of DLR on banks' behavior.

I address these challenges using micro-level data on mortgage loans and housing transactions. To identify the credit crunch channel, I compare mortgage supply by high and low DLR banks within the same ZIP code and year, thus controlling for unobservable time-varying ZIP-level mortgage demand. I also compare the supply of high (conventional) and low (Federal

Housing Administration) capital burden mortgages within the same bank, to further control for unobservable time-varying bank characteristics. Similarly, to identify the distressed sales channel, I compare mortgage outcomes for high and low DLR banks within the same ZIP code to control for local economic conditions that drive mortgage distress. In this analysis, I identify mortgages originated by high and low DLR banks before the crisis, then track them through the crisis, comparing their likelihoods of becoming distressed sales in the same ZIP code.

After examining bank-level evidence, I investigate the aggregate effects of DLR on mortgage amounts, distressed sales, and house prices. Estimating the aggregate effects of DLR presents several empirical challenges. While loan loss provisioning, lending, and risk-taking are measured at the bank level, the relevant economic outcomes are measured at the local-economy level. In addition, substitution effects and spillovers must be incorporated to capture the aggregate effects. Nonbank lenders may substitute for any reduction in high DLR banks' mortgage supply. Conversely, pullbacks by high DLR banks might be seen as a negative signal about the local economy, and thus spillover to reduce the lending of competitors. Therefore, linking bank-level decisions to local economy-level outcomes and incorporating substitution and spillover effects are critical in evaluating the aggregate effects of DLR.

I construct the ZIP-level exposure to banks' DLR using the weighted-average of individual banks' DLRs based on their market shares, and compare high and low exposure ZIP codes before and during the crisis. In this way, I link the ZIP-level exposure measure to housing market outcomes and capture any substitutions or spillovers. A concern with this design is that unobservable geographic characteristics may be correlated with both housing market outcomes and exposures to banks' DLR. For example, high DLR banks could be more aggressive and operate in regions with larger booms and busts. To address this concern, I compare ZIP codes with high and low exposure to banks' DLR within the same county and year, thus controlling for unobservable time-varying county-level economic conditions.

In addition, I use an instrumental variable approach to isolate an exogenous shift in banks' loan loss provisioning. I use the SEC's influence on public banks' loan loss provisioning as an instrument. In July 2001, the SEC issued Staff Accounting Bulletin (SAB) 102 to discourage recognizing excessive expected loan losses. The SEC's oversight of public banks can be proxied by the distance between a bank's headquarters and the closest SEC office (Kedia and Rajgopal, 2011; Jayaraman et al., 2017). Given that this distance is plausibly exogenous, I use its interaction with the public bank indicator as an instrument for a bank's loan loss provisioning.

As the last step in my analysis, I estimate the impact of house price decreases on aggregate household consumption using the formula of Berger et al. (2018). I first compute consumption responses to house price changes for an individual household, and aggregate these responses over all owner-occupied housing units in DataQuick's assessor data, which contain a market value of the property determined by a tax assessor.

I find that high DLR banks reduced mortgage supply more than low DLR banks during the crisis. This effect is stronger for low-capitalized banks and high capital burden (conventional) loans, consistent with the credit crunch theory that high DLR banks became concerned about future capital inadequacy and thus decreased their lending. The aggregate effects suggest that a one standard deviation increase in ZIP-level exposure to DLR produces a 10.6 percentage point larger decline in the growth rate of credit during the crisis. I also find that mortgages by high DLR banks in high exposure ZIP codes were more likely to end up as distressed sales, suggesting these banks took more risks before the crisis. The aggregate effects suggest that a one standard deviation increase in the ZIP-level exposure to DLR produces a 5.5 (1.0) percentage point larger increase in foreclosure rates (short sales rates) during the crisis. All these findings suggest that banks' DLR affected lending and risk-taking both at the bank level and ZIP code level.

Finally, I find that banks' DLR significantly affected house prices and household consumption during the crisis. A one standard deviation increase in the ZIP-level exposure to DLR produces a 1.6 to 1.7 percentage point larger decline in the growth rate of house prices during the crisis. In dollar terms, these estimates imply a decrease in house prices of about $3,500 for the median home sold in the United States in 2006. The estimated reduction in aggregate consumption is about $25 billion, which is about 0.28% of U.S. household consumption in 2006. The additional IV estimation also yields the same result with a larger effect, confirming that the effect of DLR on house prices is not driven by unobservable local economy and bank characteristics. Taken together, these findings suggest that banks' loan loss provisioning had nontrivial effects on the U.S. housing market during the Great Recession, and thus exacerbated the economic downturn.

My paper contributes to the literature on banks' financial reporting and economic cycles. First, it provides new evidence that banks' financial reporting can affect the economy via the household channel. Studies show banks' loan loss provisioning affects financial stability and economic cycles via corporate activities (Jiménez et al., 2017; Blattner et al., 2018). In contrast, I show that banks' loan loss provisioning likely exacerbated the downturn by reducing household wealth and thus affecting their consumption.

Second, my paper estimates the magnitude of the aggregate effects of banks' DLR on the economy. DLR has been seen as an important contributor to the crisis, but researchers and policymakers had little evidence of the economic magnitude of the effects. I quantify the impact of banks' DLR on house prices and the implied impact on household consumption.

Third, my paper provides real economy evidence on the interaction between banks' DLR and risk-taking. The relation between loan loss provisioning and risk-taking is pertinent to financial stability and is thus discussed in many papers (Barth and Landsman, 2010; Acharya and Ryan, 2016; Bertomeu et al., 2017). So far, there is evidence that banks' DLR is positively associated with equity risk measures (Bushman and Williams, 2015), but none on how and where high DLR banks take more risk. My findings suggest a potential mechanism that high DLR banks took more risk in mortgages, which led to more distressed sales during the crisis.

Finally, my paper complements studies on the effects of banks' loan loss provisioning. Acharya and Ryan (2016) call for studies with more stringent research designs to tighten causal links between banks' loan loss provisioning and its economic consequences. My paper answers this call by using various research designs to overcome the empirical challenges.

2. Background and Related Literature

2.1. Loan Loss Provisioning

The Great Recession sparked discussion of banks' financial reporting in general and their loan loss recognition in particular (Laux and Leuz, 2009, 2010; Barth and Landsman, 2010; Vyas, 2011; Beatty and Liao, 2011, 2014; Bushman and Williams, 2012, 2015; Huizinga and Laeven, 2012; Kothari and Lester, 2012; Acharya and Ryan, 2016; Bischof et al., 2018; Corona et al., 2018). Regulators and others have blamed delays in loan loss provisioning, under FAS 5's incurred loss model, for exacerbating the severity of economic downturns.[1] They argue the model's "probable" threshold for loss accrual and backward-looking nature induce banks to delay loss recognition in good times, creating an overhang of losses that carry forward to bad times. The loss overhang

[1] FAS 5's incurred loss model requires banks to accrue for credit losses only if those losses are incurred, probable, and reasonably estimable based on current information.

increases the concern for capital inadequacy, and banks reduce loan supply because raising capital is costly during downturns (Laeven and Majnoni, 2003; Dugan, 2009; Beatty and Liao, 2011; Acharya and Ryan, 2016).[2]

Studies have examined the relation between banks' loan loss provisioning and behavior such as lending and risk-taking. Empirically, Beatty and Liao (2011) find delaying loan loss provisioning is positively associated with pro-cyclicality in lending. Bushman and Williams (2012, 2015) find delaying loan loss provisioning is positively associated with capital market risks measures, because DLR reduces transparency of banks' financial reporting and thus weakens market discipline over their risk-taking. Theoretically, Bertomeu et al. (2017) suggest that banks engage in excessive risk-taking, under the incurred loss model because its higher threshold for recognizing losses undermines discipline on risk-taking.

Although banks' loan loss provisioning has attracted much attention, empirical evidence on its effects on the real economy is sparse. Jiménez et al. (2017) examine Spanish banks' adoption of dynamic loan loss provisioning in 2000.[3] They find it smooths credit supply through the cycle and increases firm-level employment growth and survival rates during downturns. Blattner et al. (2018) exploit an unexpected increase in capital requirements for Portuguese banks, by the

[2] In response to this criticism, the FASB replaced the incurred loss model of estimating credit losses with the current expected credit loss (CECL) model in Accounting Standards Update (ASU) No. 2016-13, "Financial Instruments – Credit Losses (Topic 326): Measurement of Credit Losses on Financial Instruments." For public business entities that are U.S. Securities and Exchange Commission (SEC) filers, the standards are effective for fiscal years beginning after December 15, 2019. For all other public business entities, the standards are effective for fiscal years beginning after December 15, 2020. For all other entities, the standards are effective for fiscal years beginning after December 15, 2020, and interim periods within fiscal years beginning after December 15, 2021. Finally, all entities may adopt the standards earlier as of the fiscal years beginning after December 15, 2018 (ASU 2016-13).

[3] Dynamic provisioning is called "dynamic" because it varies over the economic cycle following a specific formula. It requires banks to provision more (the dynamic provision fund) in good times to cover the realized losses in bad times. The dynamic provision fund has a regulatory ceiling and floor, and the required provisioning in good times is over and above the specific loan loss provisions whereas the required provisioning is reduced when bank profits are low and new shareholders' funds are costly to obtain (Jiménez et al., 2017).

European Banking Authority (EBA) in 2011, to examine the effects of bank capital adequacy on aggregate productivity growth. Although the EBA did not target banks' financial reporting, they find that the affected banks delayed the recognition of losses by further lending to distressed firms. As a result, this behavior affected firm-level investment and employment as well as aggregate productivity. Granja and Leuz (2017) use the termination of the thrift regulator (OTS) to examine the effect of strict supervision on bank lending and local business activity. Although they do not directly examine the effect of loan loss provisioning, they find that strict supervision led affected thrifts to recognize larger loan loss provisions by forcing them to improve their lending practices and risk management, leading to increased small business lending and local business dynamism. These three studies present evidence that banks' loan loss provisioning affects their borrowing firms' activities and thus the economy. Unlike these studies, my paper suggests banks' loan loss provisioning can affect the housing market and thus the economy.

2.2. Household Wealth, House Prices, and Economic Downturn

Many studies focus on the causes and implications of lost household wealth during recessions. Mian et al. (2013) exploit cross-sectional variation in housing wealth shocks across the United States during the Great Recession. They find the decrease in wealth from the collapse of the housing market significantly crimped consumer spending. Similarly, Mian and Sufi (2014) find that U.S. counties with larger declines in housing wealth experienced larger declines in non-tradable employment during the crisis.[4] These studies all suggest that the decline in household wealth due to the decrease in house prices significantly affected the Great Recession. Although my study does not directly test household consumption, it provides evidence that banks' financial

[4] Non-tradable industries refer to industries relying heavily on local demand such as retail and restaurants.

reporting practices contributed to the decline in house prices, suggesting the reduction in household consumption during the crisis.

2.3. Credit Expansion, Distressed sales, and House Prices

Explaining the causes of the housing market boom and its collapse during the Great Recession has been another important topic in academia. Numerous studies provide evidence that supplying credit to riskier borrowers during the boom drove up house prices and thus created a larger collapse subsequently. Mian and Sufi (2009) suggest that the expansion of subprime mortgage credit significantly increased house prices from 2002–2005. Adelino et al. (2014) find that increases in the conforming loan limit made credit cheaper and resulted in significant increases in house prices. Favara and Imbs (2015) find the bank branching deregulation across the United States expanded credit supply that significantly increased house prices.

Another stream of studies suggest that foreclosures and short sales had negative spillovers on local house prices and other local economies.[5] Campbell et al. (2011) find that foreclosed houses were sold at discounts and thus helped drag down the prices of unforced sales. Mian et al. (2015) find that foreclosures led to large declines in house prices, residential investment, and consumer demand during the recession.

The preceding studies suggest credit supply and distressed sales can significantly affect house prices. Hence, if banks' financial reporting affects their lending and risk-taking, both a credit

[5] A short sale means that the borrower sells the property for less than the outstanding mortgage balance under an agreement with the lender, and pays the proceeds to the lender (Zhu and Pace, 2015). Daneshvary and Clauretie (2012) describe three common procedures for the sale of a distressed property: (1) the lender allows a short sale by the borrower before or during the pre-foreclosure; (2) the lender initiates foreclosure under a notice of default and the borrower sells the property; and (3) the lender forecloses and sells the property as real estate owned (REO). I define foreclosures as transactions categorized by DataQuick as financial institution-owned sales (REO) or foreclosure auctions, and short sales as transactions inferred as short sales by DataQuick. DataQuick uses a proprietary model to identify short sales (Ferreira and Gyourko, 2015).

crunch and distressed sales are plausible channels through which banks' loan loss provisioning would affect house prices. I thus consider these channels in assessing the effects of banks' loan loss provisioning on house prices.

3. Data, Variable Construction, and Sample

3.1. Data Sources

I use several data sources to construct variables. To create banks' DLR measure and bank-level control variables, I use financial statement data from the Call Reports, which are available from the Federal Reserve Bank of Chicago. To create the ZIP-level exposure to banks' DLR and mortgage credit amounts, I use the Home Mortgage Disclosure Act (HMDA) data, which record the majority of mortgage applications in the United States.[6] To identify distressed sales, I use the recorder and assessor data from DataQuick, which contains deed-level information on ownership changes and loans secured by properties. I use two sources for the housing price indices: Federal Housing Finance Agency (FHFA) and CoreLogic. FHFA's price indices are available yearly at the ZIP code level and provide broad geographic coverage.[7] CoreLogic's price indices are available monthly and provide a smaller coverage but have various versions measured in different ways. I use CoreLogic's index based on Single Family Detached Home at the end of each year, because all other data are constructed at the annual level. Finally, I construct ZIP-level characteristics using various databases. From the American Community Survey (ACS), I draw data on demographics, poverty, and education.[8] From the IRS's Statistics of Income (SOI), I construct ZIP-level average

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[6] HMDA covers more than 8,800 lenders and accounts for approximately 80% of all home lending in the United States (Avery et al., 2007).

[7] Bogin et al. (2016) provide detailed descriptions of FHFA's price indices.

[8] I use "2007-2011 American Community Survey (ACS) 5-Year Estimates", which is the first survey containing information at the ZIP level. Variables from the ACS are not available yearly, and thus the same value is used for all years in the same ZIP code. Other ZIP-level controls are constructed at the annual level.

income and gross income growth rate. From the County Business Patterns (CBP), I construct ZIP-level employment growth rate and establishment growth rate. A detailed description of data sources is provided in Section A.1 of the online appendix.

3.2. Measuring Banks' DLR and ZIP-Level Exposure to Banks' DLR

I exploit cross-sectional variation across ZIP codes in pre-crisis exposure to banks' DLR to estimate the aggregate effects on loan supply, distressed sales, and house prices. To construct this measure, I take advantage of loan-level mortgage data from HMDA, because they allow for computing market shares of all mortgage lenders in a given ZIP code and year. [9] I estimate DLR at the individual bank level following the literature (Nichols et al., 2009; Beatty and Liao, 2011; Bushman and Williams, 2015; Gallemore, 2018) and then construct the ZIP-level exposure to banks' DLR using banks' mortgage market shares during the pre-crisis period. A detailed description of the construction of the ZIP-level measure follows.

First, I estimate two regressions over the most recent 12 quarters for each bank during 2004 – 2006, requiring the bank to have data for all 12 quarters on the Call Reports.

$$\begin{aligned} LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t-1} + \beta_2 \Delta NPL_{i,t-2} + \beta_3 EBLLP_{i,t} + \beta_4 Tier1Ratio_{i,t-1} \\ + \beta_5 Size_{i,t-1} + \beta_6 CoIndex_{s,t} + \epsilon_{i,t}, \end{aligned} \tag{A1}$$

$$\begin{aligned} LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 EBLLP_{i,t} \\ + \beta_6 Tier1Ratio_{i,t-1} + \beta_7 Size_{i,t-1} + \beta_8 CoIndex_{s,t} + \epsilon_{i,t}. \end{aligned} \tag{A2}$$

The dependent variable, $LLP_{i,t}$, is the bank's loan loss provision divided by lagged total loans. The primary independent variables, $\Delta NPL_{i,t}$ and $\Delta NPL_{i,t+1}$, are the changes in non-performing loans

[9] This approach is similar to that of Buchak et al. (2018). They measure regulatory capital burden at the individual bank level first, and then create a county-level measure of regulatory burden by taking the weighted averages of the individual bank-level measure, based on banks' deposit market shares.

divided by lagged total loans and included only in equation (A2). I include control variables following previous studies. $\Delta NPL_{i,t-1}$ and $\Delta NPL_{i,t-2}$ are included to control for prior loan portfolio quality changes. $EBLLP_{i,t}$ is the earnings before the loan loss provision and taxes divided by lagged total loans and is included to control for banks' incentives to smooth earnings (Ahmed et al., 1999; Bushman and Williams, 2012, 2015). $Tier1Ratio_{i,t-1}$ is the lagged tier 1 capital ratio and is included to capture capital management (Liu and Ryan, 1995, 2006). $Size_{i,t-1}$ is the natural logarithm of lagged total assets. Finally, $CoIndex_{s,t}$, the coincident index[10] measured for the state of banks' headquarters, is included to control for local economic conditions.

I compute the bank-level DLR as a negative number of the incremental explanatory power of future and current changes in the non-performing loans for the current loan loss provision (Adjusted R^2 in (A1) – Adjusted R^2 in (A2)). The measure assumes that, if a bank incorporates information about its future and current changes in non-performing loans in a more timely fashion when determining its current period loan loss provision, the incremental explanatory power is higher.

Second, I construct the ZIP-level pre-crisis exposure to banks' DLR using banks' mortgage market shares from HMDA as follows.

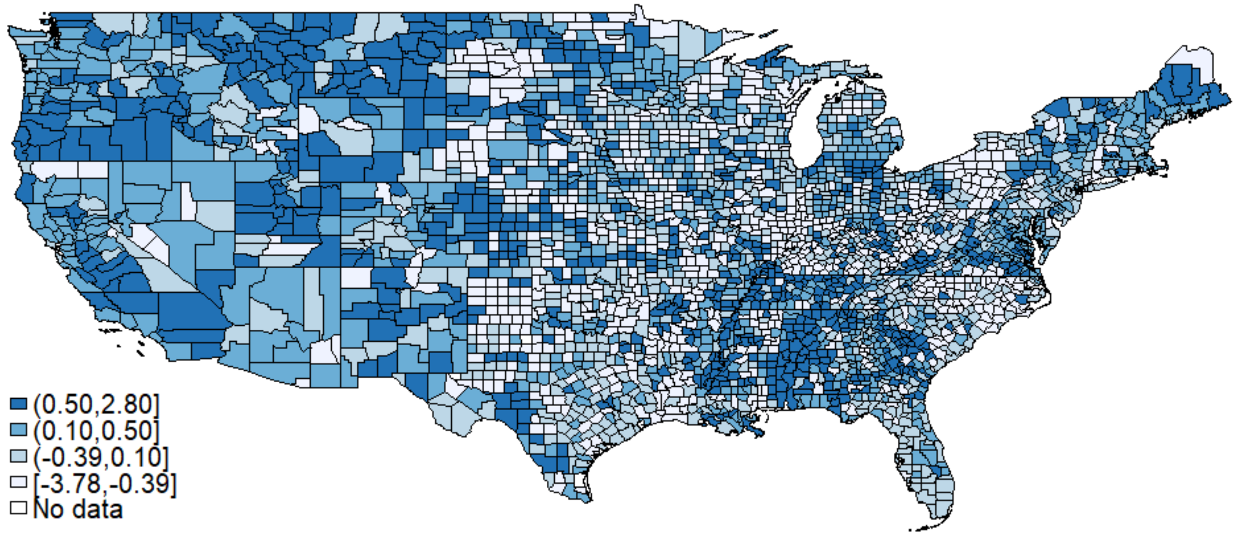
$$Exposure_z = \frac{1}{3}\sum_{t=2004}^{2006}\sum_{i\in z}\alpha_{i,z,t} \times DLR_{i,t}, \tag{A3}$$

[10] Khan and Ozel (2016) describe the coincident index as a comprehensive measure of economic activity at the state level. The index is produced monthly by the Federal Reserve Bank of Philadelphia and calculated using models with four state-level inputs: nonfarm payroll employment, unemployment rate, average hours worked in manufacturing, and wage and salary disbursements deflated by the consumer price index.

Figure 2. Regional Exposure Variation

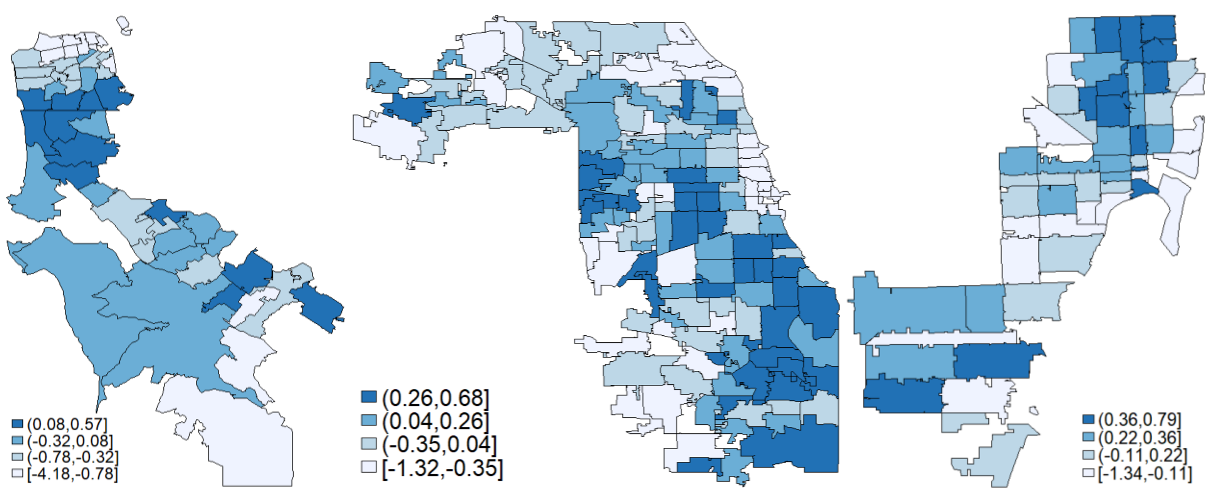
The figures present variation in regional exposure to banks' delayed loan loss recognition. Panel A presents a county map of regional exposure to banks' DLR. Panel B presents ZIP code maps for three metropolitan areas: from left to right, San Francisco area (San Francisco county and San Mateo county), Chicago area (Cook county), and Miami area (Miami-Dade county). Darker shadings reflect higher exposure.

Panel A: Exposure to Banks' DLR at the County Level



Panel B: Exposure to Banks' DLR at the ZIP Level

San Francisco Chicago Miami



where $\alpha_{i,z,t}$ is the mortgage market share of bank i at ZIP code z in year t and $DLR_{i,t}$ is the individual bank-level DLR measured using equations (A1) and (A2). That is, the ZIP-level exposure to banks' DLR before the crisis is the weighted average of individual banks' DLRs based on their mortgage market shares.

Figure 2 displays variation in geographic exposures to banks' DLR. The exposures are standardized to have a mean of zero and standard deviation of one, and darker areas indicate more exposure to banks' DLR. Panel A displays county-level variation across the United States, and Panel B shows ZIP-level variation in the exposure for three metropolitan areas (San Francisco, Chicago, and Miami). These figures suggest significant variation across areas in these exposures. Panel B, in particular, indicates that there is enough variation at the ZIP level, even within a county, which is critical to my empirical strategy using only within-county variation.

3.3. Sample Construction and Descriptive Statistics

I construct samples at various bank and geographical levels. To examine individual banks' behavior, I construct (i) a bank-ZIP-level panel, (ii) a bank-MSA-level panel, and (iii) matched HMDA–DataQuick mortgage loan-level data. To construct the bank-ZIP-level panel, I aggregate originated mortgages by banks and ZIP codes from HMDA and link the bank-level variables from the Call Reports based on having the same lender identification. The final bank-ZIP-level data contain 4,558 banks, 12,974 ZIP codes, 517,937 bank-ZIP, and 1,283,506 bank-ZIP-years during 2004–2009. To construct the bank-MSA-level panel, I use the same approach as for the bank-ZIP-level panel but aggregate originated mortgage loans by banks and MSAs. The final bank-MSA-level data contain 4,373 banks, 349 MSAs, 49,423 bank-MSAs, and 125,681 bank-MSA-years during 2004–2009. Finally, I construct the matched HMDA–DataQuick mortgage loan-level data by linking HMDA to DataQuick's loan data. As DataQuick does not provide information on the lender's identification except the name, I use a fuzzy match, based on the lender name using a similar approach as Ferreira and Gyourko (2015).[11] The final matched HMDA–DataQuick data contain 674,974 mortgage loans from 2,566 banks.[12]

To examine aggregate effects at the ZIP level, I construct ZIP-level variables by aggregating originated mortgages from HMDA and housing transactions from DataQuick. Then, I match this ZIP-level data with housing price indices and other regional covariates based on the same ZIP code. The final ZIP-level sample contains 12,978 ZIP codes and 89,391 ZIP-years during 2004–2010. The final bank-level sample, which is used to construct other data sets, contains 4,621 banks and 24,957 bank-years during 2004–2010. A more detailed description of the sample construction process is provided in Section A.2 of the online appendix.

Table 1 presents descriptive statistics for the various samples.[13] Panel A reports the bank-level statistics; the bank-level data, which are not directly used in the analysis, are used to construct important explanatory variables. For example, *DLR High* is equal to one if the average of DLR during 2004–2006 is above the bank-level sample median, and this variable is matched to other samples for the analysis. Panels B reports descriptive statistics of important variables for the bank-ZIP and the bank-MSA-level sample. Panel C reports descriptive statistics of the matched HMDA-DataQuick loan-level sample. Panel D reports descriptive statistics of the ZIP-level variables. *Exposure* is the ZIP-level pre-crisis exposure to banks' DLR, and standardized to have a mean of zero and standard deviation of one. Both the mean and median of *Foreclosure Rate* are larger than

[11] The fuzzy match process is described in Section A.2 of the online appendix.
[12] The matching rate between HMDA and DataQuick is about 21% (674,974 matched /3,160,554 originated loans for home purchase by identified banks during 2004–2006). The low rate has several explanations: (i) the DataQuick's coverage is lower than the HMDA's coverage; (ii) I use a relatively strict criterion for the match, based on the lender's name; (iii) banks usually make multiple mortgages with similar amounts in the same ZIP code, and only one of these duplicates is considered as a match.
[13] Continuous variables are winsorized at the 1st and 99th percentiles.

Table 1. Descriptive Statistics

This table presents descriptive statistics (mean, standard deviation, and first through third quartiles) for the variables defined at various levels. Panel A reports the bank-level statistics. Panel A reports the bank-level statistics. Panel B reports the bank-ZIP-level and the bank-MSA-level statistics. Panel C reports the matched HMDA-DataQuick loan-level statistics. Panel D reports the ZIP-level statistics. Finally, Panel E compares the dependent variables by high and low exposure ZIP codes for the pre-crisis and the crisis period. All variables are defined in Appendix A.

Panel A: Bank-Level Variables

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	Std. dev.	P25	Median	P75
DLR High	24,957	0.500	0.500	0.000	1.000	1.000
logAssets	24,957	12.527	1.203	11.668	12.366	13.151
Cash	24,957	0.047	0.041	0.023	0.034	0.055
Deposits	24,957	0.819	0.075	0.781	0.834	0.875
Lag Tier1 Capital Ratio	24,957	0.135	0.052	0.102	0.119	0.149
Loans to Deposits	24,957	0.843	0.187	0.732	0.855	0.965
Loan Loss Reserve	24,957	0.010	0.005	0.007	0.009	0.011
Non-Performing Loan	24,957	0.012	0.017	0.002	0.006	0.014
ROA	24,957	0.007	0.011	0.004	0.008	0.012

Panel B: Bank-ZIP and Bank-MSA-Level Variables

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	Std. dev.	P25	Median	P75
Bank-ZIP Variables						
VOL	1,283,506	2.043	3.193	0.231	0.730	2.372
DLR High	1,283,506	0.416	0.493	0.000	0.000	1.000
Bank-MSA Variables						
VOL^C	125,681	0.546	1.432	0.008	0.036	0.244
VOL^F	125,681	0.043	0.184	0.000	0.000	0.000
VOL^C - VOL^F	125,681	0.496	1.290	0.007	0.034	0.226
DLR High	125,681	0.466	0.499	0.000	0.000	1.000

Table 1. Continued

Panel C: Matched HMDA–DataQuick Loan-Level Variables

VARIABLES	(1) N	(2) Mean	(3) Std. dev.	(4) P25	(5) Median	(6) P75
Dependent Variables						
All Distressed Sale	674,974	0.057	0.232	0.000	0.000	0.000
Foreclosure	674,974	0.036	0.186	0.000	0.000	0.000
Short Sale	674,974	0.021	0.144	0.000	0.000	0.000
Main Explanatory Variables						
DLR High	674,974	0.192	0.394	0.000	0.000	0.000
Exposure High	674,974	0.490	0.500	0.000	0.000	1.000
Loan-Level Control Variables						
logAmount	674,974	5.251	0.737	4.754	5.236	5.759
logIncome	674,974	4.492	0.726	3.970	4.443	4.934
Loan-to-Income	674,974	2.489	1.205	1.611	2.424	3.273
Conventional	674,974	0.959	0.199	1.000	1.000	1.000
Sold	674,974	0.655	0.476	0.000	1.000	1.000
Jumbo	674,974	0.179	0.384	0.000	0.000	0.000
Male	674,974	0.674	0.469	0.000	1.000	1.000
Ethnicity	674,974	0.107	0.309	0.000	0.000	0.000
Owner-occupancy	674,974	0.837	0.369	1.000	1.000	1.000

Table 1. Continued

Panel D: ZIP-Level Variables

VARIABLES	(1) N	(2) Mean	(3) Std. dev.	(4) P25	(5) Median	(6) P75
Dependent Variables						
ΔlogHPI - FHFA	89,391	0.016	0.090	-0.035	0.014	0.067
ΔlogHPI - CoreLogic	41,276	-0.005	0.110	-0.066	-0.005	0.055
logCredit	89,391	10.644	1.238	9.737	10.655	11.556
ΔlogCredit	89,391	-0.112	0.293	-0.290	-0.110	0.065
Foreclosure Rate	60,598	0.117	0.137	0.019	0.066	0.161
Short Sale Rate	60,598	0.031	0.045	0.000	0.013	0.042
Main Explanatory Variables						
Exposure	89,391	0.000	1.000	-0.430	0.132	0.579
Exposure High	89,391	0.501	0.500	0.000	1.000	1.000
ZIP-Level Control Variables						
Lag Tier 1 Cap at ZIP	89,391	0.037	0.016	0.025	0.033	0.045
ΔEmployment	89,391	0.004	0.101	-0.048	-0.000	0.045
ΔEstablishment	89,391	0.004	0.052	-0.025	0.000	0.028
ΔGross Income	89,391	0.130	0.920	-0.002	0.039	0.075
logAve. Income	89,391	3.919	0.439	3.641	3.833	4.106
HHI	89,391	0.060	0.037	0.036	0.050	0.073
Nonbank Share	89,391	0.260	0.114	0.177	0.252	0.335
ΔlogNonbank Credit	89,391	-0.120	0.463	-0.385	-0.099	0.167
ZIP-Level Census Variables						
logPopulation	89,391	9.475	0.956	8.742	9.634	10.248
% African American	89,391	10.669	16.712	1.100	3.600	12.000
% Hispanic	89,391	10.936	15.594	1.900	4.500	12.500
% Poverty Population	89,389	9.581	6.967	4.300	7.900	13.000
% with Bachelor or Higher	89,391	27.205	15.750	15.300	22.500	35.700
IV Analysis Variables						
SEC Influence ZIP	89,391	-1.143	0.471	-1.386	-1.055	-0.799
Public Share	89,391	0.278	0.115	0.191	0.263	0.350
OCC Share Pre	89,391	0.441	0.198	0.309	0.399	0.516

Table 1. Continued

Panel E: High vs. Low Exposure ZIP Codes

	High Exposure ZIP			Low Exposure ZIP		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	Median	N	Mean	Median
Pre-Crisis (Year 2004 – 2006)						
ΔlogHPI - FHFA	19,062	0.090	0.079	18,949	0.074	0.065
ΔlogHPI - CoreLogic	9,513	0.086	0.072	8,079	0.072	0.059
logCredit	19,062	10.979	11.034	18,949	10.766	10.782
ΔlogCredit	19,062	-0.077	-0.064	18,949	-0.119	-0.099
Foreclosure Rate	13,119	0.045	0.023	11,995	0.045	0.022
Short Sale Rate	13,119	0.009	0.006	11,995	0.008	0.004
Crisis (Year 2007 – 2010)						
ΔlogHPI - FHFA	25,694	-0.044	-0.032	25,686	-0.023	-0.018
ΔlogHPI - CoreLogic	12,772	-0.079	-0.061	10,912	-0.052	-0.039
logCredit	25,694	10.490	10.517	25,686	10.461	10.462
ΔlogCredit	25,694	-0.158	-0.156	25,686	-0.087	-0.105
Foreclosure Rate	18,357	0.210	0.161	17,127	0.123	0.091
Short Sale Rate	18,357	0.055	0.038	17,127	0.039	0.024
All Period						
% African American	44,756	11.980	3.600	44,635	9.354	3.600
% Hispanic	44,756	12.872	4.900	44,635	8.995	4.200
% Poverty Population	44,754	10.295	8.700	44,635	8.866	7.200
% with Bachelor or Higher	44,756	24.680	21.300	44,635	29.736	24.500
logAve. Income	44,756	3.854	3.805	3.984	0.485	3.868

those of *Short Sale Rate,* which implies foreclosure is the more common method of resolving distressed mortgages. Panel E compares ZIP-level dependent variables by high and low exposure ZIP codes for the pre-crisis and the crisis period. For the pre-period, the mean of changes in log FHFA home price index (Δ*logHPI – FHFA*) is 0.090 for high exposure ZIP codes and 0.074 for low exposure ZIP codes. This implies that both areas experienced rapid growth in house prices during the pre-period but high exposure ZIP codes experienced larger growth. For the crisis, the pattern of house price growth is reversed. The mean of Δ*logHPI – FHFA* is -0.044 for high exposure ZIP codes and -0.023 is for low exposure ZIP codes. This implies that both areas experienced large decreases in house prices during the crisis but high exposure ZIP codes experienced a larger decrease. In general, high exposure ZIP codes show worse outcomes than low exposure ZIP codes in all the main dependent variables (*HPI*, *Credit*, *Foreclosure Rate*, and *Short Sale Rate*) during the crisis, consistent with my predictions. Additionally, high exposure ZIP codes have larger minority populations and more residents below the poverty line as well as fewer residents with bachelor's or higher degrees and a lower average income. These differences across regions suggest that controlling geographical characteristics is important to isolate the effects of DLR, and I address this issue using various approaches including the fixed effects and the instrumental variable.

4. Empirical Approach and Results

4.1. Identifying the Credit Crunch Channel: Bank-Level Analysis

In a credit crunch, high DLR banks would reduce loan supply during the crisis, because they had not built large capital buffers for expected losses and carried loss overhangs by delaying loss recognition. Figure 3 shows mortgage amounts originated by different lenders in high and low exposure ZIP codes. The top left panel of Figure 3 presents total mortgage amounts by all lenders.

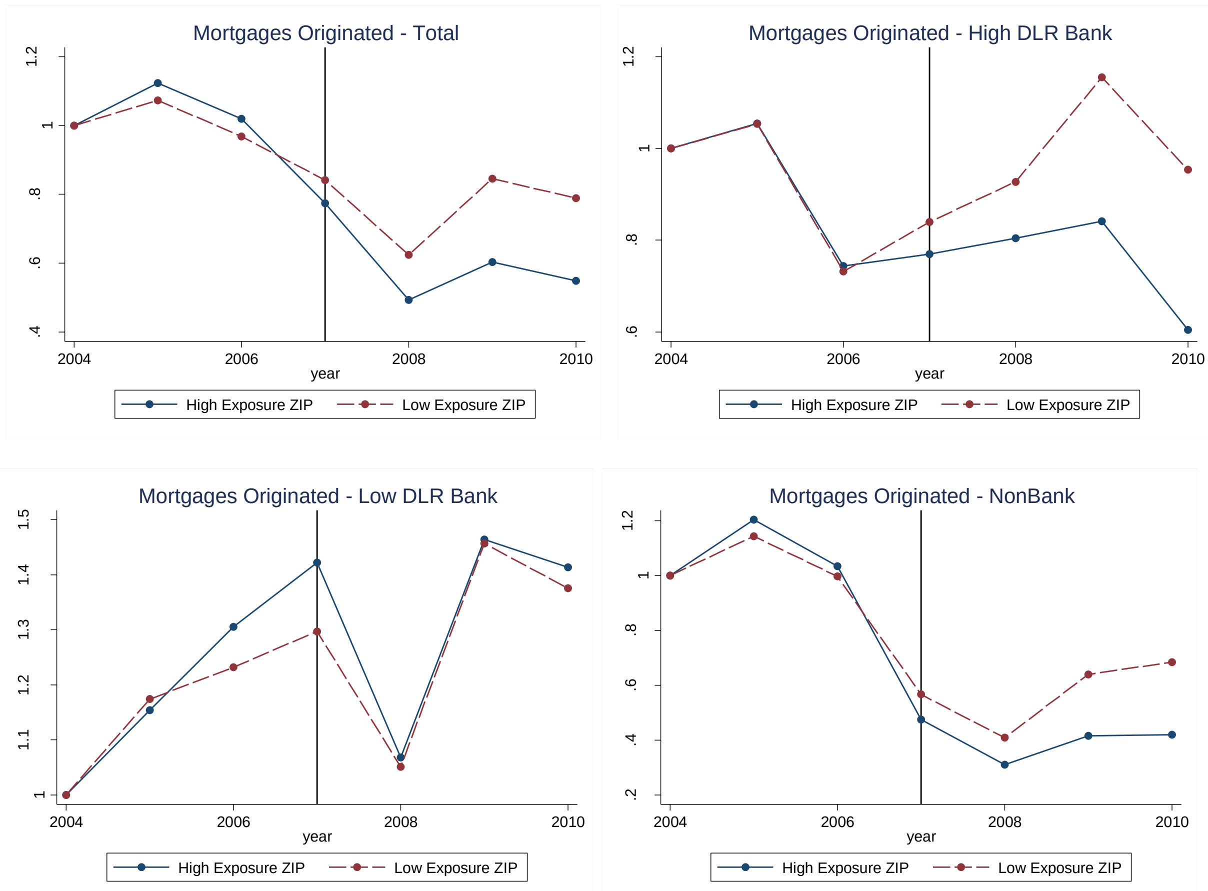
The figure suggests that high exposure ZIP codes experienced a larger credit cycle than low exposure ZIP codes, consistent with banks' DLR being positively associated with lending pro-cyclicality. However, the difference between high and low exposure ZIP codes is much more pronounced during the crisis, which suggests that banks' financial reporting plays a bigger role during bad times, consistent with the findings of Jiménez et al. (2017).[14] The top right panel of Figure 3 presents total mortgage amounts by high DLR banks and suggests that the total mortgage amounts by high DLR banks during the crisis were significantly smaller in high exposure ZIP codes than in low exposure ones. Although a causal conclusion cannot be drawn from these figures, they suggest that banks' DLR is negatively related to mortgage supply during the crisis.

I formally investigate the effect of banks' DLR on mortgage supply at the bank level. To identify *the credit crunch channel*, two empirical challenges raised by Acharya and Ryan (2016) need to be addressed: loan supply needs to be distinguished from loan demand, and financial reporting effects need to be separated from other bank characteristics such as business models and risk-taking incentives that may affect banks' lending decisions as well. I address these challenges using three approaches. First, I conduct the bank-ZIP-level analysis with ZIP-year and bank fixed effects to control for unobservable time-varying ZIP-level demand and time- invariant bank characteristics such as the business model and loan portfolio composition. The inclusion of ZIP-year fixed effects ensures that high DLR banks are compared to low DLR banks within the same ZIP code and year, mitigating a concern that the estimation is driven by high DLR banks operating in more pro-cyclical areas. I estimate the following regression model during 2004 – 2009.

[14] Jiménez et al. (2017) find that firms were not affected by the introduction of dynamic provisioning during good times because they could easily substitute credit from less affected banks. Similarly, the U.S. mortgage lending market is competitive, so borrowers may substitute mortgages from nonbank lenders when banks cannot lend to them.

Figure 3. Time Series of Mortgage Amounts Originated by Institutions

The figures present total mortgage amounts originated by different lenders in above (high) and below (low) the median ZIP-level exposure to banks' DLR. The top left panel plots total mortgage amounts by *all lenders* in high and low exposure ZIP codes. The top right panel plots total mortgage amounts by *high DLR banks* in high and low exposure ZIP codes. The bottom left panel plots total mortgage amounts by *low DLR banks* in high and low exposure ZIP codes. The bottom right panel plots total mortgages amount by *nonbank lenders* in high and low exposure ZIP codes. All the amounts are indexed to 2004.



$$VOL_{i,z,t} = \beta_1 DLR\ High_i \times Crisis_t + \beta_2 Y_{i,t} + \beta_3 Y_{i,t} \times Crisis_t + \delta_{z,t} + \lambda_i + \epsilon_{i,z,t}. \qquad (1)$$

The unit of observation in the regression is bank-ZIP-year. The dependent variable, $VOL_{i,z,t}$, is the volume of mortgages originated by bank *i* at ZIP code *z* in year *t*, and it is normalized by the total new mortgage amounts in the same ZIP-year and multiplied by 100. $DLR\ High_i$ is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank-level sample median, and $Crisis_t$ is equal to one if year is 2007–2009. The bank-level control variables, $Y_{i,t}$, include *logAssets*, *Cash*, *Deposits*, *Lag Tier 1 Capital Ratio*, *Loans to Deposits*, *Loan Loss Reserve*, *Non-Performing Loan*, and *ROA*. Additionally, the interaction of $Y_{i,t}$ and $Crisis_t$ is included to allow banks' characteristics to have different effects on the mortgage supply before and during the crisis. Finally, ZIP-year fixed effects, $\delta_{z,t}$, and bank fixed effects, λ_i, are included. All regressions are weighted by the population of the ZIP code and all variables are defined in Appendix A.

Table 2 presents results from estimation of equation (1). Column (1) provides the result from a regression without fixed effects, and the coefficient of *DLR High* × *Crisis* is significantly negative (-0.475, $p<0.01$), suggesting that high DLR banks reduced loan supply more than low DLR banks during the crisis. Column (2) provides results with the ZIP-year and bank fixed effects. The coefficient diminishes (-0.389, $p<0.01$), suggesting that decrease in loan supply was partly driven by unobservable variables. However, the coefficient remains statistically significant even after including extensive fixed effects. The coefficient of -0.389 implies that high DLR banks decreased their supply of mortgages by 0.389 percent of the total ZIP-level mortgage originations relative to low DLR banks during the crisis, all else being equal. This is economically meaningful, approximately 19% of the mean and 12% of the standard deviation of $VOL_{i,z,t}$. Columns (3) and (4) present results for the sample with below and above the median values of *Lag Tier 1 Capital Ratio* by bank and year. That is, I separately examine the credit crunch effect for low- and high-capitalized banks. The coefficient of *DLR High* × *Crisis* is significantly negative for low-capitalized banks (-0.511, $p<0.01$), whereas the coefficient for high-capitalized banks is statistically insignificant. These results suggest that the credit crunch effect arises only for low-capitalized banks, which is consistent with the theory.

Table 2. Effect of Banks' DLR on Mortgage Origination: Bank-ZIP Level

This table presents regressions of high DLR banks on new mortgage amounts at the bank-ZIP level using a following model:

$$VOL_{i,z,t} = \beta_1 DLR\ High_i \times Crisis_t + \beta_2 Y_{i,t} + \beta_3 Y_{i,t} \times Crisis_t + \delta_{z,t} + \lambda_i + \epsilon_{i,z,t}.$$

The dependent variable is the volume of mortgages originated by bank *i* at ZIP code *z* in year *t*, and it is normalized by total new mortgage amounts in the same ZIP-year and multiplied by 100. The primary independent variable is $DLR\ High_i \times Crisis_t$, where $DLR\ High_i$ is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank-level sample median, and $Crisis_t$ is equal to one if year is 2007–2009. Columns (1) and (2) report the results for the full sample, and columns (3) and (4) present results for the sample with below and above median values of *Lag Tier 1 Capital Ratio* by bank and year. The bank level controls $Y_{i,t}$ include *logAssets, Cash, Deposit, Lag Tier 1 Capital Ratio, Loans to Deposits, Loan Loss Reserve, Non-Performing Loan*, and *ROA*. The interaction term of $Y_{i,t}$ and $Crisis_t$ is included. All variables are defined in Appendix A. Regressions are weighted by the population of the ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Low Cap 1	High Cap 1
VARIABLES	VOL	VOL	VOL	VOL
DLR High×Crisis	-0.475***	-0.389***	-0.511***	0.049
	(0.128)	(0.122)	(0.160)	(0.036)
DLR High	-0.442***			
	(0.078)			
Crisis	-4.378***			
	(1.108)			
Observations	1,283,506	1,283,407	961,140	313,769
Bank Controls	YES	YES	YES	YES
Bank Controls*Crisis	YES	YES	YES	YES
ZIP-Year FE	NO	YES	YES	YES
Bank FE	NO	YES	YES	YES
Adjusted R-squared	0.255	0.405	0.421	0.264

Next, I exploit within-bank variation in different types of mortgages, to further control for unobservable time-varying bank characteristics. The prior approach cannot control for time-varying bank characteristics that could be correlated with banks' choices on loan loss provisioning as well as their lending decisions. For example, managers in high DLR banks may have worse management skills, which could be more salient during the crisis, hurting banks' health and limiting lending capability. To address this concern, I use a similar approach to that of Loutskina and Strahan (2009, 2011) who exploit the inability of Fannie Mae and Freddie Mac to purchase jumbo mortgages to examine the impact of banks' liquidity on mortgage supply.[15] Whereas Loutskina and Strahan (2009) compare jumbo and non-jumbo conventional loans, I compare conventional and Federal Housing Administration (FHA) loans, because jumbo loans have a relatively small market share, which cannot explain large declines in house prices. A conventional loan is a regular mortgage not guaranteed by any government agency, whereas an FHA loan is a mortgage insured by the Federal Housing Administration. FHA loans have a zero risk weight in calculating banks' risk-weighted assets, have lower credit risks than conventional loans, and can be easily sold to Government-Sponsored Enterprises (GSEs), in particular, Ginnie Mae. Consequently, these loans impose a lower capital burden on banks, and thus I expect that high DLR banks tightened their supply of conventional loans significantly more than FHA loans during the crisis. A key idea behind this approach is that loans within the same bank and region are likely to share unobservable demand and bank variables that may affect the bank's lending. To better understand this approach, consider the following two equations.

[15] By regulation, the Government-Sponsored Enterprises (GSEs), such as Fannie Mae and Freddie Mac, may purchase only mortgages below a specific amount. The conforming loan limit (or the jumbo cutoff) varies by county and year. In 2009, the conforming loan limit for single-family mortgages ranged from $417,000 to $794,000. Mortgages with amounts exceeding the conforming loan limit are called jumbo loans.

$$VOL^C{}_{i,m,t} = \beta_1^C DLR\ High_i \times Crisis_t + \beta_2^C Y_{i,t} + \beta_3^C Y_{i,t} \times Crisis_t$$
$$+ Unobservable\ demand_{m,t}\ or\ bank\ variables_{i,t} + \epsilon_{i,m,t}^C, \quad (2a)$$

$$VOL^F{}_{i,m,t} = \beta_1^F DLR\ High_i \times Crisis_t + \beta_2^F Y_{i,t} + \beta_3^F Y_{i,t} \times Crisis_t$$
$$+ Unobservable\ demand_{m,t}\ or\ bank\ variables_{i,t} + \epsilon_{i,m,t}^F. \quad (2b)$$

The unit of observation in these regressions is bank-MSA-year.[16] The dependent variable, $VOL^C{}_{i,m,t}$ or $VOL^F{}_{i,m,t}$, is the volume of conventional or FHA mortgages originated by bank i at MSA m in year t, and it is normalized by the total new mortgage amounts in the same MSA-year and multiplied by 100. The bank-level control variables $Y_{i,t}$ and the interaction of $Y_{i,t}$ and $Crisis_t$ is included as in equation (1). Importantly, each equation may contain unobservable demand-side or bank-specific variables that potentially bias estimation of the effect of banks' DLR on mortgage supply. Then, under the assumption that the two equations share unobservable demand-side variables and bank characteristics, the difference of the two equations removes unobservable variables as follows.

$$VOL^C{}_{i,m,t} - VOL^F{}_{i,m,t} = (\beta_1^C - \beta_1^F) DLR\ High_i \times Crisis_t + (\beta_2^C - \beta_2^F) Y_{i,t}$$
$$+(\beta_3^C - \beta_2^F) Y_{i,t} \times Crisis_t + \delta_{m,t} + \lambda_i + \eta_{i,m,t}. \quad (2c)$$

The estimation of equation (2c) provides the effect of banks' DLR on their supply of high capital-burden loans (conventional loans) compared to that of low capital-burden loans (FHA loans) within a bank-MSA-year. I include MSA-year fixed effects, $\delta_{m,t}$, to control for unobservable common shocks that affect a MSA in a given year, and bank fixed effects, λ_i, to control for unobservable time-invariant bank characteristics similar to equation (1). All regressions are weighted by MSA population.

[16] I define local markets at the MSA level instead at the ZIP level in these regressions because many banks supply only one type of loan in a given ZIP code and year.

Table 3 presents results from estimations of equations (2a) through (2c). Columns (1) through (3) report the results for the volume of conventional loans, the volume of FHA loans, and the difference of the volumes of conventional and FHA loans as the dependent variable. In columns (1) and (2), the coefficients of *DLR High* × *Crisis* are significantly negative (-0.069, $p<0.01$; -0.015, $p<0.01$), suggesting that high DLR banks reduced both conventional and FHA loan supply more than low DLR banks during the crisis. In column (3), consistent with my prediction, the coefficient of *DLR High* × *Crisis* is significantly negative (-0.051, $p<0.01$), suggesting that high DLR banks reduced conventional loan supply more, relative to FHA loan supply, during the crisis. The coefficient of -0.051 implies that high DLR banks decreased their volume of conventional loans by 0.051 percent of the total MSA-level mortgage originations, relative to FHA loans, during the crisis, all else equal. This is approximately 10% of the mean and 4% of the standard deviation of the dependent variable, which is economically meaningful. As in the bank-ZIP-level analysis, I separately examine the credit crunch effect for low- and high-capitalized banks in columns (4) and (5). The coefficient of *DLR High* × *Crisis* is significantly negative for the low-capitalized banks (-0.073, $p<0.01$) but statistically insignificant for high-capitalized banks. These results confirm that the credit crunch effect presents for only low-capitalized banks.

Finally, I use an instrumental variable approach to address the remaining concern: confounding factors may affect the two types of mortgages differently. For example, suppose a manager was optimistic about the housing market during the boom period so thus delayed loan loss recognition. Once the crisis started, the manager realized being too optimistic, adjusted her/his evaluations on the risk of mortgages, and thus decreased the supply of conventional loans more than FHA loans because FHA loans were still safe. The within-bank analysis using equation (2c) does not address this concern. To overcome this concern, an exogenous shift in banks' loan loss

Table 3. Effect of Banks' DLR on Mortgage Origination: Bank-MSA Level

This table presents regressions of high DLR banks on new mortgage amounts at the bank-MSA level. Three models are estimated as follows:

$$VOL^{C}{}_{i,m,t} = \beta_1^C DLR\ High_i \times Crisis_t + \beta_2^C Y_{i,t} + \beta_3^C Y_{i,t} \times Crisis_t + \delta_{m,t}^C + \lambda_i^C + \epsilon_{i,m,t}^C,$$

$$VOL^{F}{}_{i,m,t} = \beta_1^F DLR\ High_i \times Crisis_t + \beta_2^F Y_{i,t} + \beta_3^F Y_{i,t} \times Crisis_t + \delta_{m,t}^F + \lambda_i^F + \epsilon_{i,m,t}^F,$$

$$\begin{aligned} VOL^{C}{}_{i,m,t} - VOL^{F}{}_{i,m,t} = {} & \left(\beta_1^C - \beta_1^F\right) DLR\ High_i \times Crisis_t + \left(\beta_2^C - \beta_2^F\right) Y_{i,t} \\ & + \left(\beta_3^C - \beta_2^F\right) Y_{i,t} \times Crisis_t + \delta_{m,t} + \lambda_i + \eta_{i,m,t}. \end{aligned}$$

The dependent variables are the volume of conventional loans, FHA loans, and the difference between conventional loans and FHA loans originated by bank *i* at MSA *m* in year *t*, and they are normalized by total new mortgage amounts in the same MSA-year and multiplied by 100. The primary independent variable is $DLR\ High_i \times Crisis_t$, where $DLR\ High_i$ is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank-level sample median, and $Crisis_t$ is equal to one if year is 2007–2009. Columns (1) through (3) report the results for the full sample, and columns (3) and (4) present results for the sample with below and above median values of *Lag Tier 1 Capital Ratio* by bank and year. The bank level controls $Y_{i,t}$ include *logAssets*, *Cash*, *Deposit*, *Lag Tier 1 Capital Ratio*, *Loans to Deposits*, *Loan Loss Reserve*, *Non-Performing Loan*, and *ROA*. The interaction term of $Y_{i,t}$ and $Crisis_t$ is included. All variables are defined in Appendix A. Regressions are weighted by the population of the MSA. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)	(4)	(5)
	Full Sample	Full Sample	Full Sample	Low Cap 1	High Cap 1
VARIABLES	VOL^C	VOL^F	VOL^C – VOL^F	VOL^C – VOL^F	VOL^C – VOL^F
DLR High×Crisis	-0.069***	-0.015***	-0.051***	-0.073***	-0.012
	(0.015)	(0.003)	(0.012)	(0.016)	(0.008)
Observations	125,494	125,494	125,494	86,621	38,611
Bank Controls	YES	YES	YES	YES	YES
Bank Controls*Crisis	YES	YES	YES	YES	YES
MSA-Year FE	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Adjusted R-squared	0.547	0.377	0.533	0.555	0.289

provisioning is required. I use the SEC's influence on U.S. public banks as an instrumental variable to isolate an exogenous shift in loan loss provisioning. Bank regulators and the SEC have different views of early recognition of expected loan losses. Whereas regulators advocate for early loan loss recognition, the SEC opposes excessive early recognition, because it views this practice as building cookie jar reserves to smooth income (Beck and Narayanamoorthy, 2013; Balla and Rose, 2015; Jayaraman et al., 2017). The SEC's litigation against SunTrust Bank in 1998 for its over-provisioning led the SEC to issue guidance for loan loss provisioning practices.[17] After the SunTrust case, the SEC issued Staff Accounting Bulletin (SAB) 102 in July 2001 to discourage recognizing excessive expected loan losses. Balla and Rose (2015) provide evidence that public banks changed their practices in response to the SEC's intervention more than privately held banks, suggesting that SAB 102 created an exogenous shift to the timing of public banks' loan loss provisioning. Additionally, studies suggest that the distance between the bank and the SEC office is negatively associated with the SEC's oversight of the bank (Kedia and Rajgopal, 2011; Jayaraman et al., 2017).[18] Given that this distance is plausibly exogenous to a bank's behavior in the housing market, I use variation within public banks depending on their expected level of the SEC's influence on them. That is, I use *–log(distance)×Public* as an instrument for individual banks' loan loss provisioning following a similar approach in Jayaraman et al. (2017).[19] I then estimate the first-stage model as follows.

$$DLR\ High_i \times Crisis_t = \beta_1 SEC\ Influence\ Bank_i \times Crisis_t + \beta_2 Y_{i,t} \qquad \text{(IV1)}$$

[17] The SEC was concerned that U.S. public banks were systematically overstating their loan loss reserves in 1997. In 1998, the SEC required SunTrust Banks to reverse its loan loss reserve by $100 million by restating its earnings for 1994–1996 (Balla and Rose, 2015).

[18] I consider the following SEC offices: headquarters – Washington D.C.; regional offices – New York City; Miami; Chicago; Denver; Los Angeles. District offices are excluded following Kedia and Rajgopal (2011).

[19] *Distance* is the distance between a bank's headquarters and the closest SEC office and *Public* is an indicator variable equal to one if the bank or its parent holding company is publicly traded.

$$+\beta_3 Y_{i,t} \times Crisis_t + \delta_{z,t} + \lambda_i + \epsilon_{i,z,t}.$$

SEC Influence Bank$_i$ is and instrumental variable defined as *–log(distance)×Public*. The second-stage model is a modification of equation (1) as follows.

$$VOL_{i,z,t} = \beta_1 \widehat{DLR\ High_i \times Crisis_t} + \beta_2 Y_{i,t} + \beta_3 Y_{i,t} \times Crisis_t + \delta_{z,t} + \lambda_i + \epsilon_{i,z,t}. \qquad \text{(IV2)}$$

The unit of observation is bank-ZIP-year. The dependent variable, $VOL_{i,z,t}$, is the volume of mortgages originated by bank *i* at ZIP code *z* in year *t*, and it is normalized by the total new mortgage amounts in the same ZIP-year and multiplied by 100. The primary independent variable, $\widehat{DLR\ High_i \times Crisis_t}$, is the instrumented variable from the first-stage model. *DLR High$_i$* is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank-level sample median, and $Crisis_t$ is equal to one if year is 2007–2009. The bank-level control variables $Y_{i,t}$ and the interaction of $Y_{i,t}$ and $Crisis_t$ is included as in equation (1). ZIP-year fixed effects, $\delta_{z,t}$, and bank fixed effects, λ_i, are also included. All regressions are weighted by the population of the ZIP code and all variables are defined in Appendix A.

Table 4 reports the instrumental variable estimations of equations (IV1) and (IV2). Column (1) shows a strong first-stage relation between the instrument and banks' DLR. The partial F-statistics is 22.16 (p<0.01), which is significantly larger than the critical value of 8.96 suggested by Stock et al. (2002) and Larcker and Rusticus (2010) as needed to avoid a weak-instrument. The second-stage model is estimated in columns (2) through (4). Column (2) provides the result with the full sample, and the coefficient of $\widehat{DLR\ High_i \times Crisis_t}$ is statistically insignificant. However, once I separately examine the credit crunch effect for low- and high-capitalized banks in columns (3) and (4), the coefficient of $\widehat{DLR\ High_i \times Crisis_t}$ becomes statistically significant for the low-capitalized banks but not for the high-capitalized banks.

4.2. Identifying the Distressed sales Channel: Matched Loan-Level Analysis

Next, I examine another channel on how banks' loan loss provisioning may affect house prices: distressed sales.[20] If these sales are a factor, high DLR banks would have taken more risk-taking before the crisis, and their mortgages would have defaulted more frequently during the crisis. Consequently, homes with mortgages originated by high DLR banks would be more likely to be sold at distressed prices via foreclosures or short sales, leading to further declines in house prices. Identifying this channel requires controlling for local economic conditions that drive mortgage distress. For example, some regions might experience greater unemployment than other regions, leading to more foreclosures. I take advantage of granular mortgage loans and housing transactions data to control for these factors. I first identify mortgages originated by high and low DLR banks during the pre-crisis, using a fuzzy match between HMDA and DataQuick.[21] I then track those mortgages over the crisis period and compare their likelihoods of resulting in distressed sales in high exposure ZIP codes. To test this, I estimate the following model.

$$\begin{aligned} Distressed\ Sale_{i,j,crisis} &= \beta_1 Exposure\ High_z \times DLR\ High_i \\ &+\beta_2 X_{z,t} + \beta_3 Y_{i,t} + \beta_4 W_{i,j,t} + \delta_i + \gamma_t + \kappa_r + \lambda_z + \epsilon_{i,j,crisis}. \end{aligned} \tag{4}$$

The generalized dependent variable is $Distressed\ Sale_{i,j,crisis}$, for which I use three different specific variables: *Foreclosure, Short Sale,* and *All Distressed Sale*. These are indicator variables equal to one if mortgage *j* originated by bank *i* was foreclosed, became a short sale, or either became

[20] Although a causal direction between banks' DLR and their risk-taking is clear theoretically, it may not be clear empirically. For example, banks could expand credit to riskier borrowers because they have been delaying loan loss provisions and thus faced less discipline by market participants. On the other hand, banks may want to take more risk, so they delay loan loss provisions to make their accounting numbers better. One caveat is that I cannot fully establish a causal direction between banks' DLR and their risk-taking. However, I try to address this issue using an instrumental approach at the ZIP level in Table A10 of the online appendix.

[21] See a detailed description on the fuzzy match in Section A.2 of the online appendix.

Table 4. Effect of Banks' DLR on Mortgage Origination: IV Analysis

This table presents instrument variable regressions of high DLR banks on new mortgage amounts at the bank-ZIP level. The first-stage and the second-stage models are estimated as follows:

1st Stage: $DLR\ High_i \times Crisis_t = \beta_1 SEC\ Influence\ Bank_i \times Crisis_t + \beta_2 Y_{i,t} + \beta_3 Y_{i,t} \times Crisis_t + \delta_{z,t} + \lambda_i + \epsilon_{i,z,t}$,

2nd Stage: $VOL_{i,z,t} = \beta_1 \widehat{DLR\ High_i \times Crisis_t} + \beta_2 Y_{i,t} + \beta_3 Y_{i,t} \times Crisis_t + \delta_{z,t} + \lambda_i + \epsilon_{i,z,t}$.

SEC Influence Bank$_i$ is a bank-level variable defined as *–log(Distance)*$_i$×*Public*$_i$, where *Distance* is the distance between a banks' headquarters and the closest SEC office and *Public* is an indicator variable equal to one if the bank or its parent holding company is publicly traded. The dependent variable is the volume of mortgages originated by bank i at ZIP code z in year t, and it is normalized by total new mortgage amounts in the same ZIP-year and multiplied by 100. The primary independent variable is $\widehat{DLR\ High_i \times Crisis_t}$, the instrumented variable from the first-stage model. Column (1) reports the first-stage results, column (2) reports the second-stage results for the full sample, and columns (3) and (4) report the second-stage results for the sample with below and above median values of *Lag Tier 1 Capital Ratio* by bank and year. The bank level controls $Y_{i,t}$ include *logAssets, Cash, Deposit, Lag Tier 1 Capital Ratio, Loans to Deposits, Loan Loss Reserve, Non-Performing Loan,* and *ROA*. The interaction term of $Y_{i,t}$ and *Crisis*$_t$ are included. All variables are defined in Appendix A. Regressions are weighted by the population of the ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)	(4)
	1st Stage	2nd Stage	2nd Stage	2nd Stage
	Full Sample	Full Sample	Low Cap 1	High Cap 1
VARIABLES	VOL	VOL	VOL	VOL
IV: SEC Influence Bank×Crisis	0.018***			
	(0.004)			
DLR High×Crisis		-1.266	-2.471**	-0.809
		(0.947)	(1.012)	(0.773)
Observations	1,273,929	1,273,929	957,634	307,531
Bank Controls	YES	YES	YES	YES
Bank Controls*Crisis	YES	YES	YES	YES
ZIP-Year FE	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Adjusted R-squared	0.720	0.402	0.406	0.259
Partial F-Stat.	22.16***			

foreclosed or a short sale during 2007–2010.[22] The primary independent variable is $\textit{Exposure High}_z \times \textit{DLR High}_i$, where $\textit{Exposure High}_z$ is an indicator variable equal to one if $\textit{Exposure}_z$ is above the ZIP-level sample median and $\textit{DLR High}_i$ is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank-level sample median. The ZIP-level control variables, $X_{z,t}$, include *Lag Tier 1 Cap at ZIP*, *ΔEmployment*, *ΔEstablishment*, *ΔGross Income*, *logAve. Income*, *HHI*, *Nonbank Share*, and *ΔlogNonbank Credit*. The same bank-level control variables, $Y_{i,t}$, are included as in equation (1), and the mortgage-level control variables, $W_{i,j,t}$, include *logAmount*, *logIncome*, *Loan-to-Income*, *Male*, *Ethnicity*, *Owner-occupancy*, *Jumbo*, *Conventional*, and *Sold*. Finally, I include bank δ_i, year γ_t, race κ_r, and ZIP λ_z fixed effects.

Table 5 presents results from estimation of equation (4). Columns (1) through (3) report the results for the indicator variable of being foreclosed, being a short sale, and either being foreclosed or a short sale during 2007–2010 as the dependent variable. In columns (1) and (3), the coefficients of *Exposure High* × *DLR High* are significantly positive for *Foreclosure* and *All Distressed Sale* (0.009, p<0.01; 0.010, p<0.01). The coefficient of 0.009 (0.010) in column (1) ((3)) implies that mortgages originated by high DLR banks in high exposure ZIP codes were 0.9 (1.0) percentage points more likely to be foreclosed (distressed sales) than mortgages originated by low DLR banks during the crisis. The coefficient in column (2) for *Short Sale* is unexpectedly insignificantly different from zero. This insignificance could be due to noise and errors in the fuzzy match between HMDA and DataQuick. Because short sales are much less common than foreclosures, errors in the fuzzy match could result in worse matching and lead to less valid inferences. In general, however, the results in Table 5 are consistent with my prediction that

[22] I extend the crisis period to 2010 for the distressed sales analysis because I observe only dates when housing transactions were closed, not when houses were initially foreclosed or became a short sale. Therefore I allow one more year for a mortgage that became initially distressed during 2007–2009 to show up as a distress sale in the data.

Table 5. Effect of Banks' DLR on Distressed Sales: Matched Loan Level

This table presents regressions of high DLR banks on distressed sales using the matched loan sample between HMDA and DataQuick using a following model:

$$Distressed\ Sale_{i,j,crisis} = \beta_1 Exposure\ High_z \times DLR\ High_i$$
$$+\beta_2 X_{z,t} + \beta_3 Y_{i,t} + \beta_4 W_{i,j,t} + \delta_i + \gamma_{\mathrm{t}} + \kappa_r + \lambda_z + \epsilon_{i,j,crisis}.$$

The dependent variable is *Distressed Sale*$_{i,j,crisis}$, which can be three different variables: *Foreclosure*, *Short Sale*, and *All Distressed Sale*. These are indicator variables equal to one if a mortgage *j* is originated by bank *i* is foreclosed, became a short sale, or either become foreclosed or a short sale during 2007–2010. The primary independent variable is *Exposure High*$_z$ × *DLR High*$_i$, where *Exposure High*$_z$ is an indicator variable equal to one if *Exposure*$_z$ is above the sample median and *DLR High*$_i$ is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank-level sample median. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share*, and *ΔlogNonbank Credit*. The bank-level controls $Y_{i,t}$ include *logAssets, Cash, Deposits, Lag Tier 1 Capital Ratio, Loans to Deposits, Loan Loss Reserve, Non-Performing Loan*, and ROA. The mortgage-level controls $W_{i,j,t}$ include *logAmount, logIncome, Loan-to-Income, Male, Ethnicity, Owner-occupancy, Jumbo, Conventional*, and *Sold*. All variables are defined in Appendix A. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)
VARIABLES	Foreclosure	Short Sale	All Distressed Sale
Exposure High×DLR High	0.009***	0.001	0.010***
	(0.003)	(0.001)	(0.003)
Observations	674,519	674,519	674,519
ZIP Controls	YES	YES	YES
Bank Controls	YES	YES	YES
Mortgage Controls	YES	YES	YES
Bank FE	YES	YES	YES
Year FE	YES	YES	YES
Race FE	YES	YES	YES
ZIP FE	YES	YES	YES
Adjusted R-squared	0.068	0.021	0.077

mortgages originated by high DLR banks became distressed more frequently during the crisis, because these banks took more risk before the crisis.

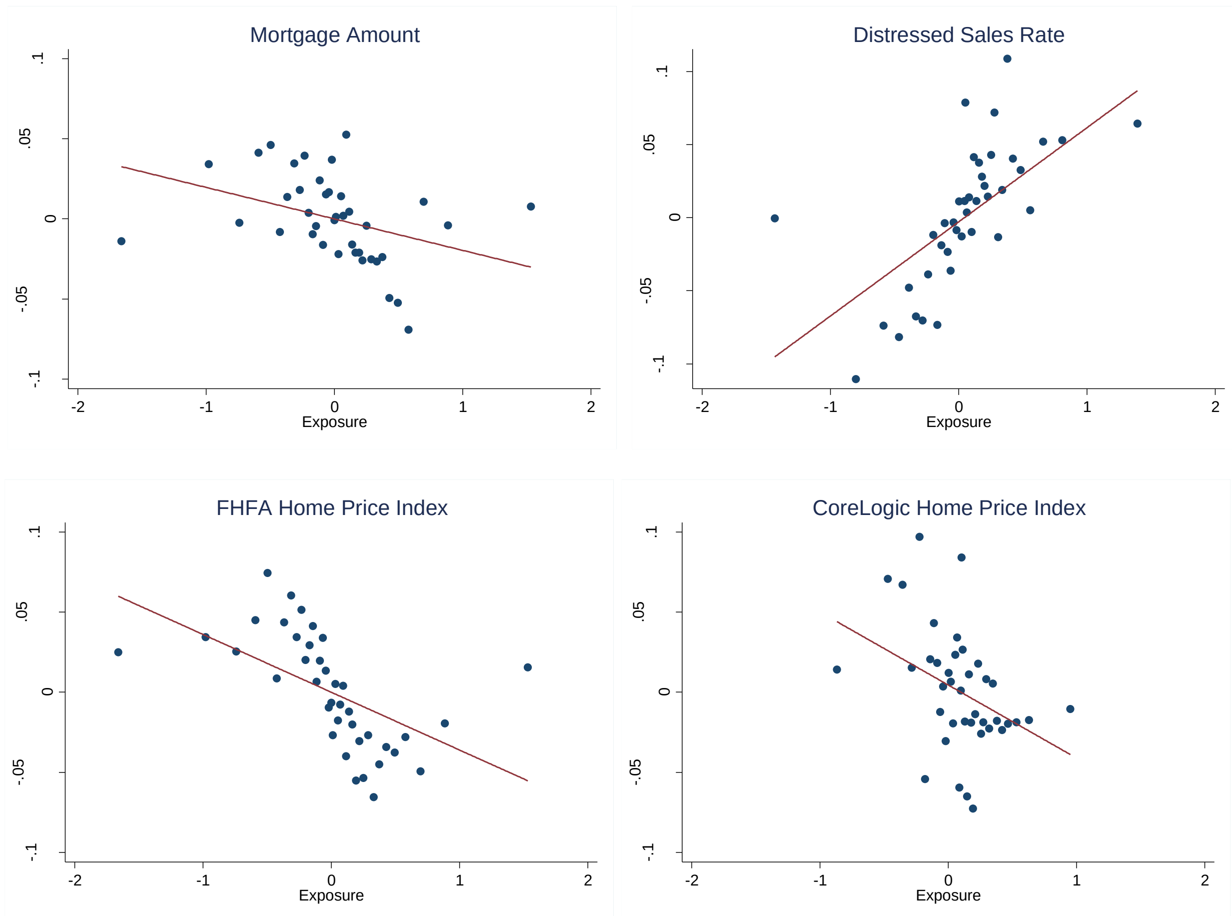
4.3. Aggregate Effects of Banks' DLR: ZIP-Level Analysis

Next, I examine the aggregate effects of banks' DLR on credit supply, distressed sales, and house prices at the ZIP level to capture any potential spillovers by high DLR banks or substitution effects by other financial institutions. I begin with a simple graphical analysis that demonstrates main findings at the ZIP level. Figure 4 indicates binned scatterplots of the exposure to banks' DLR versus various standardized outcomes during the crisis. Consistent with the credit crunch and the distressed sales hypotheses, the top left and right panels show that the exposure to banks' DLR is negatively correlated with mortgage supply changes and positively correlated with distressed sales rates during the crisis. Additionally, the two-bottom panels show that exposure to banks' DLR is negatively correlated with home price index changes during the crisis, suggesting that the decrease in mortgage supply and the increase in distressed sales hurt house prices during the crisis.

To formally estimate the aggregate effects at the ZIP level, I exploit cross-sectional variation across ZIP codes in pre-crisis exposure to banks' DLR and use a difference-in-differences research design. That is, low exposure ZIP codes to banks' DLR act as a control group and high exposure ZIP codes to banks' DLR act as a treatment group. However, this design faces an important empirical challenge that unobservable geographic characteristics such as income level, business activities, and demographics may be correlated with both housing market outcomes and exposures to banks' DLR. For example, high DLR banks could be more aggressive so they may operate in regions with larger booms and busts. To address this concern, I include several fixed effects and control variables. First, I include county-year fixed effects to control for any county-level changes in income, employment, or other variables that uniformly affect the same county

Figure 4. Binscatters for Credit Amounts, Distressed sales, and House Prices

The figures present binned scatterplots of the ZIP-level exposure to banks' DLR versus standardized housing market outcomes (i.e., mean 0 and std 1). The top left panel plots log difference in total new mortgage amounts from 2007 to 2010 on the y-axis. The top right panel plots average rate of distressed sales during the crisis on the y-axis. The bottom left panel plots log difference in Federal Housing Finance Agency (FHFA)'s home price index from 2007 to 2010 on the y-axis. The bottom right panel plots log difference in CoreLogic's home price index from 2007 to 2010 on the y-axis. All the average of ZIP-level control variables except Δ*Nonbank Credit* during the crisis and the county fixed effects are controlled.



in a given year. The inclusion of county-year fixed effects ensures that high exposure ZIP codes are compared with low exposure ZIP codes within the same county and year, and thus it addresses the concern that the estimation is driven by high DLR banks systematically operating in regions with worse economic conditions during the crisis. Second, I include ZIP code fixed effects to control for any ZIP-specific invariant components such as composition of population and geographical features that may drive house prices as well as banks' market entries. Finally, I include ZIP code characteristics such as changes in income, establishment, and employment to control for time-varying economic conditions. With these specifications, I estimate the following model.[23]

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}. \tag{5}$$

The dependent variables differ by tests. For *the credit crunch channel*, the dependent variables are $logCredit_{z,t}$ and $\Delta logCredit_{z,t}$, natural logarithm of mortgage origination amounts, or changes in natural logarithm of mortgage origination amounts at ZIP code *z* in year *t*. For *the distressed sales channel*, the dependent variables are $Foreclosure\ Rate_{z,t}$ and $Short\ Sale\ Rate_{z,t}$, the number of foreclosed sales and the number of short sales divided by the total number of housing transactions at ZIP code *z* in year *t*. Finally, for house prices, the dependent variables are $\Delta logHPI_{z,t}$, natural logarithm changes in either FHFA's and CoreLogic's price index at ZIP code *z* in year *t*. The primary independent variable is $Exposure_z \times Crisis_t$, where $Exposure_z$ is the ZIP-level pre-crisis exposure to banks' DLR, and $Crisis_t$ is equal to one if year is 2007–2009 for the loan supply and house price tests and 2007–2010 for the distressed sales tests. Additionally, I estimate equation (5) with the indicator exposure measure $Exposure\ High_z$, which is equal to one if $Exposure_z$ is above the sample median. The ZIP-level control variables, $X_{z,t}$, include *Lag Tier 1 Cap at ZIP*, Δ*Employment*, Δ*Establishment*, Δ*Gross Income*, *logAve. Income*, *HHI*, *Nonbank Share*, and Δ*logNonbank Credit*. Finally, I include county-year fixed effects $\delta_{c,t}$ and ZIP fixed effects λ_z to control for unobservable geographic characteristics, as described above. All regressions are weighted by the population of the ZIP code and all variables are defined in Appendix A.

[23] The main variables, *Exposure* and *Crisis*, are omitted in the equation because they are subsumed by the fixed effects.

First, I examine the aggregate effects of banks' DLR on mortgage supply at the ZIP level. If high DLR banks reduced lending during the crisis and other lenders either followed their lead or could not make up the difference in lending, mortgage originations would decrease more in high exposure areas than in low exposure areas. Table 6 presents results from estimation of equation (5) for mortgage supply. Columns (1) and (2) report the results with the continuous exposure measure for *logCredit* and Δ*logCredit* as the dependent variable. The coefficients of *Exposure* × *Crisis* are significantly negative for both columns (-0.143, $p<0.01$; -0.106, $p<0.01$), suggesting that high exposure ZIP codes experienced a significantly larger decrease in mortgages than low exposure ZIP codes during the crisis. The coefficient of -0.106 in column (2) implies that a one standard deviation increase in the exposure to banks' DLR produces a 10.6 percentage point decrease in the growth rate of credit amounts during the crisis, all else equal. Columns (3) and (4) report the results with the indicator exposure measure, and the coefficients of *Exposure High* × *Crisis* are significantly negative for both columns (-0.166, $p<0.01$; -0.130, $p<0.01$). The coefficient of -0.130 in column (4) implies that the growth rate of credit in high exposure ZIP codes is lower by 13.0 percentage points than in low exposure ZIP codes during the crisis, all else equal. All the ZIP-level findings suggest that the aggregate effects of banks' DLR on mortgage supply was negative and economically significant. Next, I examine the aggregate effects of banks' DLR on distressed sales at the ZIP level. If high DLR banks took more risks before the crisis and their mortgages more frequently resulted in distressed sales during the crisis, foreclosures and short sales would increase more in high exposure areas. Table 7 presents results from estimation of equation (5) for distressed sales. Columns (1) and (2) report the results with the continuous exposure measure for *Foreclosure Rate* and *Short Sale Rate* as the dependent variable. The coefficients of *Exposure* × *Crisis* are significantly positive for both columns (0.055, $p<0.01$; 0.010, $p<0.01$), suggesting that high

Table 6. Effect of ZIP-Level Exposure to Banks' DLR on Credit Amounts

This table presents regressions of the ZIP-level exposure to banks' DLR on new mortgage amounts using a following model:

$$logCredit_{z,t} \text{ } or \text{ } \Delta logCredit_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$ or $\Delta logCredit_{z,t}$, natural logarithmic of new mortgage amounts or changes in natural logarithmic of new mortgage amounts at ZIP code *z* in year *t*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Columns (1) and (2) report the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR, and columns (3) and (4) report the results with the indicator variable $Exposure\ High_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of the ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) logCredit	(4) ΔlogCredit
Exposure×Crisis	-0.143***	-0.106***		
	(0.038)	(0.024)		
Exposure High×Crisis			-0.166***	-0.130***
			(0.039)	(0.023)
Observations	73,494	73,494	73,494	73,494
ZIP Controls	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES
ZIP FE	YES	YES	YES	YES
Adjusted R-squared	0.970	0.807	0.970	0.806

exposure ZIP codes experienced larger increases in foreclosure and short sale rates than low exposure ZIP codes during the crisis. The coefficient of 0.055 (0.010) in column (1) ((2)) implies that a one standard deviation increase in the exposure to banks' DLR produces a 5.5 (1.0) percentage point increase in foreclosure rates (short sale rates) during the crisis, all else equal. Columns (3) and (4) report the results with the indicator exposure measure, and the coefficients of *Exposure High* × *Crisis* are significantly positive for both columns (0.061, $p<0.01$; 0.010, $p<0.05$). The coefficient of 0.061 (0.010) in column (3) ((4)) implies that foreclosure rates (short sales rates) in high exposure ZIP codes are higher by 6.1 (1.0) percentage points than in low exposure ZIP codes during the crisis, all else equal. All the ZIP-level findings suggest that the aggregate effect of banks' DLR on distressed sales was positive and economically significant.

Finally, I examine the effect of banks' DLR on house prices at the ZIP level. Given that high exposure ZIP codes experienced larger decreases in mortgage supply and larger increases in distressed sales, I expect that they also experienced larger decreases in house prices than low exposure ZIP codes during the crisis. Table 8 presents results from estimation of equation (5) for house prices. Columns (1) and (2) report the results with the continuous exposure measure for Δ*logHPI - FHFA* and Δ*logHPI - CoreLogic* as the dependent variable. The coefficients of *Exposure* × *Crisis* are significantly negative for both columns (-0.016, $p<0.10$; -0.017, $p<0.05$), suggesting that high exposure ZIP codes experienced larger decreases in house prices. The coefficient of -0.016 (-0.017) in column (1) ((2)) implies that a one standard deviation increase in the exposure to banks' DLR produces a 1.6 (1.7) percentage point decrease in the growth rate of the FHFA house price index (the CoreLogic house price index) during the crisis, all else equal. In dollar terms, at the median sales prices of homes sold in the United States in 2006 from DataQuick ($210,000), the estimate implies a decrease in prices of $3,360 ($3,570). Columns (3) and (4)

Table 7. Effect of ZIP-Level Exposure to Banks' DLR on Distressed Sales

This table presents regressions of the ZIP-level exposure to banks' DLR on distressed sales using a following model:

$$Foreclosure\ or\ Short\ Sale\ Rate_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are *Foreclosure Rate*$_{z,t}$ and *Short Sale Rate*$_{z,t}$, number of foreclosed sales or number of short sales divided by the total number of housing transactions at ZIP code z in year t. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Columns (1) and (2) report the results with the continuous variable *Exposure*$_z$, the ZIP-level exposure to banks' DLR, and columns (3) and (4) report the results with the indicator variable *Exposure High*$_z$, which is equal to one if *Exposure*$_z$ is above the sample median. *Crisis*$_t$ is equal to one if year is 2007–2010. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP,* Δ*Employment,* Δ*Establishment, logAve. Income, HHI, Nonbank Share*, and Δ*logNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of the ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)	(4)
VARIABLES	Foreclosure Rate	Short Sale Rate	Foreclosure Rate	Short Sale Rate
Exposure×Crisis	0.055***	0.010***		
	(0.019)	(0.003)		
Exposure High×Crisis			0.061***	0.010**
			(0.017)	(0.004)
Observations	58,901	58,901	58,901	58,901
ZIP Controls	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES
ZIP FE	YES	YES	YES	YES
Adjusted R-squared	0.882	0.877	0.880	0.876

Table 8. Effect of ZIP-Level Exposure to Banks' DLR on House Prices

This table presents regressions of the ZIP-level exposure to banks' DLR on house prices using a following model:

$$\Delta logHPI_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variable is $\Delta logHPI_{z,t}$, natural logarithmic changes in either FHFA's or CoreLogic's price index at ZIP code z in year t. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Columns (1) and (2) report the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR, and columns (3) and (4) report the results with the indicator variable $Exposure\ High_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP*, Δ*Employment,* Δ*Establishment*, *logAve. Income*, *HHI*, *Nonbank Share*, and Δ*logNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of the ZIP code. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

VARIABLES	(1) ΔlogHPI - FHFA	(2) ΔlogHPI - CoreLogic	(3) ΔlogHPI - FHFA	(4) ΔlogHPI - CoreLogic
Exposure×Crisis	-0.016*	-0.017**		
	(0.009)	(0.008)		
Exposure High×Crisis			-0.021**	-0.012***
			(0.009)	(0.004)
Observations	73,494	33,432	73,494	33,432
ZIP Controls	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES
ZIP FE	YES	YES	YES	YES
Adjusted R-squared	0.896	0.926	0.896	0.925

report the results with the indicator exposure measure, and the coefficients of *Exposure High* × *Crisis* are significantly negative for both columns (-0.021, $p<0.05$; -0.013, $p<0.01$). The coefficient of -0.021 (-0.012) in column (3) ((4)) implies that the growth rate of FHFA house price indexes (CoreLogic house price indexes) in high exposure ZIP codes is lower by 2.1 (1.2) percentage points than in low exposure ZIP codes during the crisis, all else equal. In dollar terms, the estimate implies a decrease in prices of $4,410 ($2,520).

4.4. Discussion of the Results for House Prices

A key assumption in the difference-in-differences design is that the price trends across high and low exposure ZIP codes would have been the same in the absence of the effects of banks' DLR. To assess the validity of the parallel-trends assumption, in Figure 5, I plot the estimated treatment effects for the entire sample period by including interaction terms between *Exposure* and *Year* indicator for every year except 2006, which serves as the benchmark (i.e., the coefficient is set to zero).[24] The coefficients are not statistically different from zero before the crisis but they are significantly negative during the crisis. The figures suggest that the estimation of the effects of banks' DLR on house prices is not driven by the fact that high exposure ZIP codes experienced a larger housing market boom.

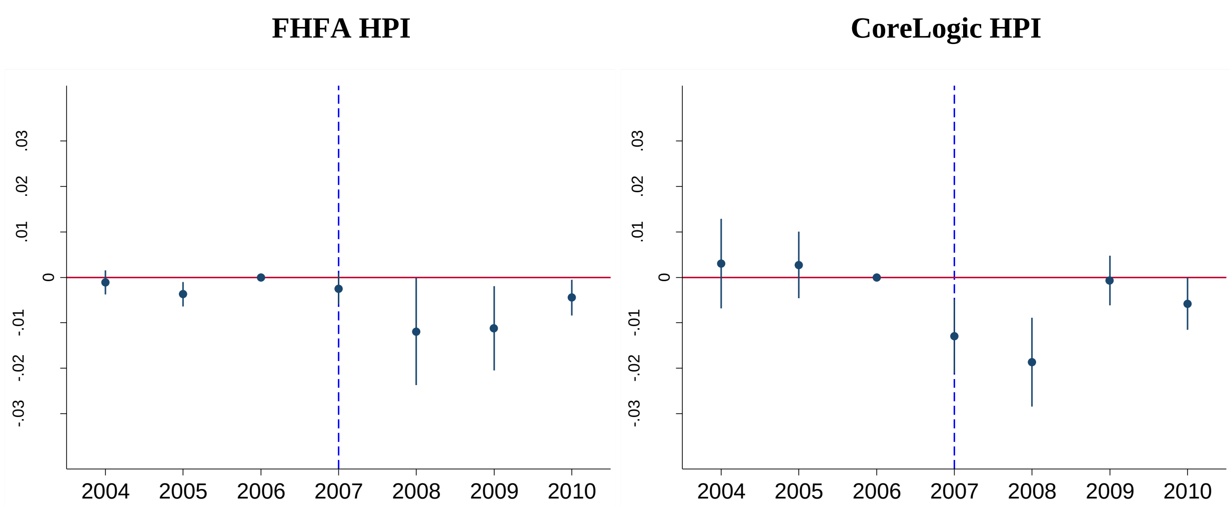
Next, I check the plausibility of the magnitude of estimates by comparing them to results of Favara and Imbs (2015). Favara and Imbs (2015) find that a percentage point increase in the growth rate of credit results in a 0.12 percentage point increase in the growth rate of house prices. On the other hand, I find that a percentage point decrease in the growth rate of credit results in a

[24] To be clear, the estimation in Table 8 uses 2007–2009 for the crisis period whereas Figure 5 presents the treatment effects up to year 2010 to provide a clear pattern of the treatment effects even after the crisis period.

Figure 5. The Effect of the ZIP-level Exposure to Banks' DLR on House Prices

The figures display OLS regression coefficients and 95% confidence intervals based on standard errors clustered at the state-level. The full set of control variables with fixed effects in equation (7) are included. To map out the pattern of exposure to banks' DLR, the interaction terms between *Exposure* and *Year* indicator for every year period except 2006, which serves as the benchmark period (i.e., the coefficient is set to zero), are included. The left panel uses log difference in Federal Housing Finance Agency (FHFA)'s home price index as a dependent variable, and the right panel uses log difference in CoreLogic's home price index as a dependent variable.

$$\Delta logHPI_{z,t} = \sum_{t=2004\ (\neq 2006)}^{2010} \beta_t Exposure_z \times I_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}$$



0.15 percentage point decrease in the growth rate of house prices.[25] The slightly larger ratio is plausible, because the estimates for the house prices may also reflect the effects of other channels including distressed sales.[26]

[25] The ratio is calculated based on the coefficients for the FHFA price index changes divided by the coefficients for credit amount changes using the continuous exposure measure (i.e., -0.016/-0.106=0.15).

[26] Alternatively, Mian et al. (2015) suggest that foreclosures were responsible for 33% of the decline in house prices during the Great Recession. If I apply their finding to my estimate in column (1) of Table 8, the distressed sales channel may explain about 0.53 percentage (0.016*0.33=0.0053), and the credit crunch channel may explain about 1.07 percentage of the decline in house prices (0.016*0.67=0.0107).

4.5. Effects of Banks' DLR on House Prices: IV Results

I use an instrumental variable approach at the ZIP level to address two remaining concerns: (i) the exposure to banks' DLR at the ZIP level could be non-random, even within a county, and (ii) banks' DLR could be correlated to unobservable bank characteristics. Same as in in the bank-level analysis, I use *–log(distance)×Public* as an instrument for individual banks' loan loss provisioning and construct a ZIP-level instrument by using the weighted-average of the individual instrument based on banks' mortgage market shares as follows.

$$SEC\ Influence\ ZIP_z = \frac{1}{3}\sum_{t=2004}^{2006}\sum_{i\in z}\alpha_{i,z,t} \times -log(Distance)_i \times Public_i. \qquad \text{(IV3)}$$

One plausible concern for the exclusion criterion is that public banks' market shares could be correlated with unobservable geographic characteristics. For example, public banks may operate more in metropolitan areas, which typically experienced larger housing booms and busts, compared to community banks. To address this concern, I include ZIP-level public banks' market shares as well as other fixed effects. By controlling these variables, the identification is mainly driven by variation in the interaction term of the distance and the public bank indicator, not just by the market share of public banks. I then estimate the first-stage model as follows.

$$Exposure_z \times Crisis_t = \beta SEC\ Influence\ ZIP_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}. \qquad \text{(IV4)}$$

SEC Influence ZIP_z is the ZIP-level instrumental variable defined as in equation (IV3). The second-stage model is a modification of equation (5) as follows.[27]

$$\Delta logHPI_{z,t} = \beta \widehat{Exposure_z \times Crisis_t} + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}. \qquad \text{(IV5)}$$

[27] I also present an IV analysis for the credit amounts and the distressed sales in Table A10 of the online appendix. The IV estimates are statistically significant and generally larger than the OLS estimates, which is consistent with the results for the house prices.

The primary independent variable is the instrumented variable, $\widehat{Exposure_z \times Crisis_t}$, from the first-stage model. *Public Share$_{z,t}$*, the market share of public banks at ZIP code z in year t, is additionally controlled, and all the ZIP-level controls and fixed effects are included same as in equation (5).

Table 9 reports the instrumental variable estimations of equations (IV4) and (IV5). Column (1) shows a strong first-stage relation between the instrument and the exposure to banks' DLR. The partial F-statistic is 85.37 ($p<0.01$), which is significantly larger than the critical value of 8.96 suggested by Stock et al. (2002) and Larcker and Rusticus (2010) as needed to avoid a weak-instrument. The second-stage model is estimated in columns (2) and (3), and all the coefficients are significantly negative. The second-stage estimate in column (2) ((3)) suggests that a one standard deviation increase in the exposure to banks' DLR produces a 5.3 (3.7) percentage point decrease in the growth rate of FHFA house price index (CoreLogic house price index) during the crisis, all else equal. In dollar terms, at the median sales prices of homes sold in the United States in 2006 from DataQuick ($210,000), this implies a decrease in prices of $11,130 ($7,770). The IV estimates are generally larger than the OLS estimates, and there could be several reasons why the OLS estimates are underestimated. First, measurement errors in the exposure measure would attenuate the OLS estimates but not the IV estimates. Second, a positive correlation between the exposure measure and any unobservable factors that positively affect house prices can create upward biases in the OLS estimates. For example, a number of interventions in the housing market by the government were implemented during the crisis.[28] If high DLR banks operated in areas hard hit by the crisis and government policies were focused on these areas, it can also create upward

[28] For example, the U.S. government issued the "Housing and Economic Recovery Act of 2008 (HERA)" and implemented various programs to boost the housing market.

Table 9. Effect of ZIP-Level Exposure to Banks' DLR on House Prices: IV Analysis

This table presents instrument variable regressions of the ZIP-level exposure to banks' DLR on house prices. The first-stage and the second-stage models are estimated as follows:

1st Stage: $Exposure_z \times Crisis_t = \beta SEC\ Influence\ ZIP_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \epsilon_{z,t}$,

2nd Stage: $\Delta logHPI_{z,t} = \beta \widehat{Exposure_z \times Crisis_t} + +\gamma X_{z,t} + \delta_{c,t} + \epsilon_{z,t}$.

SEC Influence ZIP$_z$ is an instrumental variable defined as $\frac{1}{3}\sum_{t=2004}^{2006}\sum_{i\in z}\alpha_{i,z,t} - log(Distance)_i \times Public_i$, where *Distance* is the distance between a bank's headquarters and the closest SEC office and *Public* is an indicator variable equal to one if the bank or its parent holding is publicly traded. The dependent variable is $\Delta logHPI_{z,t}$, natural logarithmic changes in either FHFA's or CoreLogic's price index at ZIP code z in year *t*. The primary independent variable is $\widehat{Exposure_z \times Crisis_t}$, the instrumented variable from the first-stage model. Column (1) reports the first-stage result, and columns (2) and (3) report the second-stage results. The ZIP-level controls $X_{z,t}$ include *Public Share*, *Lag Tier 1 Cap at ZIP*, *ΔEmployment*, *ΔEstablishment*, *logAve. Income*, *HHI*, *Nonbank Share*, *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of the ZIP code. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)
	1st Stage	2nd Stage	2nd Stage
VARIABLES	Exposure×Crisis	ΔlogHPI - FHFA	ΔlogHPI - CoreLogic
IV: SEC Influence×Crisis	0.983***		
	(0.106)		
Exposure×Crisis		-0.053**	-0.037***
		(0.025)	(0.013)
Public Share	0.321*	-0.056**	-0.018
	(0.178)	(0.025)	(0.012)
Observations	73,494	73,494	33,432
ZIP Controls	YES	YES	YES
County-Year FE	YES	YES	YES
ZIP FE	YES	YES	YES
Adjusted R-squared	0.836	0.886	0.925
Partial F-Stat.	85.37***		

biases in the OLS estimates. While it is difficult to pin down the exact reason for the difference, both the OLS and IV estimates suggest that the effects of banks' DLR on house prices during the crisis were statistically and economically meaningful.

4.6. Robustness Tests

I present a number of robustness tests in the online appendix. First, I use the loan-level mortgage approval decision as the dependent variable to examine the bank-level credit crunch effect. Studies use approval rates to better capture loan supply decisions conditional on the number of applications (Loutskina and Strahan, 2009, 2011; Xie, 2016; Kim et al., 2018; Dou et al., 2018).[29] This approach allows more stringent fixed effects, which mitigates a concern that local demand may affect the two types of mortgages differently. I include bank-year, year-loan type, bank-loan type, ZIP-year, race, and loan purpose fixed effects. Bank-year fixed effects control for any time-varying bank characteristics. Year-loan type fixed effects control for unobservable time-varying demand for different types of mortgages. Bank-loan type fixed effects control for unobservable heterogeneous demand for different types of mortgages within the same bank. The inclusion of ZIP-year fixed effects controls for unobservable loan demand in the same ZIP code and year. Finally, race and loan purpose fixed effects control for unobservable heterogeneous demand by borrowers of different races (Asian, black, white, etc.) and different loan purposes (home purchase versus refinancing). Table A1 of the online appendix presents results the loan-level mortgage approval decision. The coefficients of *Conventional* × *DLR High* × *Crisis* are -0.25 in columns (1) and (2), suggesting that high DLR banks reduced their approval rates for

[29] Mortgage approval rates may not perfectly control for the demand side because higher demand during booms can lead to increased applications by lower quality borrowers and result in lower approval rates. I address this concern by comparing conventional loans and FHA loans within the same ZIP code and same bank based on the assumption that they share unobservable demand variables to a large extent.

conventional loans by 2.5 percentage points more than FHA loans during the crisis, all else equal. Again, I separately examine the credit crunch effect for low- and high-capitalized banks in columns (3) and (4). Consistent with the credit crunch theory, the coefficient of *Conventional* × *DLR High* × *Crisis* is significantly negative for low-capitalized banks (-0.029, $p<0.01$) but statistically insignificant for high-capitalized banks.

Second, I conduct the ZIP-level tests without any fixed effects to show that my results are not driven by a peculiar choice of fixed effects structure. Table A2 of the online appendix presents the results for equation (5) with various dependent variables. The coefficients remain statistically significant, and the magnitudes of coefficients are smaller for the credit amounts but larger for the distressed sales and the house prices, which suggest that fixed effects absorb unobservable variables that might bias the OLS estimates. However, the signs of coefficients remain the same and the magnitudes of coefficients are within reasonable boundaries. These results confirm that my results are not driven by a peculiar choice of fixed effect structure.

Third, I conduct the ZIP-level tests after excluding the four "sand states" (Arizona, California, Florida, and Nevada), which are notorious for boom-and-bust housing markets; one might be concerned that my results are solely driven by these states. Table A3 of the online appendix shows that the magnitudes of coefficients are generally smaller than those in the tests with the full sample, which suggests that the effect of DLR is stronger for the sand states. However, statistical significance of the coefficients remains or becomes even stronger than the full sample, which confirms that the results are not solely driven by sand states.

Fourth, I conduct ZIP-level tests by estimating the bank-level DLR with different model specifications and an alternative proxy for the delay in loan loss provisioning. One may be concerned that the bank-level DLR is sensitive to the model specification in equations (A1) and

(A2), and thus my results are driven by a specific model choice. To address this concern, I estimate equations (A1) and (A2) over the past 20 quarters for each bank, instead over the past 12 quarters, but require a minimum of 12 quarters. Additionally, I include two variables: *ConsLoan*, the proportion of consumer loans in total loans, and *ReLoan*, the proportion of real estate loans in total loans. These variables are included to address the concern that loan portfolio composition is associated with banks' loan loss provisioning (Bhat et al., 2016). Table A4 of the online appendix shows that the coefficients resemble the main ones and they remain statistically significant. Next, I use ALWN (-1* Loan Loss Allowance/Non-performing Loan) as an alternative proxy to delaying loan loss provisions, similar to Beatty and Liao (2011). Table A5 of the online appendix confirms that signs and statistical significance of coefficients remain similar.

Fifth, I construct the ZIP-level exposure measure in different ways. I estimate the exposure measure without year 2006 observations to address the concern that equation (A2) uses the first quarter of 2007 in estimating DLR so that DLR could be mechanically correlated with dependent variables during the crisis. Table A6 of the online appendix shows that all the results remain similar. In addition, I estimate the exposure excluding top three ZIP codes where individual banks originated their mortgages the most to address the concern that the results are mostly driven by banks' major markets. Table A7 of the online appendix shows that all the results remain similar.

Sixth, I conduct ZIP-level tests with more stringent control variables. I include interaction terms between the ZIP-level controls and the crisis-period dummy. Table A8 of the online appendix shows that signs and statistical significance of coefficients remain similar, but their magnitudes are smaller than those in the main tests. This attenuation is expected if banks' financial reporting affected other regional economic conditions via decreased loan supply and more distressed sales. For this reason, it is not clear whether these interactions should be included in the main regressions. Therefore I perform this analysis only as a robustness check, similar to the work of Granja and Leuz (2017). In addition, I include additional bank characteristics at the ZIP Level including *logAssets*, *Cash*, *Deposits*, *Loans to Deposits*, *Loan Loss Reserve*, *Non-Performing Loan*, and *ROA*. These variables are constructed using banks' mortgage market shares at the ZIP level similar to the exposure measure. Table A9 of the online appendix shows that all the results remain similar.

Finally, I conduct an additional IV analysis. I use *OCC Share Pre* as a new instrumental variable. Studies suggest that national banks, supervised by the Office of the Comptroller of the Currency (OCC), face greater regulatory scrutiny, and strict regulators expect more conservative financial reporting choice, such as timely loan loss provisioning (Agarwal et al., 2014; Costello et al., 2016; Nicoletti, 2017). Based on this rationale, I use an average of OCC banks' market shares in a ZIP code during the pre-crisis (*OCC Share Pre*) as a new instrumental variable. Table A11 of the online appendix presents the new IV analysis for house prices. All the first- and second-stage coefficients of interest are statistically significant, and the magnitude of the IV estimates remain similar to the results in Table 9.

5. Aggregate Effects for Household Consumption

A number of studies document a causal impact of house price changes on household consumption (Mian et al., 2013; Kaplan et al., 2016). Given that banks' DLR had a significant effect on house prices, a natural follow-up question would be the implied effect on household consumption. I estimate the household consumption effect using a rule-of-thumb formula, suggested by Berger et al. (2018). They provide a formula for the individual response of non-durable consumption to a house price shock as follows.

$$\frac{\Delta C_{it}}{\frac{\Delta P}{P}} = MPC_{it} \times P_{t-1} H_{ii-1}(1-\delta), \qquad \text{(A4)}$$

where MPC_{it} is the individual marginal propensity to consume out of transitory income shocks and $P_{t-1}H_{it-1}(1-\delta)$ is the value of the individual's home after depreciation.

To estimate the reduction in aggregate consumption, I first split the sample into deciles based on the ZIP-level exposure variable and treat the lowest decile as a control group following Mian and Sufi (2012) and Berger et al. (2016). The median standardized ZIP-level exposure is -1.840 for the bottom decile and increases to 1.371 for the top decile. I then compute the percentage change in prices for each group g as follows.

$$\frac{\Delta P_g}{P_g} = \beta \times (Exposure_g - Exposure_{bottom}), \qquad \text{(A5)}$$

where β is the coefficient -0.016 (-0.017) from column (1) ((2)) of Table 8. Then, the price change factor for each group ($\frac{\Delta P_g}{P_g}$) is applied to all owner-occupied housing units in DataQuick's assessor data.[30] Finally, I compute reduction in consumption for each housing unit using equation (A4) and aggregate them. If *MPC* is assumed at 0.06, as in Mian et al. (2013), aggregate reduction in consumption induced by banks' DLR is about \$24.51 ~ \$26.04 billion. This is about 0.27% ~ 0.29% of U.S. household consumption in 2006 (\$9.021 trillion, FRED Economic Data). This exercise relies on too many assumptions to emphasize a particular number; however, the calculation

[30] The assessor data cover 1,819 counties accounting for 91.8% of the U.S. population (Berger et al., 2016). I use only units built before 2007 and drop units missing the year of being built. The assessor file provides a tax value of the property, a market value of the property determined by a tax assessor, and an assessment year. I use the market value in the estimation but use the tax value if the market value is missing. Assessments are not necessarily made every year and DataQuick provides only one assessment for each property. To overcome this issue, I modified the value of property, using the ZIP-level FHFA's HPI and an assumed depreciation rate δ to obtain its value in 2006. For example, if the assessment value in 2012 is provided, I obtain its value in 2006 by $P_{06}H_{06} = (P_{12}H_{12}) \times (\frac{P_{06}}{P_{12}}) \times (\frac{1}{(1-\delta)^6})$. The depreciation rate is assumed as 2.2%, following Berger et al. (2018).

suggests that the consumption reduction induced by the decrease in house prices, due to banks' DLR, is economically nontrivial.

6. Conclusion

I study whether banks' delayed loan loss recognition (DLR) influenced their lending and risk-taking in the U.S. mortgage market and the aggregate effects of banks' DLR on house prices and household consumption during the Great Recession. I find that high DLR banks reduced mortgage lending during the crisis and their high risk-taking before the crisis led to more distressed sales during the crisis. Consequently, high exposure ZIP codes experienced larger declines in credit and larger increases in distressed sales, leading to larger declines in house prices. In dollar terms, the estimates imply a standard deviation increase in the ZIP-level exposure to DLR produces a decrease in house prices of about $3,500 for the median home sold in 2006, and a reduction in aggregate household consumption of about $25 billion. Taken together, these findings suggest that banks' loan loss provisioning had nontrivial effects on the U.S. housing market during the Great Recession, and thus exacerbated the economic downturn.

My paper contributes to the literature on banks' financial reporting and economic cycles. I present evidence that banks' loan loss provisioning has real effects on loan supply and risk-taking. In addition, I quantify the impact of banks' DLR on house prices and the implied impact on household consumption, which can help gauge the impact of banks' financial reporting on economic downturns. My results suggest that banks' loan loss provisioning can affect economic downturns via the household channel.

I conclude by suggesting a future research question. My paper implies that the new current expected credit loss (CECL) standard may affect the economy via the household channel, to the extent that it will discipline banks with respect to their loan loss provisioning, though I do not directly study the new CECL standard. As Acharya and Ryan (2016) indicate, the effects of banks' financial reporting choices, under an existing accounting regime (the incurred loss model), are not necessarily generalizable to a new regime (the expected loss model), because the new regime will affect other bank characteristics and economic conditions that may also influence bank reporting choices. Therefore, while the mechanisms I identify may generalize to the new regime, the magnitudes may not. In addition, my study is based on the Great Recession, when the housing market experienced an unprecedented collapse. While my estimates of the effects of banks' DLR on house prices and household consumption were based on conservative assumptions, the effects of banks' DLR on the economy would likely be smaller for other downturns. Hence, an open question is whether my findings would pertain under the CECL standard and, if so, what the magnitudes would be.

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Appendix A. Description of Variables

Variable	Description	Source
Dependent Variables		
ΔlogHPI - FHFA	Natural logarithm changes in FHFA home price index at the ZIP level.	FHFA
ΔlogHPI - CoreLogic	Natural logarithm changes in CoreLogic home price index at the ZIP level.	CoreLogic
logCredit	Natural logarithm of new mortgage amounts at the ZIP level.	HMDA
ΔlogCredit	Natural logarithm changes in new mortgage amounts at the ZIP level.	HMDA
VOL	New mortgage amounts by an individual bank at the ZIP level divided by the total new mortgage amounts in the same ZIP-year and multiplied by 100.	HMDA
VOL^C	New conventional mortgage amounts by an individual bank at the MSA level divided by the total new mortgage amounts in the same MSA-year and multiplied by 100.	HMDA
VOL^F	New FHA mortgage amounts by an individual bank at the MSA-level divided by the total new mortgage amounts in the same MSA-year and multiplied by 100.	HMDA
$VOL^C – VOL^F$	Difference between VOL^C and VOL^F.	HMDA
Approve	An indicator variable equal to one if a mortgage application is approved, whether or not the borrower accepts the loan and zero otherwise.	HMDA
Foreclosure Rate	Number of foreclosed sales divided by the total number of housing transactions in the same ZIP code and the same year; foreclosures include *REO Liquidation (type S)* and *Foreclosure Auction (type A)* in the DataQuick's transaction file.	DataQuick
Short Sale Rate	Number of short sales divided by the total number of housing transactions in the same ZIP code and the same year; short sales include *Inferred Short Sale (type I)* in the DataQuick's transaction file. A short sale is a transaction that the borrower sells the property for less than the outstanding mortgage balance under the agreement with the lender, and pays the proceeds to the lender.	DataQuick
Foreclosure	An indicator variable equal to one if a mortgage is foreclosed during 2007–2010 and zero otherwise.	DataQuick
Short Sale	An indicator variable equal to one if a mortgage becomes a short sale during 2007–2010 and zero otherwise.	DataQuick

All Distressed Sale	An indicator variable equal to one if a mortgage is foreclosed or becomes a short sale during 2007–2010 and zero otherwise.	DataQuick
Explanatory Variables of Interest		
DLR	The adjusted R-squared from estimating equation (A1) minus the adjusted R-squared from equation (A2); both equations are estimated within each bank over the prior 12 quarters during 2004–2006.	Call Reports
DLR High	Indicator variable equal to one if the average of *DLR* during 2004–2006 is above the bank-level sample median and zero otherwise.	Call Reports
Exposure	Weighted average of individual banks' *DLR* based on banks' mortgage market shares during 2004–2006 at the ZIP-level. This variable is standardized to have mean of zero and standard deviation of one.	Call Reports, HMDA
Exposure High	Indicator variable equal to one if *Exposure* is above the ZIP-level sample median and zero otherwise.	Call Reports, HMDA
Crisis	An indicator variable equal to one if year is 2007, 2008, and 2009 (also one if year is 2010 for the distressed sales analysis) and zero otherwise.	
Conventional	Indicator variable equal to one if an application is conventional and zero otherwise.	HMDA
Control Variables – ZIP Level		
Lag Tier 1 Cap at ZIP	Weighted average of individual banks' *Lag Tier 1 Capital Ratio* based on their mortgage market shares at the ZIP level.	Call Reports, HMDA
ΔEmployment	Percentage change in total number of employees at the ZIP level.	CBP
ΔEstablishment	Percentage change in total number of establishments at the ZIP level.	CBP
ΔGross Income	Percentage change in total adjust gross income at the ZIP level; data for year 2003 is missing so the percentage change for year 2004 is calculated based on year 2002 and is annualized then.	IRS SOI
logAve. Income	Natural logarithm of the average adjust gross income at the ZIP level (in $ thousands).	IRS SOI
HHI	Herfindahl-Hirschman Index ("HHI"); the sum of squared market shares of all lenders at the ZIP level.	HMDA
Nonbank Share	The market share of nonbank lenders at the ZIP level; nonbanks are lenders not under the regulatory oversight of OCC, FRS, FDIC, NCUA, or OTS.	HMDA
ΔlogNonbank Credit	Natural logarithmic changes in originated mortgage loan amounts by nonbanks at the ZIP level.	HMDA

logPopulation	Natural logarithm of total population at the ZIP level; the value is estimated based on the collected data from 2007–2011.	ACS
% African American	Percentage of Black or African American population at the ZIP level; the value is estimated based on the collected data from 2007–2011.	ACS
% Hispanic	Percentage of Hispanic or Latino population at the ZIP level; the value is estimated based on the collected data from 2007–2011.	ACS
% Poverty Population	Percentage of population below poverty level at the ZIP level; the value is estimated based on the collected data from 2007–2011.	ACS
% with Bachelor or Higher	Percentage of population with bachelor's degree or higher at the ZIP level; the value is estimated based on the collected data from 2007–2011.	ACS
SEC Influence Bank	*–log(distance)×public*.	SEC, HMDA
SEC Influence ZIP	Weighted average of *–log(distance)×public* based on banks' mortgage market shares during 2004–2006 at the ZIP level.	SEC, HMDA
Public Share	The market share of public banks at the ZIP level.	HMDA
OCC Share Pre	The average of OCC banks' market shares at the ZIP level during the pre-crisis period.	HMDA
Control Variables – Bank Level		
logAssets	Natural logarithm of total assets.	Call Reports
Cash	Cash divided by total assets.	Call Reports
Deposits	Deposits divided by total assets.	
Lag Tier1 Capital Ratio	Lagged value of Tier 1 capital divided by risk-weighted assets.	Call Reports
Loans to Deposits	Loans and leases (net of unearned income) divided by total deposits.	Call Reports
Loan Loss Reserve	Allowance for loan and lease losses divided by total assets.	Call Reports
Non-Performing Loan	Loans not accruing interest or accruing interest but 90 days or more past due (net of debt securities and other assets) divided by total assets.	Call Reports
ROA	Net income divided by total assets.	Call Reports
Distance	The distance between banks' headquarters and their closest SEC office; Headquarters – Washington D.C.; Regional Offices – New York City; Miami; Chicago; Denver; Los Angeles.	SEC
Public	Indicator variable equal to one if the bank or its parent holding company (identified using "RSSD9348 – ID of the regulatory high holder" or "RSSD9364 – ID of the financial high holder" from Call Reports) is publicly traded; trading status is	Federal Reserve Bank of New York

	identified using the CRSP-FRB link table (20161231).	
Control Variables – Loan Level		
Jumbo	An indicator variable equal to one if the size of mortgage is larger than the conforming limit set by Fannie Mae and Freddie Mac.	HMDA, FHFA
logAmount	Natural logarithm of mortgage amount (in $ thousands).	HMDA
logIncome	Natural logarithm of mortgage applicant's annual income (in $ thousands).	HMDA
Loan-to-Income	Loan amount divided by mortgage applicant's annual income.	HMDA
Male	An indicator variable equal to one if the mortgage applicant is male and zero otherwise.	HMDA
Ethnicity	An indicator variable equal to one if the mortgage applicant is Hispanic or Latino and zero otherwise.	HMDA
Owner-occupancy	An indicator variable equal to one if the mortgaged home is owner occupied and zero otherwise.	HMDA
Variables for DLR construction		
LLP	Loan loss provision divided by lagged total loans.	Call Reports
ΔNPL	Change in non-performing loans divided by lagged total loans.	Call Reports
EBLLP	Earnings before the loan loss provision and taxes divided by lagged total loans.	Call Reports
Tier 1 Ratio	Tier 1 capital divided by risk-weighted assets.	Call Reports
Size	Natural logarithm of total assets.	Call Reports
CoIndex	Coincident index at the state level.	Call Reports
ConsLoans	Consumer loans divided by total loans.	Call Reports
ReLoans	Real estate loans divided by total loans.	Call Reports

Online Appendix

Online Appendix A. Data Sources and Sample Construction

The paper combines various proprietary and public data sources. This appendix describes each data source in detail and the process of sample construction.

Online Appendix A.1. Data Sources

(1) Consolidated Reports of Condition and Income (a.k.a. Call Reports)

All banks in the U.S. are required to file quarterly financial statement with their regulators. The Call Reports data is publicly available by the Federal Financial Institutions Examination Council (FFIEC) and by the Federal Reserve Bank of Chicago.

(2) The Home Mortgage Disclosure Act (HMDA)

HMDA records the majority of mortgage applications in the U.S. on a yearly basis. The data contains (i) loan information – application outcome, loan type and purpose, loan amount, etc., (ii) applicant information – race, sex, income, (iii) purchaser information – type of purchaser, and (iv) geography information – state, MSA, county, census tract. The HMDA data is publicly available by the Federal Financial Institutions Examination Council (FFIEC).

(3) DataQuick

DataQuick is a proprietary data containing information on real estate appraisal and transactions in the U.S., and was made available through the Fama-Miller Center for Research in Finance and the Initiative on Global Markets at the University of Chicago Booth School of Business. DataQuick consists of three main files: assessor, transaction, and loan. The assessor file contains information on individual properties used to assess property taxes such as appraised values. The transaction file includes information about the sale of the property such as an indicator for distressed sales, information on buyers and sellers. Finally, the loan file contains information about the financing of home purchases such as value of loans taken and interest rate.

(4) Federal Housing Finance Agency (FHFA) Home Price Index

FHFA's price indices are available at the yearly level, and have the largest coverage for the U.S. ZIP codes. Bogin, Doerner and Larson (2016) provide detailed information about the construction of the index, and they describe the final database covers 914 CBSAs, 2,742 counties, 879 3-digit ZIP codes, and 17,936 5-digit ZIP codes. The data is publicly available by the Federal Housing Finance Agency.

(5) CoreLogic Home Price Index

CoreLogic price indices are proprietary data, and were made available through the Fama-Miller Center for Research in Finance and the Initiative on Global Markets at the University of Chicago Booth School of Business. The indices are available at the monthly level but have a smaller coverage for the U.S. ZIP codes compared to FHFA's HPI. Berger et al. (2016) describe that the CoreLogic index is a variant of the Case-Shiller index measuring price changes in repeatedly transacted properties, and covers 7,169 ZIP codes and 1,267 counties. The index has various versions measured based on different type of properties and transactions. I use an index based on *Single Family Detached Home*: an index for not a condominium, not a duplex with a shared wall, not an apartment building, and no boarders or long-term tenants.

(6) Geographic Control Variables

From the American Community Survey (ACS), I draw data on demographics, poverty, and education at the ZIP level. I use "2007-2011 American Community Survey 5-Year Estimates", which is the first survey containing information at the ZIP level. This survey contains demographic variables estimated based on the collected data from 2007–2011. Yearly variables are not available from the ACS and thus the same value is used for all years of my sample. Consequently, the variables from the ACS are omitted once the ZIP code fixed effects are included in regressions. From the IRS' Statistics of Income (SOI), I construct average income and gross income growth rate at the ZIP level. From the County Business Patterns (CBP), I construct employment and establishment growth rate at the ZIP level. All variables from the SOI and the CBP data are ZIP-by-year panel. Finally, from the Federal Reserve Banks of Philadelphia, I draw the coincidence index at the state level and the index is used to estimate the bank-level DLR.

Online Appendix A.2. Sample Construction

(1) Bank-Level Variables from Call Reports

I obtain banks' financial statement data during 2004–2010 from the Call Reports data to construct the bank-level variables. When I construct the bank-level DLR, I extend the sample to 2002 because I require the bank to have at least 12 quarters of financial statement to estimate the equations (A1) and (A2).

(2) Mortgage Applications from HMDA

I obtain mortgage applications during 2004–2010 from the HMDA data. I drop mortgage applications for amounts less than $1,000 and for which the borrower has income under $10,000 because mortgage values smaller than $1,000 are rounded up to $1,000, and borrower income is censored at $10,000 (Dell'Ariccia et al. 2008). I exclude mortgage applications from Alaska, Hawaii, and offshore U.S. territories. Additionally, I only use conventional and FHA-insured mortgages (*Loan Type*=1 and 2), one to four-family mortgages (*Property Type*=1), and home purchase and refinancing mortgages (*Loan Purpose*=1 and 3). Finally, I eliminate all application records except the following actions: (i) loan originated, (ii) application approved but loan not originated, or (iii) application denied. Dell'Ariccia et al. (2008) describe that other actions represent dubious statuses or loans purchased by other financial institutions and thus including them may double-count some of applications.

HMDA provides information at the county and the census tract level, but not at the ZIP level. To construct the ZIP-level data, I match census tracts to ZIP codes using "ZIP Code Tabulation Area (ZCTA) Relationship Files" from the US census. When a census tract is not exactly overlapped with one ZIP code, I assign that census tract to a ZIP code containing the largest population of it.

(3) Link Call Reports to HMDA

Linking Call Reports to HMDA is a critical task in the analysis. HMDA provides "Reporter Panel", which contains information about all institutions that reported under HMDA. I identify same lenders by matching *RSSD9001* in Call Reports and *Respondent RSSD ID* in Reporter Panel. Then, I merge the reporter panel with mortgage applications based on the same *Respondent ID* and the same *Agency Code*.

(4) Distressed Sales from DataQuick

I obtain distressed sales (foreclosures and short sales) data during 2004–2010 from DataQuick. I clean and merge the data retrieved from the DataQuick's assessor, transactions, and loans file following a similar approach in Berger et al. (2017). I begin with the transaction file during 2004–2010. Then, I apply the following filters:

(a) Including only resales and new construction (types R and S in *SR_TRAN_TYPE*);

(b) Including only arm's length transactions. The arm's length indicator in DataQuick is from a "model" that classifies whether resales are genuine arm's length transactions, and it excludes refinances and intermediate documents in a distress sale process according to Berger et al. (2016);

(c) Keeping only the transaction with the highest transfer value if there are duplicates with the same property and transaction date.

Then, I combine the cleaned transaction file with the assessor file to identify a ZIP code of each property, and remove transactions without information in the assessor file. Next, I combine this merged data to the loan file using only the first loan attached to the transaction (DataQuick provides up to three loans attached to the paperwork on a closed sale). Finally, I identify distressed sales using *Distress Indicator* provided by DataQuick. I classify *REO Liquidation* (type S) and *Foreclosure Auction* (type A) as foreclosures and *Inferred Short Sale* (type I) as short sales.

(5) Link HMDA to DataQuick

I link HMDA to the DataQuick's loan file to identify which loans were ended up being distressed during the crisis. DataQuick does not provide information on lenders' identification except their names. Therefore, I conduct a fuzzy match based on the lender name following a similar approach in Ferreira and Gyourko (2015). First, I match each transaction to a mortgage in HMDA based on year, ZIP code, lender name, and exact loan amount. To match the lender name, I compress spaces in the lender name, extract the first eight characters, and use "COMPGED" function in SAS to compute costs for dissimilarity between two lenders' names. Then, I delete matches if the cost is more than 500. "COMPGED" function returns a generalization of the Levenshtein edit distance, which is a measure of dissimilarity between two strings (see more explanation for the function:

http://support.sas.com/documentation/cdl/en/lrdict/64316/HTML/default/viewer.htm#a002206133.htm). Then, if there are multiple matches, one of them is randomly assigned as a match and unassigned matches are dropped. For the remaining unmatched observations, I conduct the same match procedure based on year, ZIP code, lender name, but allow loan amounts to differ by ± $1,000. Same as for the first match procedure, if there are multiple matches; one of them is randomly assigned as a match.

Online Appendix B. Summary Statistics and Distributions of Adj. R^2s and DLR

Table A0 presents summary statistics of Adj. R2s for equation (A1), (A2), and the difference between them (i.e., bank-level DLR) during 2004 – 2006. Figure B1 presents distributions of Adj. R2 for equation (A1), (A2), and the difference between them (i.e., bank-level DLR) during 2004 – 2006.

Table A0: Summary Statistics of Adj. R^2s and DLR

VARIABLES	(1) N	(2) mean	(3) sd	(4) p25	(5) p50	(6) p75
Adj. R2 for (A1)	51,602	0.269	0.447	-0.035	0.335	0.633
Adj. R2 for (A2)	51,602	0.313	0.571	0.013	0.467	0.760
DLR	51,602	-0.044	0.396	-0.230	-0.003	0.178

Figure A1: Distributions of Adj. R^2s and DLR

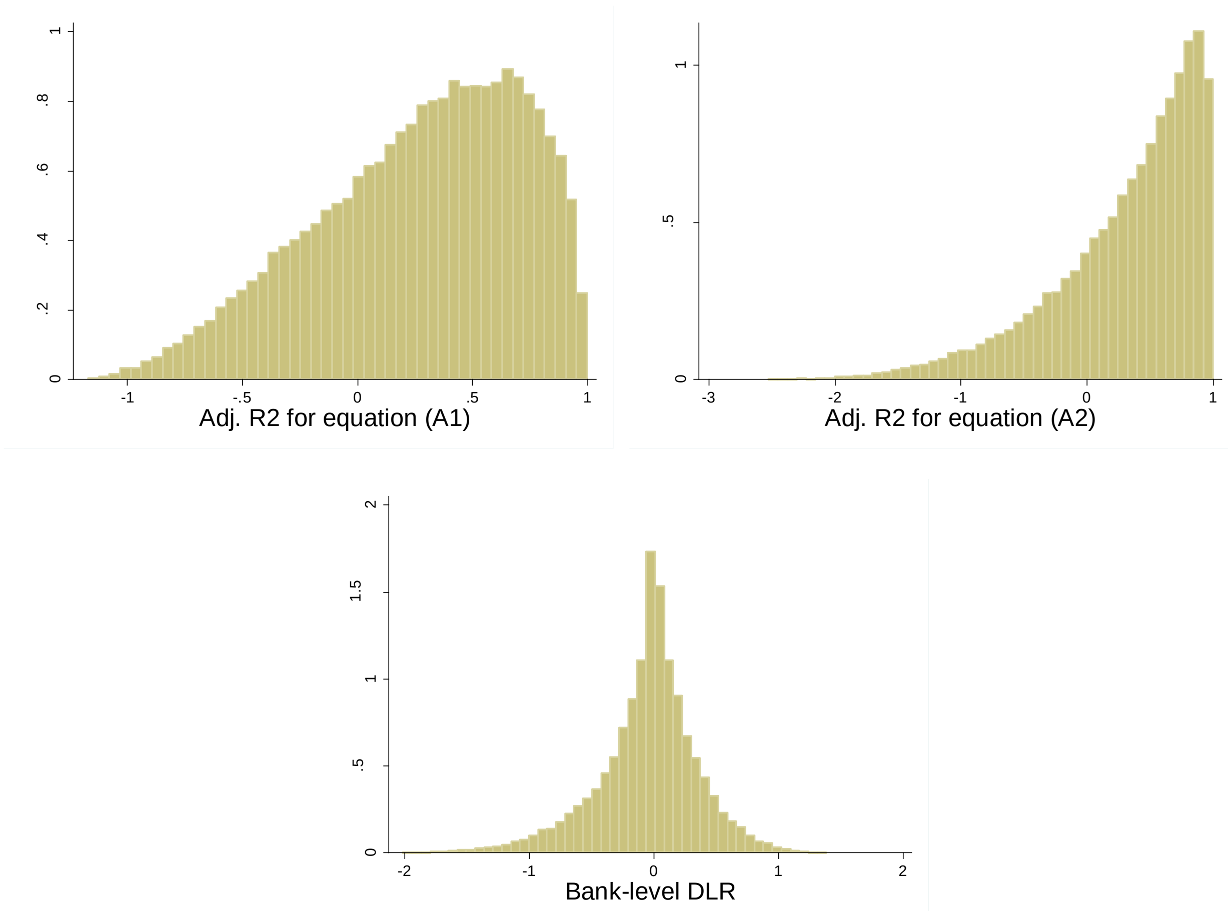

Table A1. Effect of Banks' DLR on Mortgage Approval: Application Level

This table presents regressions of the high DLR banks on mortgage approval:

$$
\begin{aligned}
Approve_{i,j,t} = \beta_1 Conventional_{i,j,t} \times DLR\ High_i \times Crisis_t + \beta_2 W_{i,j,t} + bank * year,\\
year * loan\ type, bank * loan\ type,\\
ZIP * year, race, loan\ purpose\ fixed\ effects + \epsilon_{i,j,t}.
\end{aligned}
$$

The dependent variable is $Approve_{i,j,t}$, an indicator variable equal to one if a mortgage application *j* is approved by bank *i* in year *t*. The primary independent variable is $Conventional_{i,j,t} \times DLR\ High_i \times Crisis_t$, where $Conventional_{i,j,t}$ is an indicator variable equal to one if an application is conventional, $DLR\ High_i$ is an indicator variable equal to one if the average of DLR during 2004–2006 is above the bank--level sample median, and $Crisis_t$ is equal to one if year is 2007–2009. Column (1) reports the results for the full sample, column (2) reports the results for the sample without jumbo loans, and columns (3) and (4) present results for the sample with below and above median values of *Lag Tier 1 Capital Ratio* by bank and year. The bank-level controls. The mortgage-level controls $W_{i,j,t}$ include *logAmount*, *logIncome*, *Loan-to-Income*, *Male*, *Ethnicity*, and *Owner-occupancy*. All variables are defined in Appendix A. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)	(4)
	Full Sanple	Excluding Jumbo Loans	Low Cap 1	High Cap 1
VARIABLES	Approve	Approve	Approve	Approve
Conventional×DLR High×Crisis	-0.025***	-0.025***	-0.029***	0.020
	(0.007)	(0.007)	(0.007)	(0.025)
Observations	17,067,708	15,987,188	14,178,126	2,885,067
Mortgage Controls	YES	YES	YES	YES
Bank-Year FE	YES	YES	YES	YES
ZIP-Year FE	YES	YES	YES	YES
Bank-Loan Type FE	YES	YES	YES	YES
Year-Loan Type FE	YES	YES	YES	YES
Race FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Adjusted R-squared	0.141	0.140	0.138	0.179

Table A2. ZIP-Level Analysis – Without Fixed Effects

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables using a following model:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure* $Rate_{z,t}$, *Short Sale* $Rate_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable *Exposure* $High_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share, ΔlogNonbank Credit, logPopulation, % African American, % Hispanic, % Poverty Population,* and *% with Bachelor or Higher*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logCredit	ΔlogCredit	Foreclosure Rate	Short Sale Rate	ΔlogHPI - FHFA	ΔlogHPI - CoreLogic
Exposure	-0.134***	-0.061***	0.072***	0.016**	-0.034*	-0.031**
×Crisis	(0.049)	(0.022)	(0.024)	(0.007)	(0.017)	(0.013)
Exposure	0.184***	0.037***	-0.020*	0.001	0.014*	0.013**
	(0.067)	(0.010)	(0.011)	(0.003)	(0.008)	(0.006)
Crisis	-0.325***	0.031*	0.117***	0.037***	-0.116***	-0.125***
	(0.076)	(0.017)	(0.016)	(0.008)	(0.020)	(0.012)
Observations	76,587	76,587	60,597	60,597	76,587	35,356
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	NO	NO	NO	NO	NO	NO
Zip FE	NO	NO	NO	NO	NO	NO
Adjusted R-squared	0.573	0.540	0.484	0.385	0.510	0.605

Table A2. Continued

Panel B: Results with the Indicator Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High	-0.234***	-0.112***	0.112***	0.024**	-0.060*	-0.038**
×Crisis	(0.078)	(0.034)	(0.030)	(0.011)	(0.030)	(0.018)
Exposure High	0.399***	0.064***	-0.032**	0.002	0.026*	0.017**
	(0.123)	(0.016)	(0.013)	(0.004)	(0.014)	(0.008)
Crisis	-0.210***	0.087***	0.065***	0.027***	-0.087***	-0.108***
	(0.048)	(0.019)	(0.010)	(0.008)	(0.014)	(0.011)
Observations	76,587	76,587	60,597	60,597	76,587	35,356
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	NO	NO	NO	NO	NO	NO
Zip FE	NO	NO	NO	NO	NO	NO
Adjusted R-squared	0.580	0.541	0.486	0.384	0.511	0.602

Table A3. ZIP-Level Analysis – Excluding Sand States

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables after excluding four sand states (AZ, CA, FL, and NV) using a following model:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure* $Rate_{z,t}$, *Short Sale* $Rate_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable *Exposure* $High_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. ***, **, and * denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure	-0.103***	-0.080***	0.032***	0.008**	-0.006***	-0.007***
×Crisis	(0.024)	(0.016)	(0.004)	(0.003)	(0.002)	(0.002)
Observations	62,261	62,261	45,829	45,829	62,261	24,697
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.971	0.763	0.870	0.821	0.824	0.860

Panel B: Results with the Indicator Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High	-0.134***	-0.113***	0.041***	0.008***	-0.010***	-0.007***
×Crisis	(0.033)	(0.021)	(0.008)	(0.003)	(0.002)	(0.002)
Observations	62,261	62,261	45,829	45,829	62,261	24,697
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.971	0.763	0.870	0.819	0.824	0.860

Table A4. ZIP-Level Analysis – Constructing DLR with Different Model Specifications

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables. The bank-level DLR is measured with a new specification using 20 quarters (instead of 12 quarters) and controlling loan composition. The following model is estimated:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure Rate*$_{z,t}$, *Short Sale Rate*$_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable *Exposure High*$_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logCredit	ΔlogCredit	Foreclosure Rate	Short Sale Rate	ΔlogHPI - FHFA	ΔlogHPI - CoreLogic
Exposure	-0.169***	-0.129***	0.058***	0.009**	-0.017*	-0.017**
×Crisis	(0.037)	(0.022)	(0.019)	(0.003)	(0.009)	(0.007)
Observations	73,494	73,494	58,901	58,901	73,494	33,432
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.971	0.811	0.883	0.876	0.896	0.926

Panel B: Results with the Indicator Exposure Measure

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	logCredit	ΔlogCredit	Foreclosure Rate	Short Sale Rate	ΔlogHPI - FHFA	ΔlogHPI - CoreLogic
Exposure High	-0.178***	-0.139***	0.062***	0.009*	-0.020*	-0.013**
×Crisis	(0.038)	(0.023)	(0.018)	(0.005)	(0.010)	(0.005)
Observations	73,494	73,494	58,901	58,901	73,494	33,432
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.970	0.807	0.880	0.875	0.896	0.925

Table A5. ZIP-Level Analysis – Using ALWN as a Proxy for Delaying Loan Loss Provision

This table presents regressions of the ZIP-level exposure to banks' ALWN on various dependent variables. The ZIP-level exposure is measured with ALWN (-1*Loan Loss Allowance/Non-performing Loan) instead of DLR. The following model is estimated:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure* $Rate_{z,t}$, *Short Sale* $Rate_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' ALWN. Panel B reports the results with the indicator variable *Exposure* $High_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure (ALWN) Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure (ALWN)	-0.072***	-0.048***	0.020***	0.002***	-0.006***	-0.003**
×Crisis	(0.013)	(0.009)	(0.005)	(0.001)	(0.002)	(0.001)
Observations	73,494	73,494	58,901	58,901	73,494	33,432
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.969	0.801	0.875	0.874	0.895	0.925

Panel B: Results with the Indicator Exposure (ALWN) Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High (ALWN)	-0.152***	-0.113***	0.038***	0.004***	-0.011***	-0.005***
×Crisis	(0.015)	(0.010)	(0.006)	(0.001)	(0.004)	(0.001)
Observations	73,494	73,494	58,913	58,913	73,494	33,432
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.970	0.803	0.876	0.874	0.895	0.925

Table A6. ZIP-Level Analysis – Constructing Exposure without Year 2006

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables. The ZIP-level exposure is measured without year 2006 observations. The following model is estimated:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure Rate*$_{z,t}$, *Short Sale Rate*$_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable *Exposure High*$_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP,* Δ*Employment,* Δ*Establishment, logAve. Income, HHI, Nonbank Share,* and Δ*logNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure	-0.105***	-0.081***	0.040***	0.009**	-0.010*	-0.011*
×Crisis	(0.030)	(0.018)	(0.014)	(0.004)	(0.006)	(0.005)
Observations	73,462	73,462	58,888	58,888	73,462	33,426
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.970	0.803	0.877	0.876	0.895	0.925

Panel B: Results with the Indicator Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High	-0.111***	-0.092***	0.042***	0.006	-0.012*	-0.008**
×Crisis	(0.032)	(0.019)	(0.013)	(0.004)	(0.007)	(0.003)
Observations	73,462	73,462	58,888	58,888	73,462	33,426
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.969	0.802	0.876	0.875	0.895	0.925

Table A7. ZIP-Level Analysis – Constructing Exposure without Top 3 Mortgage Markets

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables. The ZIP-level exposure is measured without top three ZIP codes where individual banks originated their mortgages the most in each year during 2004–2006. The following model is estimated:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure Rate*$_{z,t}$, *Short Sale Rate*$_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable *Exposure High*$_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure	-0.133***	-0.098***	0.056***	0.010***	-0.015*	-0.016**
×Crisis	(0.039)	(0.025)	(0.021)	(0.004)	(0.008)	(0.007)
Observations	73,530	73,530	58,902	58,902	73,530	33,436
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.970	0.806	0.881	0.876	0.896	0.926

Panel B: Results with the Indicator Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High	-0.166***	-0.128***	0.061***	0.010**	-0.021**	-0.012***
×Crisis	(0.039)	(0.023)	(0.018)	(0.004)	(0.010)	(0.004)
Observations	73,530	73,530	58,902	58,902	73,530	33,436
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.970	0.806	0.881	0.876	0.896	0.925

Table A8. ZIP-Level Analysis – Controlling Interaction Terms of ZIP Variables and Crisis

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables using a following model:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma_1 X_{z,t} + \gamma_2 X_{z,t} \times Crisis_t + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, *Foreclosure Rate*$_{z,t}$, *Short Sale Rate*$_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable *Exposure High*$_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. The interaction term of $X_{z,t}$ and $Crisis_t$ is included. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure	-0.008	-0.016*	0.013*	0.008***	-0.006**	-0.008*
×Crisis	(0.012)	(0.008)	(0.008)	(0.002)	(0.003)	(0.004)
Observations	73,494	73,494	58,901	58,901	73,494	33,432
ZIP Controls	YES	YES	YES	YES	YES	YES
ZIP Controls*Crisis	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.976	0.851	0.898	0.878	0.900	0.927

Panel B: Results with the Indicator Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High	-0.021	-0.029***	0.023***	0.008**	-0.009***	-0.005***
×Crisis	(0.014)	(0.010)	(0.006)	(0.003)	(0.003)	(0.002)
Observations	73,494	73,494	58,901	58,901	73,494	33,432
ZIP Controls	YES	YES	YES	YES	YES	YES
ZIP Controls*Crisis	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.976	0.851	0.898	0.877	0.900	0.927

Table A9. ZIP-Level Analysis – Controlling Bank Characteristics at the ZIP Level

This table presents regressions of the ZIP-level exposure to banks' DLR on various dependent variables. The following model with additional bank characteristics at the ZIP level is estimated:

$$y_{z,t} = \beta Exposure_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \lambda_z + \epsilon_{z,t}.$$

The dependent variables are $logCredit_{z,t}$, $\Delta logCredit_{z,t}$, $Foreclosure\ Rate_{z,t}$, $Short\ Sale\ Rate_{z,t}$, $\Delta logHPI_{z,t}$-*FHFA*, and $\Delta logHPI_{z,t}$-*CoreLogic*. The primary independent variable is the interaction term of the exposure measure and the crisis-period indicator. Panel A reports the results with the continuous variable $Exposure_z$, the ZIP-level exposure to banks' DLR. Panel B reports the results with the indicator variable $Exposure\ High_z$, which is equal to one if $Exposure_z$ is above the sample median. $Crisis_t$ is equal to one if year is 2007–2009 for the credit amounts and house prices, and is equal to one if year is 2007–2010 for the distressed sales. The ZIP-level controls $X_{z,t}$ include *Lag Tier 1 Cap at ZIP, ΔEmployment, ΔEstablishment, logAve. Income, HHI, Nonbank Share,* and *ΔlogNonbank Credit*. In addition, bank-level controls are *logAssets, Cash, Deposit, Loans to Deposits, Loan Loss Reserve, Non-Performing Loan,* and *ROA* are constructed at the ZIP level using banks' mortgage market shares, and are included in all regressions. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

Panel A: Results with the Continuous Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure	-0.097***	-0.088***	0.038***	0.008***	-0.011*	-0.014**
×Crisis	(0.024)	(0.019)	(0.013)	(0.002)	(0.006)	(0.006)
Observations	73,498	73,498	58,900	58,900	73,498	33,419
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.972	0.811	0.889	0.877	0.899	0.926

Panel B: Results with the Indicator Exposure Measure

VARIABLES	(1) logCredit	(2) ΔlogCredit	(3) Foreclosure Rate	(4) Short Sale Rate	(5) ΔlogHPI - FHFA	(6) ΔlogHPI - CoreLogic
Exposure High	-0.116***	-0.109***	0.044***	0.008**	-0.015**	-0.010***
×Crisis	(0.026)	(0.017)	(0.010)	(0.003)	(0.006)	(0.003)
Observations	73,498	73,498	58,900	58,900	73,498	33,419
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.972	0.811	0.889	0.877	0.899	0.926

Table A10. ZIP-Level Analysis – IV Analysis for Credit Amounts and Distressed Sales

This table presents instrument variable regressions of the ZIP-level exposure to banks' DLR on various dependent variables. The first-stage and the second-stage models are estimated as follows:

1st Stage: $Exposure_z \times Crisis_t = \beta SEC\ Influence\ ZIP_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \epsilon_{z,t}$,

2nd Stage: $y_{z,t} = \beta \widehat{Exposure_z \times Crisis_t} + \gamma X_{z,t} + \delta_{c,t} + \epsilon_{z,t}$.

SEC Influence ZIP$_z$ is an instrumental variable defined as $\frac{1}{3}\sum_{t=2004}^{2006}\sum_{i\in z}\alpha_{i,z,t} - log(Distance)_i \times Public_i$, where *Distance* is the minimum distance between a bank's headquarters and the closest SEC office and *Public* is an indicator variable equal to one if the bank or its parent holding is publicly traded. Columns (1) – (3) report the results for the credit amounts, and columns (4) – (6) report the results for the distressed sales. The primary independent variable is $\widehat{Exposure_z \times Crisis_t}$, the instrumented variable from the first-stage model. The ZIP-level controls $X_{z,t}$ include *Public Share, Lag Tier 1 Cap at ZIP,* Δ*Employment,* Δ*Establishment, logAve. Income, HHI, Nonbank Share,* Δ*logNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. $***$, $**$, and $*$ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)	(4)	(5)	(6)
		Credit Amount			Distressed Sales	
	1st Stage	2nd Stage	2nd Stage	1st Stage	2nd Stage	2nd Stage
VARIABLES	Exposure× Crisis	logCredit	ΔlogCredit	Exposure× Crisis	Foreclosure Rate	Short Sale Rate
IV: SEC Influence	0.983***			0.985***		
×Crisis	(0.106)			(0.109)		
Exposure High		-0.476***	-0.397***		0.139***	0.014**
		(0.074)	(0.047)		(0.040)	(0.006)
Public Share	0.321*	-0.221**	0.066	0.364*	0.091**	0.034***
	(0.178)	(0.101)	(0.072)	(0.187)	(0.041)	(0.007)
Observations	73,494	73,494	73,494	85,780	58,901	58,901
ZIP Controls	YES	YES	YES	YES	YES	YES
County-Year FE	YES	YES	YES	YES	YES	YES
Zip FE	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.836	0.964	0.745	0.863	0.864	0.877
Partial F-Stat.	85.37***			82.31***		

Table A11. ZIP-Level Analysis – IV Analysis using OCC Share Pre

This table presents instrument variable regressions of the ZIP-level exposure to banks' DLR on house prices. The first-stage and the second-stage models are estimated as follows:

1st Stage: $Exposure_z \times Crisis_t = \beta OCC\ Share\ Pre_z \times Crisis_t + \gamma X_{z,t} + \delta_{c,t} + \epsilon_{z,t}$,

2nd Stage: $\Delta logHPI_{z,t} = \beta \widehat{Exposure_z \times Crisis_t} + \gamma X_{z,t} + \delta_{c,t} + \epsilon_{z,t}$.

OCC Share Pre$_z$ is an instrumental variable defined as an average of OCC banks' market shares in ZIP code *z* during the pre-crisis. The dependent variable is $\Delta logHPI_{z,t}$, natural logarithmic changes in either FHFA's or CoreLogic's price index at region *z* in year *t*. The primary independent variable is $\widehat{Exposure_z \times Crisis_t}$, the instrumented variable from the first-stage model. The ZIP-level controls $X_{z,t}$ include *Public Share*, *Lag Tier 1 Cap at ZIP*, *ΔEmployment*, *ΔEstablishment*, *logAve. Income*, *HHI*, *Nonbank Share*, *ΔlogNonbank Credit*. All variables are defined in Appendix A. Regressions are weighted by the population of ZIP code. Standard errors in parentheses are clustered at the state level. ∗∗∗, ∗∗, and ∗ denote significance at the one percent, five percent, and ten percent levels in two-tailed tests.

	(1)	(2)	(3)
	1st Stage	2nd Stage	2nd Stage
VARIABLES	Exposure×Crisis	ΔlogHPI - FHFA	ΔlogHPI - CoreLogic
IV: OCC Share Pre×Crisis	-6.580***		
	(0.682)		
Exposure×Crisis		-0.052**	-0.039***
		(0.026)	(0.013)
Observations	73,494	73,494	33,432
ZIP Controls	YES	YES	YES
County-Year FE	YES	YES	YES
ZIP FE	YES	YES	YES
R-squared	0.854	0.888	0.925
Partial F-Stat.	93.19***		

Table A12. Supplemental Tables – Correlation Matrix

This table presents correlation matrix of the ZIP-level pre-crisis exposure to banks' DLR and various dependent variables. Panel A reports the pre-crisis period (year 2004–2006) and Panel B reports the crisis period (year 2007–2010).

Panel A: Correlation Matrix (Year 2004 – 2006)

	(1) Exposure	(2) ΔlogHPI - FHFA	(3) ΔlogHPI - CoreLogic	(4) logCredit	(5) ΔlogCredit	(6) Foreclosure Rate	(7) Short Sale Rate
Exposure	1						
ΔlogHPI - FHFA	0.188***	1					
ΔlogHPI - CoreLogic	0.103***	0.723***	1				
logCredit	0.151***	0.385***	0.179***	1			
ΔlogCredit	0.133***	0.453***	0.373***	0.012	1		
Foreclosure Rate	-0.019*	-0.467***	-0.255***	-0.365***	-0.005	1	
Short Sale Rate	0.052***	-0.147***	-0.226***	0.058***	-0.004	0.059***	1

Panel B: Correlation Matrix (Year 2007 – 2010)

	(1) Exposure	(2) ΔlogHPI - FHFA	(3) ΔlogHPI - CoreLogic	(4) logCredit	(5) ΔlogCredit	(6) Foreclosure Rate	(7) Short Sale Rate
Exposure	1						
ΔlogHPI - FHFA	-0.208***	1					
ΔlogHPI - CoreLogic	-0.178***	0.499***	1				
logCredit	-0.021**	0.175***	0.061***	1			
ΔlogCredit	-0.167***	0.287***	0.615***	0.278***	1		
Foreclosure Rate	0.302***	-0.624***	-0.235***	-0.336***	-0.212***	1	
Short Sale Rate	0.168***	-0.440***	-0.029***	0.034***	0.112***	0.424***	1