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Bank Lending Channel and Changing Credit Standards in the Residential Mortgage Market

Salman Tahsin
University of Arkansas, Fayetteville

Bank Lending Channel and Changing Credit Standards in the Residential Mortgage Market

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Salman Tahsin
University of Louisiana at Monroe
Bachelor of Business Administration in Finance, 2009
University of Louisiana at Monroe
Master of Business Administration, 2010

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University of Arkansas

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Dr. Timothy J. Yeager
Dissertation Director

Dr. Wayne Lee
Committee Member

Dr. Scott Hsu
Committee Member

Abstract

My dissertation examines the relationship between bank conditions and the residential mortgage market. The first essay investigates the effect of bank distress on the residential mortgage market during the 2007-09 financial crisis. We use the county-aggregated change in the ratio of jumbo to nonjumbo mortgage acceptance rate as an instrumental variable to control for endogeneity between bank distress and county economic conditions. The median decrease in the instrumental variable explains an additional 1.5 percentage point decline in county home prices and a 20 basis point rise in the county unemployment rate, which represent 15% and 5%, respectively, of their median changes between 2007 and 2009. The second essay investigates how changes in bank credit standards between 2001 and 2006 affected county-level credit supply for residential mortgages. We introduce the ratio of conventional loan acceptance rate to FHA loan acceptance rate as a more accurate measure of residential credit standard than SLOOS. The ratio shows that credit standards eased significantly between 2001 and 2006, which increased mortgage originations and contributed to the housing boom. A one standard deviation weakening in credit standards leads to a 1.4% increase in loan acceptance rate, which represents 18.5% of the standard deviation in loan acceptance rate between 2001 and 2006.

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Tahsin, Salman and Timothy Yeager, 2017, A Residential Bank Lending Channel During the Financial Crisis, Paper submitted for review.

I. Introduction

My dissertation investigates linkages between bank conditions and the residential mortgage market before and during the financial crisis. Bank distress along with the disruption in the securitization markets adversely affected the housing market and economic activity between 2007 and 2009. The bank lending channel normally operates in the commercial lending market, but it can also occur in the residential market when a large share of mortgage originators become distressed simultaneously and the securitization market collapses, reducing the ability of creditworthy borrowers to obtain financing from alternate sources. The first essay documents a residential bank lending channel effect during the 2007-09 financial crisis by showing that bank distress led to a decline in economic activity. The most distressed banks reduced lending to otherwise creditworthy borrowers after securitization markets collapsed. Mortgage acceptance rates fell more in counties where banks were more distressed, which contributed to the decline in home prices and employment. Using the most conservative estimates, we find that the median increase in bank distress accounts for an additional 1.5 percentage point decline in county home prices and a 20 basis point rise in the county unemployment rate, which represent 15% and 5%, respectively, of their median changes between 2007 and 2009.

The second essay focuses on the residential mortgage expansion that contributed to the 2007-2009 financial crisis. One factor that played a major role in the mortgage expansion was the easing of credit standards by lenders. We examine the impact of changing credit standards on residential mortgage supply, especially during the housing boom years of 2001 to 2006. First. we propose an innovative ratio (CF Ratio) as a more accurate measure of residential credit standards than SLOOS. CF Ratio is the ratio of the conventional loan acceptance rate to the Federal Housing Administration (FHA) loan acceptance rate. It reveals sharply loosening credit standards between 2001 and 2006, which increased loan originations to lower creditworthy borrowers and contributed to the housing boom. After controlling for loan demand, borrower characteristics and county conditions, we show that the CF Ratio can partially explain the mortgage credit expansion at the county level. A one standard deviation easing of the CF Ratio can explain a 1.4% increase in loan acceptance rate; this represents 18.5% of the standard deviation in loan acceptance rate between 2001 and 2006.

Essay 1

A Residential Bank Lending Channel During the Financial Crisis

Salman Tahsin and Timothy J. Yeager

We document a residential bank lending channel on county-level housing and employment between 2007 and 2009. Our innovation is to use the county-aggregated change in the jumbo to nonjumbo mortgage acceptance rate proposed by Loutskina and Strahan (2009) as an instrumental variable to control for the endogeneity between bank distress and county economic activity. Mortgage acceptance rates fell more in counties where banks were more distressed, which contributed to the decline in home prices and employment. The economic significance of our results are modest, but not negligible. The median decrease in the instrumental variable accounts for an additional 1.5 percentage point decline in county home prices and a 20 basis point rise in the county unemployment rate, which represent 15% and 5%, respectively, of their median changes between 2007 and 2009.

A. Introduction

We empirically document a residential bank lending channel effect on county-level housing markets and employment between 2007 and 2009 resulting from widespread bank distress and the disruption in private-label mortgage-backed securities (MBS) markets. Research on the bank lending channel typically focuses on the reduction in economic activity from a contraction in commercial lending rather than residential mortgage lending because the effects from the bank lending channel come from a disruption of relationships between lenders and borrowers that take time to replace (Bernanke, 1983; Ashcraft, 2005; Chava and Purnanandam, 2011; Gan, 2007; Jiménez, Ongena, Peydra, and Saurina, 2012; Lemmon and Roberts 2010; Carvalho, Ferreira and Matos, 2015). While many business loans depend on long-term relationships to overcome the information asymmetry between borrower and lender, relationships in mortgage lending are far less important because the information asymmetry is easily resolved through verification of household income and assets reported on a standardized application. If a particular bank refuses to approve a mortgage loan to a creditworthy household, healthier banks stand ready to make the loan. In addition, securitization has weakened (Loutskina and Strahan, 2009) the link between bank health and mortgage lending. Even a severely distressed bank should be willing to originate a mortgage to earn fee income if the loan can be sold easily to another entity. Consequently, the mortgage market is not the usual place to search for evidence of the bank lending channel.

To be sure, the economic contraction that resulted from the bursting of the housing bubble can be explained quite well without a bank lending channel. As the housing supply surged beyond the capacity of the population to absorb it, home prices fell sharply across the country, impairing household net worth (Mian, Rao and Sufi, 2013). Mian and Sufi (2014) find that deterioration in housing net worth played a significant role in the sharp decline in U.S. employment between 2007 and 2009.

Nevertheless, it is possible under certain conditions for the bank lending channel to operate in the mortgage market and impose real effects on the economy. Such conditions emerge when: 1) a large share of mortgage originators become distressed simultaneously, reducing the ability of creditworthy homeowners to obtain financing from alternate lenders; and 2) the securitization market is disrupted so that banks must hold certain mortgages in their portfolios because they can no longer sell them into the secondary market.

Such conditions plausibly existed during the financial crisis and Great Recession. Figure 1 shows the annual percentage of loan applications from 2001 through 2009 at all privately held depository institutions, the top ten publicly traded originators, and all other publicly traded originators. Despite the intense competition in the mortgage market, the top 10 originators in a given year account for about 42% of all originations. During the financial crisis, many large financial institutions such as Citigroup, Countrywide, Wachovia, and Washington Mutual rapidly approached insolvency before either failing, merging with healthier banks in hastily arranged transactions, or receiving significant government aid. The simultaneous distress of many large banks likely made it difficult for many creditworthy households to find alternative lenders quickly.

Evidence also exists that the private-label securitization market was severely disrupted after the second quarter of 2007. Because Fannie Mae and Freddie Mac (the mortgage GSEs) were taken into conservatorship immediately in September 2008 by the federal government, their roles as prime mortgage securitizers continued without interruption. The private-label RMBS market, however, collapsed. Calem, Covas, and Wu (2013) show that jumbo and alt-A MBS issuance effectively shut down beginning in the third quarter of 2007. The stress in the jumbo market is reflected in Figure 2, which plots the spread between the yields on the 30-year fixed-rate jumbo and the 30-year conforming mortgage between 2006 and 2009. The spread rose consistently from the second half of 2007 through 2008 before receding somewhat in 2009. The disruption of the jumbo securitization market combined with banks' need for liquidity reduced the willingness of distressed banks to originate even high quality jumbo loans because they were unwilling to hold those loans in their portfolios. Indeed, Calem et. al show that banks with greater reliance on the jumbo securitization market and lower capital ratios reduced their share of jumbo originations to total originations more than other banks after the second quarter of 2007. Even if banks make mortgage loans when securitization markets are disrupted, they are more likely to transfer the risk to the consumer. Fuster and Vickery (2015) show that banks are far less willing to originate 30-year fixed-rate mortgages when the securitization market is impaired, transferring the interest rate risk to the households.

Our contribution to the literature is to empirically document a residential bank lending channel effect during the financial crisis by showing at the county level that bank distress combined with the disruption in securitization markets contributed to the decline in economic activity. The central challenge in these types of studies is to control for the endogeneity between bank distress and county performance. We minimize endogeneity concerns by using an innovative measure of bank distress first explored by Loutskina and Strahan (2009), which is the county-level change in the ratio of the acceptance rates of jumbo and nonjumbo loans between 2006 and 2008. By definition, jumbo loans exceed the loan size threshold of the mortgage Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. A bank that makes a jumbo loan runs the risk of expending precious liquidity by holding the loan in portfolio, especially when financial markets are in turmoil. Most nonjumbo loans, in contrast, are conforming loans that are eligible for purchase by the mortgage GSEs, so banks have assurances that such loans can easily be sold. The key insight is that jumbo acceptance rates should decline more than nonjumbo acceptance rates when banks are in distress because banks need to conserve liquidity and boost capital ratios. Consequently, a decline in a bank's ratio of jumbo to nonjumbo loans *in a given county* is more likely to be driven by bank distress than changes in economic or housing market conditions because changes in those real variables should have similar effects on a bank's willingness to make jumbo and nonjumbo loans in that county.

We run two-stage regressions where the first stage regresses a county's overall change in home purchase loan acceptance rates between 2006 and 2008 on the change in jumbo to nonjumbo acceptance rates over the same period. In the second stage, we regress changes in county housing and economic variables between 2007 and 2009 on the estimated change in acceptance rates from the first stage. We hypothesize that a county with a steeper decline in the jumbo to nonjumbo acceptance ratio will have a steeper decline in the overall loan acceptance rate. This correlation is not simply mechanical. The decline in the jumbo to nonjumbo acceptance ratio is a proxy for bank distress, and at the margin distressed banks should be reluctant to approve all types of nonconforming applications including subprime and near-prime loans. In the regressions, we include the county shares of subprime and jumbo loans originated in 2006 as explanatory variables to control for the adverse effects from subprime lending, and to ensure that the results are not driven by a glut of jumbo housing in the boom years.

Carefully controlling for applicant characteristics and demand and supply factors that affect county-level housing markets and employment, we show that counties with the median decrease in the mortgage acceptance rate between 2006 and 2008 experience an additional 1.5 percentage point decline in home prices between 2007 and 2009. Counties also experience an additional 20 basis point increase in the unemployment rate, and a 1.7 percentage point decline in construction employment growth. These changes represent 15%, 5%, and 7.5%, respectively, of their median changes between 2007 and 2009. We conclude that the economic significance of the residential bank lending channel during the financial crisis is modest, but not negligible.

As robustness, we run a second set of tests using propensity score matching. We match counties with otherwise similar profiles in the 2006 pre-crisis year, where banks in one county but not the other subsequently experience a sharp reduction in the jumbo to nonjumbo acceptance ratio. The results are consistent with the two-stage least squares results. We find that in counties where the jumbo to nonjumbo ratio drops sharply, mean home prices decline by 1.2 percentage points, and the unemployment rate increases by 30bp relative to the control group.

We run several additional robustness tests. In one set of tests we use failure probability and expected default frequency (EDF) as alternative measures of bank distress. The residential bank lending channel is much stronger in these tests, accounting for about 40% of the decline in home prices between 2007 and 2009. These results, however, likely overestimate the bank lending channel effect because of the endogeneity between county distress and bank distress. We also run the initial regressions (using the jumbo to nonjumbo instrumental variable), but we include refinancing home loans in the sample along with home purchase loans. Although the coefficients have similar economic significance to the base results, most of the coefficients are statistically insignificant. We interpret these results as showing that the residential bank lending channel operates more strongly through the inability of households to purchase homes rather than refinance homes.

The paper proceeds as follows. Section II describes the methodology, and Section III describes the data and summary statistics. Section IV presents the main results, Section V discusses propensity score matching, and Section VI presents several robustness tests. Section VII concludes.

B. Methodology

In this section, we explain the methodology used to identify the effect of the residential bank lending channel on county housing markets and employment, and we introduce the structural model for our two-stage empirical specification.

Our primary objective is to examine the effect of bank distress (combined with the shutdown of the private-label residential securitization market) on county home prices and employment. Equation (1) models the cross-sectional home price (*Home Price*) change between 2007 and 2009 for county *k* as a function of changes between 2006 and 2008 in applicant profiles (*Applicant*), housing supply and demand (*Housing*), and the county-aggregated acceptance rate (*Accept*) for home purchase loans. This one-year lag structure allows time for bank distress and the ensuing credit contraction to affect housing and economic conditions. We also include controls for county-level economic profiles prior to the onset of the financial crisis (*Precrisis*). Bold font indicates vectors. All else equal, home prices should increase more in counties with increases in creditworthy applicants, strong housing and economic conditions, and high loan acceptance rates.

$$\Delta Home\ Price_{k,07-09} = \alpha_0 + \boldsymbol{\alpha_1\ \Delta Applicant_{k,06-08}} + \boldsymbol{\alpha_2\ \Delta Housing_{k,06-08}} + \boldsymbol{\alpha_3\ \Delta Accept_{k,06-08}} + \boldsymbol{\alpha_4\ Precrisis_{k,06}} + u_{k,07-09} \tag{1}$$

The residential bank lending channel affects home prices indirectly through a reduction in acceptance rates by distressed banks, which in turn reduces effective housing demand. In addition to bank distress, acceptance rates are determined by applicant characteristics and housing and economic conditions. We expect the county-level change in the acceptance rate for home purchase loans between periods 2006 and 2008, modeled in Equation (2), to be negatively correlated with changes in bank distress, and positively correlated with changes in applicant creditworthiness, housing market conditions, and pre-crisis county profiles with less exposure to the housing sector. The intercept γ_0 captures changes in acceptance rates common across counties such as changes in national economic conditions and credit standards.

$$\Delta Accept_{k,06-08} = \gamma_0 + \boldsymbol{\gamma_1\ \Delta Bank\ Distress_{k,06-08}} + \boldsymbol{\gamma_2 \Delta Applicant_{k,06-08}} + \boldsymbol{\gamma_3\ \Delta Housing_{k,06-08}} + \boldsymbol{\gamma_4\ Precrisis_{06}} + v_{k,06-08} \tag{2}$$

Substituting the predicted value $(\widehat{Accept}_k)$ from Equation (2) into Equation (1), we derive in Equation (3):

$$\Delta Home\ Price_{k,07-09} = \beta_0 + \boldsymbol{\beta_1}\ \boldsymbol{\Delta Applicant_{k,06-08}} + \boldsymbol{\beta_2}\ \boldsymbol{\Delta Housing_{k,06-08}} +$$

$$\beta_3\ \Delta\widehat{Accept}_{k,06-08} \ + \boldsymbol{\beta_4}\ \boldsymbol{Precrisis_{k,06}} + \varepsilon_{k,07-09} \qquad (3)$$

The two-stage procedure requires that we find an instrumental variable for county-aggregated bank distress that is correlated with the change in loan acceptance rates but uncorrelated with home prices changes. Otherwise, a decrease in home prices in a given county could endogenously increase bank distress to the extent that banks are exposed to residential real estate in the county. Our instrumental variable is the change in the ratio of jumbo to nonjumbo acceptance rates between 2006 and 2008. For each county, we compute the acceptance ratio of jumbo loan applications (A_J) to nonjumbo loan applications (A_{NJ}) in the crisis year t, less the same acceptance ratio in t-1, or $\Delta(A_J/A_{NJ})=(A_J/A_{NJ})_t$ - $(A_J/A_{NJ})_{t-1}$. This instrumental variable should be positively correlated with loan acceptance rates because both ratios should decline given an increase in bank distress. It should also be uncorrelated with county housing (and employment) decline assuming that the decline affects jumbo and nonjumbo housing markets similarly within a county. Although Loutskina and Strahan (2009) and Calem et al. (2013) focus primarily on loan volumes rather than acceptance rates, we focus exclusively on acceptance rates because they inherently control for changing loan demand.

In addition to a change in county home prices, second-stage dependent variables include change in net worth, residential investment, unemployment rates, and several measures of employment. Explanatory variables are classified as applicant characteristics, housing market characteristics, and pre-crisis profiles. Applicant controls include income growth (*Income Growth*) and changes in loan-to-income ratios (ΔLTI) of jumbo and nonjumbo applicants between 2006 and 2008 and their squared values to capture nonlinearities. Housing market controls include the change in foreclosure rates between 2006 and 2008 obtained from RealtyTrac, and the change in loan applications between 2006 and 2008. Finally, pre-crisis control variables include the subprime share and jumbo share, respectively, of loan originations in the county in 2006 (*Subprime Share 2006* and *Jumbo Share 2006*). These variables capture the pre-crisis reliance of the county housing market on subprime and jumbo lending. Changes in home prices and loan applications between 2002 and 2006 capture the intensity of the housing boom. Precrisis controls also include the ratios of non-tradable, tradable, and construction employment in 2006; and the poverty rate and log of households in 2000. Following Mian and Sufi (2013), the regression is weighted by the county population to better reflect the importance of each county to the national economy. Regressions without weights give similar results.

As robustness to the instrumental variable approach, we perform a second set of tests where we match otherwise similar counties in socioeconomic composition and housing profile pre-crisis, but the counties have different groups of mortgage lenders with different levels of distress during the crisis as measured by our instrumental variable.

We use the propensity score matching (PSM) technique as described by Heckman, Ichimura, and Todd (1997, 1998) to match counties. We separate counties into quintiles by their change in jumbo to nonjumbo acceptance rates between 2006 and 2008. The binary *Bank Distress* variable is assigned a value equal to 1 for counties in the lowest two quintiles where banks experienced the highest distress, and a value equal to 0 for counties in the highest two quintiles where banks experienced the least distress. The middle quintile is excluded from the matching to more cleanly separate the counties. We estimate the probability of a geographic area having distressed banks with the following logit model:

$$Bank\ Distress_{k,06-08} = \beta_0 + \boldsymbol{\beta_1}\ \boldsymbol{\Delta Applicant_{k,06-08}} + \boldsymbol{\beta_2}\ \boldsymbol{\Delta Housing_{k,06-08}} + \boldsymbol{\beta_3}\ \boldsymbol{\Delta Precrisis_{k,06-08}} + \varepsilon_{k,06-08} \quad (4)$$

The propensity score regression includes the same set of control variables used in the main regression equation (3) except for the estimated change in acceptance rates and the square of the jumbo loan to income ratio. The nearest neighbor option matches each distressed county with the healthy county that has the closest propensity score within a caliper distance of 0.005. The mean differences in the relevant housing and economic variables are then computed. The results are weighted by the number of households in a county. If two or more counties have the same propensity score and are tied for nearest neighbor, all tied counties are matched. Unmatched distressed counties are those where no suitable healthy county could be matched.

C. Data and Summary Statistics

In this section, we describe the loan application, bank, and county data and present summary statistics. Residential mortgage loan applications in the U.S. are reported by most financial institutions under the Home Mortgage Disclosure Act (HMDA). The annual dataset contains all loan applications received by the reporting institutions, and it includes the loan decision, which allows us to identify the effect of bank distress on the loan approval decision. The HMDA data are freely available from the Federal Financial Institutions Examination Council (FFIEC) and from the National Archives. Reporting institutions include banks, credit unions, savings institutions and other non-depository lenders.[1] From the HMDA data for the years 2006-2009, we keep only the home purchase loan applications because the credit contraction from bank distress directly affects the economy through the inability of households to purchase, rather than refinance homes. As robustness, we run the full

[1] See http://www.ffiec.gov/hmda/hmdaproducts.htm for access to the data. For a depository institution to be covered under HMDA, it must meet certain criteria including the following: (i) Total assets are above a certain threshold; (ii) it has a presence in an MSA; and (iii) it is federally insured or regulated. For a non-depository institution to be covered under HMDA, it must meet these criteria: (i) It is a for-profit institution; (ii) mortgage loan originations equal or exceed 10 percent of its total loan originations or equal $25 million or more; (iii) it has a presence in an MSA; and (iv) either its total assets or the number of mortgage loan originations cross a certain threshold. For more information on the HMDA coverage criteria, please see www.ffiec.gov/hmda.

set of tests on home purchase and refinancing data. We exclude Federal Housing Administration (FHA) applications, Veterans Administration (VA) applications, and other applications where we are certain that the loans are explicitly guaranteed by the federal government. For these loans, the bank's approval decision is not likely to be influenced by its health because the loans can be sold to the government at any time.

The inability to accurately identify conforming loans potentially bias our results. The ideal measure of bank distress is the change in the ratio of jumbo to *conforming* loan acceptance rates because in theory a change in bank distress would affect only the numerator. In practice, we use the change in the ratio of jumbo to *nonjumbo* acceptance rates as the instrumental variable because we cannot distinguish ex-ante between conforming and nonconforming applications given the absence of credit scores and more detailed applicant information in the HMDA data. Subprime applications, for example, are classified as nonjumbo .[2] The inclusion of nonconforming loans in the denominator of the jumbo to nonjumbo acceptance ratio biases against finding a residential bank lending channel. The bias occurs because acceptance rates of nonconforming loans (especially subprime loans) surely fell sharply between 2006 and 2008, which increases the county jumbo to nonjumbo acceptance ratio while the overall county acceptance rate is decreasing. A similar concern is that we cannot perfectly identify jumbo loans in 2008 because Congress increased the loan limits to a maximum of $729,000 in designated high-cost areas during the year, but the HMDA data only include the year of origination. We keep the jumbo limit at $417,000 for the entire year 2008. Classifying some conforming loans as

[2] We can (imperfectly) identify subprime loans after they have been made because HMDA reporters are required to include the interest rate spread—the difference between the annual percentage rate on a loan and the rate on Treasury securities of comparable maturity—for higher priced mortgages. We define subprime mortgages as those where the spread is equal to or greater than 3 percentage points over the average prime offer rate for first-lien loans, or 5 percentage points for subordinate-lien loans. Subprime loans large enough to qualify as jumbo loans are classified as subprime.

jumbo loans in that year increases the jumbo to nonjumbo acceptance ratio, which also biases against finding a residential bank lending channel.

Panel A of Table 1 lists the number of HMDA loan applications in our dataset each year between 2006 and 2009 along with the mean values of applicant characteristics for jumbo and nonjumbo loans. In total, there are 7.2 million loan applications in the sample, with the number of applications declining each subsequent year from 2.9 million to 719,000. The mean nonjumbo loan acceptance rate ranges between 82% and 84% while the mean jumbo loan acceptance rate declines from 80% in 2006 to 77% in 2008. Although the mean decline in acceptance rates seems modest, the variation across counties is much larger, and the cross-county variation is what matters for our analysis. The mean nonjumbo loan to income ratio is the lowest in 2006 at 2.1, and peaks at 2.6 in 2008, potentially reflecting a relatively stronger applicant pool as credit standards tightened and weaker households quit applying. Indeed, mean applicant income and loan amount requested also peak in 2008. Similar trends are observed with jumbo applications. Between 2006 and 2008, the jumbo applicant share declines from 10% to 6% while the loan volume share falls from 32% to 19%.

Summary statistics of bank characteristics are in Panel B of Table 1. The number of unique lenders each year averages about 4,400, and the average bank holds about $3.3 billion in assets.

Table 2 describes the county-level variables used in the two-stage regression analysis. When we aggregate to the county level, we require a minimum of 17 jumbo loan applications each year, which drops the number of county observations from 812 to 478. Panel A of Table 2 contains a comprehensive list of variables, definitions, and data sources. They are grouped by dependent and explanatory variables and by (county) housing, employment, applicant, and county pre-crisis characteristics.

Panel B of Table 2 displays summary statistics across the 478 counties in the sample. The remarkable decline in housing variables reflects the severity of the crash. Mean county home prices declined 12.8% between 2007 and 2009; residential investment (building permits) declined by an average of 54.6%, and construction employment fell by 23.8%. Loan demand also plummeted. Home purchase applications surged 54% between 2002 and 2006, but they declined 58% between 2006 and 2008. Foreclosures rates jumped 567% over the period. The mean (median) decline in our instrumental variable, the ratio of jumbo to nonjumbo acceptance rates between 2006 and 2008, was 3.5% (5.0%). We note the high standard deviations of many of these variables, which reflects the significant heterogeneity of the impact of the financial crisis across the counties.

D. Two-Stage Regression Results

In this section, we document the effect of the residential bank lending channel on county housing and employment during the financial crisis. All else equal, bank distress reduces banks' willingness to extend illiquid mortgages to creditworthy applicants, which contracts mortgage credit and shifts the demand for houses to the left, leading to declines in home prices, residential investment, and employment.

We begin by validating the ratio of jumbo to nonjumbo acceptance rates as a measure of bank distress. We use that ratio as an instrumental variable to control for endogeneity between county economic distress and bank distress, and to identify the bank lending channel mechanism as a contraction in mortgage credit by more distressed banks.

Loutskina and Strahan (2009) and Calem et al. (2013) show that banks that are more liquidity constrained reduce the volume and acceptance rates of jumbo loans relative to nonjumbo loans. We show in Table 3 that this pattern holds as well for counties where banks are more distressed. We first aggregate the HMDA loan application data by bank and county in a given year so that each observation represents a unique bank-county pairing. We then regress the ratio of jumbo to nonjumbo acceptance rates on failure probability and applicant characteristics for each year between 2006 and 2009. Failure probability is modeled after the Federal Reserve's failure model (Cole and Gunther, 1995) and is explained in the Appendix. The failure probability coefficient is negative and statistically significant each year, showing that more distressed banks reduce jumbo lending relative to nonjumbo lending.

Table 4 reports the two-stage regression results with changes in housing market conditions and the unemployment rate as the dependent variables. The first column reports the first-stage regression where the dependent variable is the county change in loan acceptance rates between 2006 and 2008. For most counties, the dependent variable is negative because acceptance rates fell during that period. The key explanatory variable is the instrumental variable, $\Delta(A_J/A_{NJ})$ *2006-08*, which is the ratio of the jumbo to non-jumbo acceptance rates in 2008, less the same ratio in 2006. Again, the variable is negative for most counties because banks contracted jumbo lending more than nonjumbo lending between 2006 and 2008; consequently, we expect the regression coefficient to be positive. Indeed, the coefficient is positive and statistically significant, indicating that bank distress contributed to the decline in loan acceptance rates. Note that we include all the control variables from the second stage in the first stage as well to improve the model fit.

Columns 2 through 5 of Table 4 report the second-stage regression results. The key explanatory variable is the estimated change in county acceptance rates between 2006 and 2008, *Estimated* ΔA *2006-08*. Negative values in the explanatory variable reflect declines in the acceptance rates between 2006 and 2008. Home prices, net worth, and residential investment declined between 2007 and 2009 as well, so we expect the regression coefficients to be positive. Unemployment rates, however, increased so the coefficient should be negative for that regression. All four of the coefficients have the expected signs and are statistically significant at least at the 10% level. Several of the control variables are also statistically significant and have the expected signs, resulting in strong model fits. The coefficients on the shares of subprime and jumbo mortgages in 2006 consistently have the expected signs and are statistically significant, indicating that counties with more of these pre-crisis loan originations experienced sharper downturns.

The economic significance from the second-stage predicted variable is modest. A county with the median decline in estimated acceptance rates between 2006 and 2008 experiences an additional 1.5% decline in home prices, which accounts for 15% of the 10.3% percent median drop in home prices between 2007 and 2009. Similarly, the estimated additional changes in net worth, residential investment, and unemployment are -1.1%, -2.8%, and 0.2%, respectively, accounting for 17%, 5%, and 5%, respectively, of their median changes between 2007 and 2009.

Table 5 reports second-stage regression results of changes in various county employment growth categories. Although each of the coefficients for the estimated change in acceptance rates has the expected positive sign, only the effects on tradable and construction employment are statistically significant at the 10% level or better. The economic significance of the bank lending channel on these two employment sectors is notable. A county with the estimated median change in the acceptance rate between 2006 and 2008 experiences an additional 5.4% decline in tradable employment and an additional 1.7% decline in construction employment, which accounts for 29% and 8%, respectively, of their median changes between 2007 and 2009. The model fits of the regressions with non-tradable and tradable employment growth as the dependent variables are relatively weak so we are reluctant to draw strong conclusions from those results. The shares of subprime and jumbo originations in 2006 had robust and negative effect on overall employment growth, but the effects on various employment sectors were more tenuous especially for the subprime share.

In sum, our regression analysis identifies a specific bank lending channel where aggregate bank distress in a given county leads to reduced loan acceptance rates, which contributes to the housing and employment contraction. Collectively, the bank lending channel accounts for about 15% of the median county decline in home prices and net worth, 5% of the increase in the unemployment rate, and 8% of the decline in construction employment.

E. Propensity Score Matching

As robustness to the instrumental variable approach, we use propensity score matching to match counties that were otherwise similar in socioeconomic composition and housing profiles pre-crisis, but relied on different portfolios of mortgage lenders with different levels of distress during the crisis as measured by the change in the ratio of jumbo to nonjumbo acceptance rates between 2006 and 2008. This approach potentially reduces noise relative to regression analysis by eliminating from the matching the counties that had high bank distress during the financial crisis because they had vastly different socio-economic characteristics relative to counties with low bank distress.

The logit regression used to match the counties is presented in Equation (4). The binary dependent variable *BkDistress* is assigned a value of 1 for counties in the two quintiles where banks experienced the highest decline in the acceptance ratio of jumbo to nonjumbo loans between 2006 and 2008, and 0 for counties in the two quintiles where banks experienced the least decline. The middle quintile is excluded from the matching to more cleanly separate the counties. Explanatory variables are identical to those used in the second stage regressions in Tables 4 and 5 with the exception of the estimated change in acceptance rates and the square of the jumbo loan to income ratio. The nearest-neighbor PSM technique matches each county with distressed banks with the most similar county with non-distressed banks. Matching with replacement is allowed so that each healthy-bank county in the sample is unique, but the distressed-bank counties may be matched more than once.

Panel A of Table 6 presents the mean differences in the outcome variables between counties with high- and low-distressed banks. Counties with distressed banks between 2006 and 2008 experience an additional decline of 1.2% in home price, 3.8% in net worth, and 2.5% in residential investment between 2007 and 2009 relative to counties with health banks. In addition, the unemployment rate in counties with distressed banks increases by 30bp more. Each of these differences is statistically significant at the 1% level. These results are similar to the base regressions results in Tables 4 and 5.

Panel B of Table 6 reports the PSM results for the employment growth variables. Mean total employment growth between 2007 and 2009 is 60bp lower for counties with distressed banks, and the difference is statistically significant. However, results for the components of employment growth have unexpected signs. Counties with distressed banks experience an additional increase of 1% in non-tradable employment, 5.1% in tradable employment, and 6.5% in construction employment.

F. Robustness

We run several robustness tests on our two-stage regression results. First, we substitute the jumbo to nonjumbo acceptance ratio with two alternative measures of bank distress: failure probability and expected default frequency (EDF).

Failure probability is a measure of a bank's insolvency risk computed from its financial statements (described in the Appendix). County-level failure probability is the weighted average of the failure probabilities of all banks with applications from mortgage applicants in a given county, weighted by each bank's share of the total requested loan amount during the year. Three important differences exist between the jumbo to nonjumbo acceptance ratio and failure probability. First, the former is computed from loan application data in a given county, while the latter is computed at the bank level. The jumbo to nonjumbo ratio implicitly assumes that a distressed bank can respond differently in each county where it makes jumbo loans. A bank's failure probability, on the other hand, is more blunt because a bank is assumed to curtail residential loan acceptance rates uniformly across counties. Second, we can compute failure probability only for commercial banks and thrifts; changes in lending by credit unions due to distress are excluded. Third, endogeneity is more of a concern with failure probability as the measure of bank distress because the deterioration in economic activity in the county may directly influence the health of the bank if it does significant business in that county.

Table 7, Panel A reports the results from two-stage regressions substituting the change in the county-aggregated jumbo to nonjumbo acceptance ratio for the change in the county-aggregated failure probability. For brevity, we report only the key explanatory variables, and we omit the non-tradeable and tradeable regression results. First-stage results in the first column show, as expected, that the loan acceptance rates decline more between 2006 and 2008 in counties where banks have higher aggregated failure probability. Second-stage results in columns 2-7 show that the estimated change in loan acceptance rates lead to statistically significant declines in housing and economic outcomes. Moreover, the results are economically large. The median change in county-aggregated acceptance rates between 2006 and 2008 represent 39% of the decline in median home prices, 34% of the decline in median net worth, 11% of the decline in median residential investment, 7.5% of the median increase in the unemployment rate, 33% of the median decline in total employment, and 7% of the decline in construction employment. In sum, the residential bank lending channel appears even stronger when bank distress is measured with failure probability.

EDF is a proxy for insolvency risk derived from a publicly traded firm's equity valuation. Distance to default (DD) is the difference between the firm's market value of assets and its liabilities payable within one period, divided by a one standard deviation change in the market value of assets. The market value of assets and the volatility of assets returns are, however, not directly observable. Recognizing that equity is a call option on the underlying market value of a firm, we can use option pricing models to compute a firm's DD solely from a firm's market value of equity, equity volatility, and book value of debt (Merton, 1974). Higher values of DD imply lower default probabilities. Applying a probability distribution to DD yields the EDF. We use the Black-Sholes option pricing model as described by Crosbie and Bohn (2003) and translate one year DD into EDFs using a normal distribution.

County-level EDF is the weighted average of the EDF of all banks with applications from mortgage applicants in a given county, weighted by each bank's share of the total requested loan amount during the year. As with failure probability, EDF is computed at the bank (holding company) level and implicitly assumes that each bank curtails residential loan acceptance rates uniformly across counties. Because EDF can only be computed for publicly traded banks and thrifts, it excludes effects from distress at all privately held depository institutions. Endogeneity, however, is less of a concern with EDF than failure probability because most publicly traded banks are large and operate across many counties so that deterioration in economic activity in a given county will have a relatively small direct effect on the bank's health.

Panel B of Table 7 presents the key two-stage regression results using the change in EDF from 2006 to 2008 as the instrumental variable. As expected, first-stage results show a statistically significant inverse relationship between county EDF and the change in loan acceptance rates between 2006 and 2008. In addition, all second-stage coefficients on the estimated change in acceptance rates have the expected signs and all are statistically significant except the regression with the total employment change between 2007 and 2009. Again, the economic significance of the results are large. The median change in county-aggregated loan acceptance rates between 2006 and 2008 represent 39% of the decline in median home prices, 36% of the decline in median net worth, 8% of the decline in median residential investment, 11% of the median increase in the unemployment rate, and 11% of the median declines in total employment and construction employment.

Results from alternate measures of bank distress are consistent with the base results presented in Tables 4 and 5. Moreover, the economic significance of the results with failure probability and EDF as measures of bank distress are much larger. We view the results in Table 7 as benchmarks for the maximum influence from the residential bank lending channel because they do not control as well for the potential endogeneity between county performance and bank distress, nor do they provide flexibility for bank to respond differently to distress across counties.

Our final robustness test reverts to our initial measure of bank distress, but it expands the sample to include refinancing applications in addition to home purchase applications. Our story thus far is that the residential bank lending channel affects a county primarily through a reduction in the demand for homes because distressed banks deny loans to creditworthy applicants. It is also possible that the county is adversely affected if creditworthy applicants are denied refinancing loans because overall spending in the county is reduced.

Table 8 reports the key two-stage regression results using the broader sample of HMDA loan applications. The first stage shows, as expected, a positive and statistically significant relationship between the change in the jumbo to nonjumbo acceptance ratio and the change in the county acceptance rate. With one exception, the second-stage coefficients on the estimated change in acceptance rate have the expected signs but only the coefficient for the net worth regression is statistically significant. However, the economic significance of the coefficients are nearly identical to those of the base results. These results suggest that the residential bank lending channel operates primarily through the denial of home purchase loans.

G. Conclusion

We document a modest residential bank lending channel effect on county housing and economic markets between 2007 and 2009. Households had a more difficult time obtaining financing in counties where banks were more distressed because the banks were reluctant to use precious liquidity to make long-term home loans that they may not be able to sell in the secondary market. After controlling for endogeneity between bank distress and county housing and economic conditions using the change in the acceptance ratio of jumbo and nonjumbo loans, our best estimate is that bank distress accounts for an additional decline in county home prices of 1.5%, and an additional increase in the unemployment rate of 20 basis points. These changes represent 15% and 5%, respectively, of the median changes in these variables between 2007 and 2009.

Loutskina and Strahan (2009) document a relationship between bank condition and their willingness to extend mortgage loans that are difficult to sell. Calem et. al (2013) show that banks did indeed contract jumbo lending during the financial crisis. Our contribution is to document a residential bank lending channel by showing that bank health has real effects on the economy. Our results expand the growing bank lending channel literature that documents a connection between bank distress and economic contraction during the financial crisis.

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I. Appendix

In the mid-1990s, the Federal Reserve developed an econometric model to estimate the probability of bank failure within the next two years. Initially called FIMS, it is commonly referred to as the SEER model. (Cole et. al, 1995). Although the coefficients of the model are confidential, the explanatory variables are not. We use bank failure and call report data from 1986 to 1993 to estimate a failure probability model using the same explanatory variables as the SEER model. Miller, Olson, and Yeager (2015) show that estimates from failures during this time period outperform estimates updated from bank failures during the financial crisis period between 2006 and 2008. We then use the estimated coefficients to compute failure probabilities for banks and thrifts in our sample. The estimated model is as follows:

Failure Probability = *f*(-1.7351 + 0.0974*past30_ta + 0.1411*past90_ta + 0.1116*nacc_ta + 0.0611*oreo_ta + 0.0038*cm_ta - 0.1233*eq_ta - 0.0006*qroa - 0.0201*sec_ta + 0.0235*jumbo_ta)

where *f*(.) is the inverse of the probit function.

The definitions of the explanatory variables used in the model are as follows:

- past30_ta: Loans past due 30-90 days/total assets
- past90_ta: Loans past due 90+ days/total assets
- nacc_ta: Nonaccrual loans/total assets
- oreo_ta: Other real estate owned (OREO)/total assets
- cm_ta: Commercial and industrial loans/total assets
- eq_ta: equity/total assets
- qroa: quarterly annualized net income/average assets
- sec_ta: Investment securities/total assets
- jumbo_ta: Large time deposits/total assets

Figure 1. Loan application market share by bank category, 2001-2009
This figure displays the annual percentage of conventional home purchase loan applications received by privately held banks, the top 10 publicly traded banks, and all other publicly traded banks. The figure is based on HMDA applications to lenders who are either depository institutions or are affiliated with depository institutions. Depository institutions include commercial banks, savings and loan associations, savings banks, and credit unions.

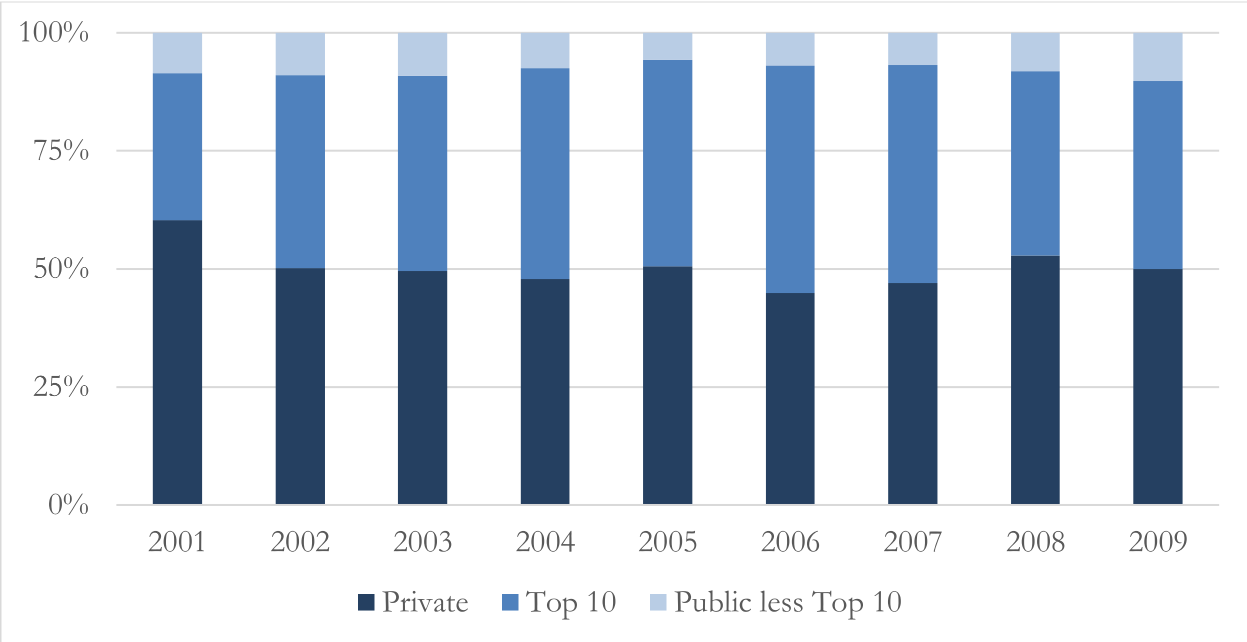

Figure 2: Spread of 30 Year Jumbo Yield over 30 Year Conforming Yield

This figure plots the monthly yield spread % between 30-year fixed-rate jumbo mortgages and 30-year fixed-rate conforming mortgages between 2006 and 2009. Jumbo mortgage yields are from Bankrate.com. Yields on conventional mortgages are from the Freddie Mac Primary Mortgage Market Survey.

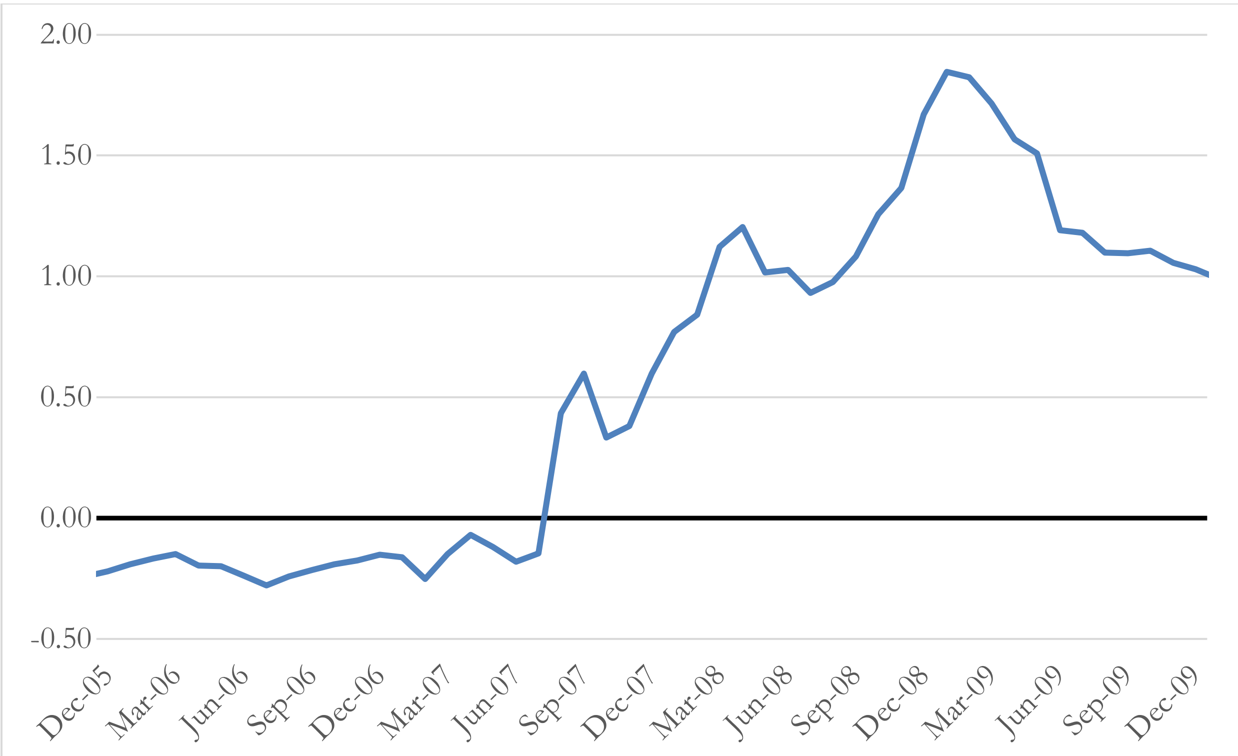

Table 1. Summary Statistics for Loan Applications and Bank Characteristics

Panel A. Home purchase loan applications

This panel displays summary statistics of loan application data in our sample, split by jumbo status. From the full HMDA dataset, we retain conventional home purchase applications received by depository institutions and their affiliates. Home purchase loans are those secured for the purpose of purchasing a dwelling. Conventional applications exclude FHA and VA loans, but they include jumbo and subprime borrowers. Jumbo loans exceed the size limit for eligibility to be purchased by the mortgage GSEs. We also report summary statistics on subprime originations because subprime loans can only be observed upon origination. In general, subprime loans are those with APRs more than 300bp above the prime rate. See Table 2 for a more precise definition.

	2006	2007	2008	2009
Total number of loan applications	2,911,093	2,448,655	1,175,740	718,767

Nonjumbo Applications (means)	2006	2007	2008	2009
Loan acceptance rate	0.83	0.82	0.83	0.84
Loan amount requested ($000s)	162.6	179.3	219.5	212.2
Loan-to-income ratio	2.1	2.3	2.6	2.5
Income of applicant ($000s)	90.9	93.1	101.2	99.8

Prime Jumbo Applications (means)	2006	2007	2008	2009
Loan acceptance rate	0.80	0.76	0.77	0.81
Loan amount requested ($000s)	679.7	719.3	921.8	910.7
Loan-to-income ratio	3.1	3.1	2.9	2.8
Income of applicant ($000s)	267.6	289.3	424.3	437.8
Jumbo application share	0.10	0.11	0.06	0.05
Jumbo loan volume origination share	0.32	0.31	0.19	0.17

Subprime Originations (means)	2006	2007	2008	2009
Loan amount ($000s)	164.0	194.0	185.0	169.0
Loan-to-income ratio	1.9	2.2	2.1	1.7
Income of applicant ($000s)	94.0	98.0	103.0	116.0
Subprime loan volume origination share	0.16	0.10	0.04	0.03

Panel B. Characteristics of All Bank Lenders

This panel displays the number of unique depository institutions by year that reported loan applications. Mean assets are weighted by the number of applications from each institution.

Lender Variables	2006	2007	2008	2009
Unique Lenders	4377	4378	4550	4401
Total Assets ($mil)	3,228	3,587	3,172	3,387

Table 2. Summary statistics of economic and bank distress indicators by county

Panel A provides definitions and data sources for the key variables in the sample.

Panel A. Definitions		
Category	Variable	Definition
		Dependent Variables
County Housing Outcomes	ΔHome Price 2007-09	Growth rate in county median home price between 2007 and 2009. Home Price data are from Zillow.com.
	ΔNet Worth 2006-09	Growth rate in county net worth from 2006 to 2009. Net Worth is defined as: stocks + bonds + housing – debt. Data are publicly available at Amir Sufi's website: http://faculty.chicagobooth.edu/amir.sufi/chronology.html
	ΔResidential Investment 2007-09	Growth rate in county residential investment from 2007 to 2009. Residential investment is based on the cost of construction from residential building permits. Data are from the U.S. Census Bureau.
County Employment Outcomes	ΔUnemployment Rate 2007-09	County unemployment rate in 2009 less unemployment rate in 2007. Unemployment data are from the Bureau of Labor Statistics.
	ΔEmp Total 2007-09	Growth rate of total county employment from 2007 to 2009. Data are from the U.S. Census Bureau.
	ΔEmp Non-Tradable 2007-09	Growth rate of county employment in the non-tradable sector from 2007 to 2009. Non-tradable employment includes restaurant and retail jobs. We use the employment data at the four-digit industry level to group the industry types into three categories of non-tradable, tradable, and construction, following Mian and Sufi (2014). Data are from the U.S. Census Bureau.
	ΔEmp Tradable 2007-09	Growth rate of county employment in the tradable sector from 2007 to 2009. Tradable employment comprises jobs in industries that have imports and exports of at least $10,000 per worker or total exports and imports of more than $500 million. We categorize tradable employment following Mian and Sufi (2014). Data are from the U.S. Census Bureau.
	ΔEmp Construction 2007-09	Growth rate of county employment in the construction sector between 2007 and 2009. Construction employment includes jobs in industries associated with construction, real estate, or land development. We categorize construction employment following Mian and Sufi (2014). Data are from the U.S. Census Bureau.
Loan Acceptance Rate	ΔA 2006-08	County-level acceptance rate (A) on all sample loan applications in 2008 less acceptance rate in 2006. Acceptance rates are weighted by loan amount. HMDA Data are from the Federal Financial Institutions Examination Council (FFIEC).

Table 2 (Cont.). Summary statistics of economic and bank distress indicators by county

Panel A. Definitions		
Category	Variable	Definition
		Explanatory Variables
Bank Distress Measures (Instrumental Variables)	$\Delta(A_J/A_{NJ})$ 2006-08	County-level acceptance rate of jumbo loan applications (A_J) divided by the acceptance rate of nonjumbo loan applications (A_{NJ}) in 2008 less the acceptance rate of jumbo loan applications divided by the acceptance rate of nonjumbo loan applications in 2006, or $(A_J/A_{NJ})_{2008}$ - $(A_J/A_{NJ})_{2006}$. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	ΔFP 2006-08	County-level failure probability (FP) in 2008 less FP in 2006. Bank FP is aggregated at the county level and weighted by the bank's application market share in that county. Data are from call report data obtained from the Federal Financial Institutions Examination Council (FFIEC).
	ΔEDF 2006-08	County-level Expected Default Frequency (EDF) in 2008 less EDF in 2006. Bank EDF is aggregated at the county level and weighted by the bank's application market share in that county. Data are from CRSP and Compustat.
Applicant Profiles	$\Delta(LTI_{All})$ 2006-08	Change in county-level loan-to-income ratio of all loan applications from 2008 to 2006, or $(LTI_{All})_{2008}$ - $(LTI_{All})_{2006}$. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	$\Delta(LTI_{All}$ squared) 2006-08	Same as $\Delta(LTI_{All})$ 2006-08 except that all LTI ratios are squared.
	INC_{All} Growth 2006-08	County mean all applicant income growth from 2006 to 2008, or $[(INC_{All})_{2008}$ - $(INC_{All})_{2006}]$ / $(INC_{All})_{2006}$. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	$\Delta(LTI_J)$ 2006-08	County-level loan-to-income ratio of jumbo loan applications (LTI_J) in 2008 less the LTI of jumbo loan applications in 2006, or $(LTI_J)_{2008}$ - $(LTI_J)_{2006}$. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	$\Delta(LTI_J$ squared) 2006-08	Same as $\Delta(LTI_J)$ 2006-08 except that all LTI ratios are squared.
	INC_J Growth 2006-08	County mean jumbo applicant income growth from 2006 to 2008, or $[(INC_J)_{20}$ $(INC_J)_{2006}]$ / $(INC_J)_{2006}$. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	$\Delta(LTI_{NJ})$ 2006-08	County-level loan-to-income ratio of non-jumbo loan applications (LTI_{NJ}) in 2008 less the LTI of non-jumbo loan applications in 2006, or $(LTI_{NJ})_{2008}$ - $(LTI_{NJ})_{200}$ HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
	$\Delta(LTI_{NJ}$ squared) 2006-08	Same as $\Delta(LTI_{NJ})$ 2006-08 except that all LTI ratios are squared.
	INC_{NJ} Growth 2006-08	County mean non-jumbo applicant income growth from 2006 to 2008, or $[(INC_{NJ})_{2008}$ - $(INC_{NJ})_{2006}]$ / $(INC_{NJ})_{2006}$. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).

Table 2 (Cont.). Summary statistics of economic and bank distress indicators by county

Panel A. Definitions		
Category	Variable	Definition
		Explanatory Variables
Housing Market Characteristics	ΔForelosure Rate 2006-08	Foreclosure rate is the number of foreclosures in a county x 1000 ÷ the total number of housing units. Foreclosure data are collected from RealtyTrac, and the number of housing units data are collected from the Census Bureau.
	ΔApplications 2006-08	Growth rate in the county-level number of home purchase loan applications from 2006 to 2008. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
Pre-crisis County Profile	Subprime Share 2006	County-level ratio of the loan amount of subprime loan originations to all loan origination in a county in 2006. We define subprime loans as those with interest rate spreads (the difference between the annual percentage rate (APR) on a loan and the rate on Treasury securities of comparable maturity) equal to or greater than 3 percentage points over the average prime offer rate for first-lien loans, or 5 percentage points for subordinate-lien loans. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
	Jumbo Share 2006	County-level ratio of the loan amount of jumbo loan originations to all loan originations in a county in 2006. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	ΔApplications 2002-06	Growth rate in the county-level number of home purchase loan applications from 2002 to 2006. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
	ΔHome Price 2002-06	Growth rate in county median home price between 2002 and 2006. Home Price data are collected from Zillow.com.
	Non-Tradable Ratio 2006	Proportion of total county employment in 2006 in the non-tradable sector. Data are collected from the U.S. Census Bureau.
	Tradable Ratio 2006	Proportion of total county employment in 2006 in the tradable sector. Data are collected from the U.S. Census Bureau.
	Construction Ratio 2006	Proportion of total county employment in 2006 in the construction sector. Data are collected from the U.S. Census Bureau.
	Poverty Rate 2000	Proportion of a county population living below the poverty line. Poverty rate data are collected from the U.S. Census Bureau.
	Log(Households) 2000	Natural log of the total number of households in 2000. Data are collected from the U.S. Census Bureau.

Table 2 (Cont.). Summary statistics of economic and bank distress indicators by county
Panel B. County summary statistics

Category	Variable	N	Mean	Std. Dev.	Min	Max	Median
	Dependent Variables						
County Housing Outcomes	ΔHome Price 2007-09	478	-0.128	0.116	-0.448	0.322	-0.103
	ΔNet Worth 2006-09	444	-0.096	0.102	-0.723	0.026	-0.066
	ΔResidential Investment 2007-09	478	-0.546	0.189	-0.937	0.238	-0.558
County Employment Outcomes	ΔUnemployment Rate 2007-09	478	0.048	0.016	0.015	0.099	0.046
	ΔEmp Total 2007-09	478	-0.038	0.030	-0.113	0.050	-0.034
	ΔEmp Non-Tradable 2007-09	478	-0.065	0.074	-0.297	0.139	-0.063
	ΔEmp Tradable 2007-09	457	-0.224	0.227	-0.727	0.114	-0.184
	ΔEmp Construction 2007-09	478	-0.238	0.138	-0.625	0.172	-0.221
Acceptance Rate	ΔA 2006-08	478	-0.014	0.032	-0.122	0.087	-0.010
	Explanatory Variables						
Bank Distress (Instrumental Variables)	$\Delta(A_J/A_{NJ})$ 2006-08	478	-0.035	0.099	-0.173	0.156	-0.050
	ΔFP 2006-08	478	0.029	0.014	0.006	0.087	0.026
	ΔEDF 2006-08	478	0.306	0.059	0.103	0.509	0.310
Applicant Profiles	$\Delta(LTI_{All})$ 2006-08	478	0.351	0.181	-0.060	0.980	0.333
	$\Delta(LTI_{All}$ squared) 2006-08	478	1.554	0.923	-0.603	3.334	1.500
	INC_{All} Growth 2006-08	478	0.066	0.116	-0.225	0.349	0.076
	$\Delta(LTI_J)$ 2006-08	478	-0.014	0.296	-0.494	0.583	-0.024
	$\Delta(LTI_J$ squared) 2006-08	478	0.142	1.962	-3.063	3.892	0.026
	INC_J Growth 2006-08	478	0.303	0.363	-0.426	1.039	0.248
	$\Delta(LTI_{NJ})$ 2006-08	478	0.384	0.184	-0.065	0.683	0.370
	$\Delta(LTI_{NJ}$ squared) 2006-08	478	1.730	1.023	-0.576	3.528	1.650
	INC_{NJ} Growth 2006-08	478	0.067	0.105	-0.209	0.428	0.076
Housing Market Characteristics	ΔForelosure Rate 2006-08	478	5.670	5.185	-1.046	13.823	4.306
	ΔApplications 2006-08	478	-0.578	0.112	-0.836	-0.115	-0.585
Pre-crisis County Profile	Subprime Share 2006	478	0.149	0.064	0.037	0.416	0.137
	Jumbo Share 2006	478	0.193	0.151	0.018	0.610	0.144
	ΔApplications 2002-06	478	0.543	0.414	-0.309	2.912	0.507
	ΔHome Price 2002-06	478	0.521	0.317	-0.015	1.836	0.470
	Non-Tradable Ratio 2006	478	0.442	0.135	0.025	0.728	0.449
	Tradable Ratio 2006	478	0.056	0.046	0.000	0.123	0.044
	Construction Ratio 2006	478	0.232	0.070	0.011	0.327	0.231
	Poverty Rate 2000	478	0.102	0.044	0.021	0.252	0.095
	Log(Households) 2000	478	11.3	1.0	8.0	14.0	11.3

Table 3. Effect of bank distress on jumbo to nonjumbo acceptance rates

This table shows results from annual regressions of the ratio of jumbo acceptance rates to nonjumbo acceptance rates on failure probability and applicant characteristics. Each observation represents a unique bank-county combination. ***, **, * represent 1%, 5%, and 10% level of significance, respectively.

	Dependent Variable: A_J/A_{NJ}			
	2006	2007	2008	2009
Failure Probability	-0.516**	-1.392***	-0.842***	-0.449***
	(0.22)	(0.20)	(0.15)	(0.16)
LTI_J squared	-0.009***	0.001	-0.009***	-0.014***
	(0.00)	(0.00)	(0.00)	(0.00)
LTI_J	0.013	-0.054***	0.002	0.027
	(0.02)	(0.02)	(0.02)	(0.03)
Log (INC_J)	0.004	0.015	0.032**	-0.009
	(0.01)	(0.01)	(0.01)	(0.02)
LTI_{NJ} squared	0.018***	0.021***	0.033***	0.044***
	(0.00)	(0.00)	(0.00)	(0.01)
LTI_{NJ}	-0.077***	-0.101***	-0.220***	-0.256***
	(0.02)	(0.02)	(0.03)	(0.03)
Log(INC_{NJ})	-0.044***	0.007	-0.058***	-0.016
	(0.01)	(0.01)	(0.02)	(0.02)
Constant	1.264***	1.068***	1.396***	1.458***
	(0.10)	(0.11)	(0.14)	(0.17)
County FE	Yes	Yes	Yes	Yes
Observations	15,389	14,864	9,383	6,210
R-squared	0.017	0.019	0.038	0.034

Table 4. Two-stage regressions of bank distress on county housing and employment

Results from two-stage least squares regressions. The first stage, reported in column 1, regresses the change in the county acceptance rate (ΔA) between 2006 and 2008 (acceptance rate in 2008 less acceptance rate in 2006) on the instrumental variable and control variables. The instrumental variable is the change in the ratio of the jumbo acceptance rate to the nonjumbo acceptance rate, Δ(AJ/ANJ), between 2006 and 2008. Second-stage regressions in columns 2-5 regress county housing market indicators and unemployment rate on the estimated change in the county acceptance rate between 2006 and 2008. Standard errors in parentheses. ***, **, * represent 1%, 5%, and 10% level of significance, respectively.

	Explanatory Variables	1st Stage: ΔA 2006-08	ΔHome Price 2007-09	ΔNet Worth 2006-09	ΔResidential Investment 2007-09	ΔUnemp Rate 2007-09
Bank Distress	$\Delta(A_J/A_{NJ})$ 2006-08	0.060***				
		(0.01)				
	Predicted ΔA 2006-08		1.476**	1.103*	2.780*	-0.210*
			(0.67)	(0.61)	(1.52)	(0.11)
Applicant Profile	ΔLTI_J squared 2006-08	-0.002	0.002	0.000	-0.009	-0.000
		(0.00)	(0.01)	(0.01)	(0.02)	(0.00)
	ΔLTI_J 2006-08	0.002	-0.022	0.006	0.083	0.008
		(0.02)	(0.06)	(0.06)	(0.14)	(0.01)
	INC_J Growth 2006-08	0.006	-0.025	-0.002	0.058	0.002
		(0.01)	(0.02)	(0.02)	(0.04)	(0.00)
	ΔLTI_{NJ} squared 2006-08	0.013*	0.027	-0.019	-0.057	0.001
		(0.01)	(0.02)	(0.02)	(0.05)	(0.00)
	ΔLTI_{NJ} 2006-08	-0.061	-0.002	0.079	0.231	-0.022
		(0.04)	(0.13)	(0.12)	(0.28)	(0.02)
	INC_{NJ} Growth 2006-08	0.014	0.484***	0.263***	0.059	-0.041***
		(0.01)	(0.04)	(0.04)	(0.09)	(0.01)

Table 4 (Cont.). Two-stage regressions of bank distress on county housing and employment

	Explanatory Variables	1st Stage: ΔA 2006-08	ΔHome Price 2007-09	ΔNet Worth 2006-09	ΔResidential Investment 2007-09	ΔUnemp Rate 2007-09
Housing Market	ΔForelosure Rate 2006-08	0.000	-0.003***	-0.003***	-0.000	0.000***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	ΔApplications 2006-08	0.043**	0.066	0.037	0.392***	-0.039***
		(0.02)	(0.06)	(0.05)	(0.13)	(0.01)
Pre-crisis County Profile	Subprime Share 2006	-0.091***	-0.488***	-0.623***	-0.505**	0.039**
		(0.03)	(0.10)	(0.09)	(0.23)	(0.02)
	Jumbo Share 2006	-0.014	-0.221***	-0.126***	-0.293***	0.024***
		(0.01)	(0.03)	(0.03)	(0.08)	(0.01)
	ΔApplications 2002-06	-0.009***	0.025**	0.036***	-0.007	0.002
		(0.00)	(0.01)	(0.01)	(0.02)	(0.00)
	ΔHome Price 2002-06	-0.024***	-0.000	-0.029	0.227***	-0.011***
		(0.01)	(0.02)	(0.02)	(0.05)	(0.00)
	Non-Tradable Ratio 2006	-0.013	0.053	0.092**	-0.022	0.000
		(0.02)	(0.04)	(0.04)	(0.10)	(0.01)
	Tradable Ratio 2006	0.117***	-0.363***	-0.456***	-0.740**	0.071***
		(0.03)	(0.13)	(0.12)	(0.29)	(0.02)
	Construction Ratio 2006	0.007	-0.194***	-0.088	-0.205	0.017
		(0.03)	(0.07)	(0.06)	(0.16)	(0.01)
	Poverty Rate 2000	0.073**	-0.010	-0.126	-0.432*	0.063***
		(0.03)	(0.11)	(0.09)	(0.24)	(0.02)
	Log(Households) 2000	-0.003	0.003	0.009*	0.052***	-0.003***
		(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
	Constant	0.065***	-0.015	-0.035	-0.719***	0.044***
		(0.02)	(0.07)	(0.07)	(0.17)	(0.01)
	Observations	478	478	444	478	478
	R-squared	0.394	0.703	0.737	0.205	0.519

Table 5. Second-stage regressions of bank distress on county employment

Second-stage results of county employment growth between 2007 and 2009 regressed on the estimated change in county acceptance rate between 2006 and 2008. The first stage (see Table 4, column 1) regresses the change in the county acceptance rate (ΔA) between 2006 and 2008 on the change in the ratio of the jumbo acceptance rate to the nonjumbo acceptance rate, Δ(AJ/ANJ), between 2006 and 2008. Second-stage regressions in columns 1-4 regress various measures of employment growth on the estimated change in the county acceptance rate between 2006 and 2008. Standard errors in parentheses. ***, **, * represent 1%, 5%, and 10% level of significance, respectively.

	Explanatory variables	ΔEmp Total 2007-09	ΔEmp Non-Tradable 2007-09	ΔEmp Tradable 2007-09	ΔEmp Construction 2007-09
	Estimated ΔA 2006-08	0.243	0.113	5.303***	1.647*
		(0.22)	(0.54)	(2.00)	(0.86)
Applicant Profile	ΔLTI_J squared 2006-08	-0.002	0.000	0.029	-0.012
		(0.00)	(0.01)	(0.03)	(0.01)
	ΔLTI_J 2006-08	0.008	0.023	-0.100	0.074
		(0.02)	(0.05)	(0.18)	(0.08)
	INC_J Growth 2006-08	0.004	0.020	-0.035	0.030
		(0.01)	(0.01)	(0.05)	(0.02)
	ΔLTI_{NJ} squared 2006-08	0.001	-0.006	-0.105	0.024
		(0.01)	(0.02)	(0.07)	(0.03)
	ΔLTI_{NJ} 2006-08	0.044	0.047	0.614*	-0.009
		(0.04)	(0.10)	(0.37)	(0.16)
	INC_{NJ} Growth 2006-08	0.036***	0.002	0.053	0.338***
		(0.01)	(0.03)	(0.12)	(0.05)

Table 5 (Cont.). Second-stage regressions of bank distress on county employment

	Explanatory variables	ΔEmp Total 2007-09	ΔEmp Non-Tradable 2007-09	ΔEmp Tradable 2007-09	ΔEmp Construction 2007-09
Housing Market	ΔForelosure Rate 2006-08	-0.001**	0.000	-0.001	-0.002**
		(0.00)	(0.00)	(0.00)	(0.00)
	ΔApplications 2006-08	0.081***	0.095**	-0.124	0.346***
		(0.02)	(0.05)	(0.17)	(0.07)
Pre-crisis County Profile	Subprime Share 2006	-0.088***	0.045	0.222	0.159
		(0.03)	(0.08)	(0.30)	(0.13)
	Jumbo Share 2006	-0.056***	-0.076***	0.063	-0.207***
		(0.01)	(0.03)	(0.10)	(0.04)
	ΔApplications 2002-06	0.011***	0.011	0.037	0.001
		(0.00)	(0.01)	(0.03)	(0.01)
	ΔHome Price 2002-06	0.021***	-0.012	0.175**	0.023
		(0.01)	(0.02)	(0.07)	(0.03)
	Non-Tradable Ratio 2006	-0.045***	-0.052	-0.142	0.166***
		(0.01)	(0.03)	(0.13)	(0.06)
	Tradable Ratio 2006	-0.104**	-0.063	-0.241	0.016
		(0.04)	(0.10)	(0.38)	(0.16)
	Construction Ratio 2006	0.019	0.081	0.214	-0.180**
		(0.02)	(0.06)	(0.21)	(0.09)
	Poverty Rate 2000	-0.016	0.018	-0.086	-0.235*
		(0.03)	(0.08)	(0.31)	(0.13)
	Log(Households) 2000	0.002	0.004	0.040**	0.037***
		(0.00)	(0.00)	(0.02)	(0.01)
	Constant	0.004	-0.049	-0.835***	-0.489***
		(0.02)	(0.06)	(0.22)	(0.10)
	Observations	478	478	457	478
	R-squared	0.429	0.050	0.087	0.440

Table 6. Propensity score matching

This table reports the results from propensity score matching. Counties are sorted in ascending order by the aggregated ratio of the change in the jumbo to nonjumbo acceptance rate between 2006 and 2008. Counties in the lowest two quintiles have the most distressed banks, and are classified as distressed counties; counties in the highest two quintiles are classified as healthy counties. The middle quintile is dropped from the sample. The propensity score regression regresses county status (distressed or healthy) on the same set of control variables used in the second-stage regression in Tables 4 and 5, with the exception of the estimated change in acceptance rates and the square of the jumbo loan to income ratio. The regression is weighted by the number of households in a county. The nearest neighbor option matches each distressed county with the healthy county that has the closest propensity score within a caliper distance of 0.005. The mean difference in the relevant housing and economic variables is then computed. If two or more counties have the same propensity score and are tied for nearest neighbor, all tied counties are matched. Unmatched distressed counties are those where no suitable healthy county could be matched. Panel A lists the results for the housing market and unemployment rate, and Panel B lists the results for the various measures of employment growth. Standard errors in parentheses. ***, **, * represent 1%, 5%, and 10% level of significance, respectively.

Panel A.	ΔHome Price 2007-09	ΔNet Worth 2006-09	ΔResidential Investment 2007-09	ΔUnemp Rate 2007-09
Mean difference	-0.012***	-0.038***	-0.025***	0.003***
(Standard errors)	(0.000)	(0.000)	(0.000)	(0.000)
Match characteristics	Number of counties			
Number of matches	191	176	191	191
Distinct number of distressed counties	170	144	170	170
Unmatched distressed counties	22	32	22	22

Panel B.	Emp Growth 2007-09	Non-Tradable Growth 2007-09	Tradable Growth 2007-09	Construction Growth 2007-09
Mean difference	-0.006***	0.010***	0.051***	0.065***
(Standard errors)	(0.000)	(0.000)	(0.000)	(0.000)
County type	Number of counties			
Number of matches	191	191	178	191
Distinct number of distressed counties	170	170	155	170
Unmatched distressed counties	22	22	31	22

Table 7. Two-stage regressions with alternative measures of bank distress

Results from two-stage least squares regressions. The first stage, reported in column 1, regresses the change in the county acceptance rate (ΔA) between 2006 and 2008 (acceptance rate in 2008 less acceptance rate in 2006) on the instrumental variable and control variables. Control variables are the same as those in the base regression in Table 4, but most are omitted for brevity. In Panel A, the instrumental variable is the change in the county-aggregated bank failure probability, and in Panel B, it is the change in the county-aggregated bank expected default frequency (EDF) between 2006 and 2008. Second-stage regressions in columns 2-7 regress changes in county housing and employment outcomes between 2007 and 2009 on the estimated change in the county acceptance rate between 2006 and 2008 and control variables. Standard errors in parentheses. ***, **, * represent 1%, 5%, and 10% level of significance, respectively.

Variables	1st Stage: ΔA 2006-08	ΔHome Price 07-09	ΔNet Worth 06-09	ΔResidential Investment 07-09	ΔUnemp Rate 2007-09	ΔEmp Total 2007-09	ΔEmp Construction 2007-09
ΔFP 2006-08	-0.633***						
	(0.14)						
Estimated ΔA 2006-08		3.957***	2.249***	6.299***	-0.342***	1.133***	1.446*
		(0.99)	(0.68)	(1.27)	(0.11)	(0.20)	(0.77)
Subprime Share 2006	-0.032	-0.321*	-0.501***	-0.124	0.022	0.022	0.100
	(0.03)	(0.17)	(0.11)	(0.21)	(0.02)	(0.03)	(0.13)
Observations	478	478	444	478	478	478	478
R-squared	0.380	0.160	0.543	0.290	0.387	0.410	0.416

Panel B. Expected default frequency

Variables	1st Stage: ΔA 2006-08	ΔHome Price 07-09	ΔNet Worth 06-09	ΔResidential Investment 07-09	ΔUnemp Rate 2007-09	ΔEmp Total 2007-09	ΔEmp Construction 2007-09
ΔEDF 2006-08	-0.108***						
	(0.03)						
Estimated ΔA 2006-08		3.909***	2.341***	4.409***	-0.486***	0.364	2.449**
		(1.07)	(0.73)	(1.42)	(0.14)	(0.22)	(0.96)
Subprime Share 2006	-0.079***	-0.325*	-0.492***	-0.313	0.007	-0.054	0.200
	(0.03)	(0.17)	(0.12)	(0.23)	(0.02)	(0.04)	(0.15)
Observations	478	478	444	478	478	478	478
R-squared	0.375	0.174	0.522	0.268	0.176	0.356	0.244

Table 8. Two-stage regressions including refinancing applications

Results from two-stage least squares regressions. Sample includes HMDA applications to depository institutions and affiliates for home purchase and refinancing loans. The first stage, reported in column 1, regresses the change in the county acceptance rate (ΔA) between 2006 and 2008 (acceptance rate in 2008 less acceptance rate in 2006) on the instrumental variable and control variables. Control variables are the same as those in the base regression in Table 4, but most are omitted for brevity. The instrumental variable is the change in the ratio of the jumbo acceptance rate to the nonjumbo acceptance rate, Δ(AJ/ANJ), between 2006 and 2008. Second-stage regressions in columns 2-7 regress changes in county housing and employment outcomes between 2007 and 2009 on the estimated change in the county acceptance rate between 2006 and 2008 and control variables. Standard errors in parentheses. ***, **, * represent 1%, 5%, and 10% level of significance, respectively.

VARIABLES	1st Stage: ΔA 2006-08	ΔHome Price 2007-09	ΔNet Worth 2006-09	ΔResidential Investment 2007-09	ΔUnemp Rate 2007-09	ΔEmp Total 2007-09	ΔEmp Construction 2007-09
$\Delta(A_J/A_{NJ})$ 2006-08	0.023*						
	(0.01)						
Estimated ΔA 2006-08		1.764	4.375***	5.194	-0.165	0.031	-2.791
		(1.62)	(1.28)	(3.27)	(0.26)	(0.52)	(2.42)
Subprime Share 2006	-0.073*	-0.085	-0.109	-0.897***	0.064***	-0.136***	-0.232
	(0.04)	(0.15)	(0.12)	(0.31)	(0.02)	(0.05)	(0.23)
Jumbo Share 2006	(0.04)	(0.15)	(0.12)	(0.31)	0.024***	-0.039***	-0.098
	0.007	-0.282***	-0.186***	-0.385***	(0.01)	(0.01)	(0.06)
Observations	478	478	444	478	478	478	478
R-squared	0.750	0.662	0.787	0.304	0.477	0.374	0.132

Essay 2

Bank Credit Standards and the Residential Mortgage Boom

Salman Tahsin

We examine how changes in lender credit standards affect credit supply for residential mortgages. We introduce the CF Ratio – the conventional loan acceptance rate to the FHA loan acceptance rate – as a more accurate measure of residential credit standards than SLOOS. Our measure reveals sharply loosening credit standards between 2001 and 2006, which increased loan originations to low creditworthy borrowers and contributed to the housing boom. Unlike SLOOS, the CF Ratio partially explains the mortgage credit boom. At the county level, a one standard deviation easing of credit standards leads to a 1.4 percentage point increase in the loan acceptance rate, which represents 18.5% of the standard deviation in the loan acceptance rate between 2001 and 2006.

A. Introduction

Residential mortgage credit expansion fueled the housing bubble leading to the 2007-2009 financial crisis. This rapid growth in credit can be partially explained by fundamentals such as falling interest rates and rising incomes after the 2000-2001 recession. The resulting increase in home prices created a feedback effect by creating additional equity that new or existing homeowners could draw upon for financing. Fundamentals, however, were not strong enough to explain the credit boom (Mian and Sufi, 2009).

One important factor was the easing of credit standards by lenders, which was especially evident in the loans made to subprime borrowers. Duca et al. (2012) find that down payment ratios during the subprime boom years were lower for first-time home buyers, reflecting easier lending standards and a greater share of loans originated to comparatively riskier applicants. Dell'ariccia et al. (2012) find that MSAs with an increase in loan applications experienced a decline in lending standards. Lenders gave relatively less importance to the loan-to-income ratios of applicants in these MSAs, suggesting that lending standards were lax.

The Senior Loan Officer Opinion Survey (SLOOS) is the most widely used measure of credit standards. A quarterly survey conducted by the Federal Reserve, SLOOS asks loan officers whether they have changed credit standards on different loan types. The reported measure for a given loan type is the net percentage of banks with tighter lending standards (e.g. banks tightening less banks loosening) so that positive (negative) values represent tightening (loosening) standards. Until the second quarter of 2007, the survey asked about residential mortgage lending standards as a whole. It has since disaggregated mortgages into several categories and added separate questions about the lending standards of each of those categories.[3]

[3] Survey data about residential mortgage loans were reported from 1990 to 2007. Starting in the second quarter of 2007, the data were reported individually for prime, nontraditional (alternative mortgage loans such as

Despite its ubiquity, SLOOS has several limitations as a measure of residential mortgage credit standards. First, loan officers participating in the survey might express their views based on the condition of the economy instead of commenting on independent changes in bank lending standards. Consistent with this view, Cunningham (2006) finds that SLOOS does not predict well the changes in residential mortgage loans.[4] Second, SLOOS does not allow for meaningful comparison of credit standards across time because it provides the direction, but not the level of credit standards. We do not know, for example, how much tighter credit conditions are in 2017 relative to 2007. Changes to the survey questions over time only add to this uncertainty. Finally, the publicly available survey reports only the nationally aggregated lending standards of all participating banks each quarter; it does not capture the geographic variation in lending standards.

Our first objective is to propose a measure of residential mortgage credit standards that is more accurate than SLOOS. Our measure, which we call the CF Ratio, is the ratio of the conventional loan acceptance rate to the Federal Housing Administration (FHA) loan acceptance rate. Conventional loans are mortgages that are not guaranteed or insured by any government agency at origination. These loans include conforming loans (those eligible for purchase by the GSEs) and nonconforming loans. Nonconforming loans include subprime and jumbo loans. The key insight is that lenders have far more discretion over nonconforming loan credit standards than conforming and FHA credit standards because minimum underwriting standards for the latter groups are set externally. Consequently, a loosening of credit standards reflected in higher jumbo and subprime acceptance rates will lead to a higher CF Ratio. Unlike the survey-based SLOOS measure, the CF Ratio is based on

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interest only loans) and subprime mortgage loans. Beginning with the first quarter of 2015, the survey was disaggregated into seven loan categories: GSE-Eligible (for purchase by GSEs); Government; QM non-jumbo non-GSE (Qualified Mortgage not eligible for purchase by GSEs); QM-jumbo; non-QM jumbo; non-QM non-jumbo; and subprime. Survey questions for prime and nontraditional mortgage loans were discontinued. For more details, please visit www.federalreserve.gov.

[4] In contrast, Lown and Morgan (2006) and Bassett et al. (2014) show that SLOOS can predict commercial lending and macroeconomic activity.

actual lender decisions, provides an absolute rather than relative measure of credit standards, and can be computed for various geographies across the U.S. Two disadvantages are that the CF Ratio has an annual frequency rather than quarterly, and it has a relatively long lag time because the ratio is constructed from the annual Home Mortgage Disclosure Act (HMDA) loan application database.

Figure 1 plots the CF Ratio and SLOOS between 1995 and 2013.[5] SLOOS is inverted in the figure so that an increase in both ratios represents more lax credit standards. The correlation between the CF Ratio and the inverted SLOOS metric is -0.06. The correlation is not only low but negative; that is, when the CF Ratio shows easing lending standards, SLOOS shows tightening lending standards. The CF Ratio shows tightening lending standards between 1995 and 1998, and rapidly easing standards between 1998 and 2005. Loosening standards between 1998 and 2005 reflect the buildup of the housing bubble, consistent with the literature (Duca et al. 2012). Standards tightened sharply between 2007 and 2009, which was likely influenced by the financial crisis. Standards started to ease in 2010 and kept loosening until 2013, reflecting the recovery of the economy and financial institutions. On the other hand, SLOOS shows modest easing between 1995 and 2000 and modest tightening between 2001 and 2003. The tightening between 2001 and 2003 is inconsistent with the significant expansion in residential mortgage credit during these years. SLOOS then shows loosening standards between 2003 and 2006, followed by a dramatic tightening between 2007 and 2010, reflecting the financial crisis. Finally, between 2010 and 2013, SLOOS shows loosening lending standards, reflecting the recovery in the residential market.

Using national loan application data, we regress the loan acceptance decision first on the CF Ratio and then on SLOOS over the full 1995 to 2013 sample period. We find a statistically significant and positive correlation between the CF Ratio and the loan acceptance decision throughout the sample

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[5] Because of changes to the SLOOS survey, beginning with the second quarter of 2007, we average the SLOOS survey data for prime and subprime loans, weighted by their share of HMDA loan originations each year. Nontraditional loans are excluded because we cannot identify their share of loan originations in our sample.

period. The SLOOS coefficients are also statistically significant and positive in the 1995-2000 and 2001-2006 periods, but the coefficient sign is opposite of what we would expect because it implies that tightening credit standards increase the probability of the loan's acceptance. The coefficients of SLOOS in the 2007-2013 and 1995-2013 periods are statistically significant and negative but the coefficients are negligible.

Our second objective is to use the CF Ratio to examine the effect of changing credit standards on residential mortgage supply, especially during the housing boom years of 2001 to 2006. We run county-level regressions of loan acceptance rates on the CF ratio and find that a one standard deviation increase in the CF Ratio between 2001 and 2006 leads to a 1.4 percentage point increase in the overall county loan acceptance rate, representing 18.5% of the standard deviation in loan acceptance rates. We separate the conventional loan types into prime and subprime and find that the relaxation of credit standards boosted subprime lending much more than prime lending. A one standard deviation increase in the CF Ratio increased subprime acceptance rates by 3.0 percentage points, which represents 38.2% of the standard deviation in subprime acceptance rates.

Finally, we assess the ability of the CF Ratio to explain county-level changes in mortgage credit over the full 1995 to 2013 sample period. We find that the ratio's explanatory power is statistically significant throughout the sample period, and the economic significance is stronger in the 1995-2000 period relative to the 2001-2006 period.

The rest of the paper is organized as follows. Section 2 describes our hypotheses and methodology in context with the academic literature. Section 3 describes the data and summary statistics. Section 4 presents the results, and Section 5 concludes.

B. Hypotheses and Methodology

Our study is related to several papers that examine the subprime credit boom (Loutskina and Strahan, 2009; Mian and Sufi, 2009; Nadauld and Sherlund, 2013; Keys et al. 2010; Demyanyk and

Van Hemert, 2011). These papers focus on the supply-side factors that contributed to credit expansion. They support the notion that growth in subprime securitization reduced monitoring incentives of lenders, which led to an increase in credit supply for residential mortgages. Our objective is to introduce a measure that captures mortgage lending standards directly, and use that measure to estimate the correlation with residential mortgage credit expansion.

We propose three closely connected hypotheses stated in alternative form:

H1: the CF ratio is a valid measure of credit standards both at the national and county levels;

H2: the CF Ratio is a more accurate measure of national credit standards than SLOOS; and

H3: the CF Ratio is positively correlated with an economically and statistically significant expansion of mortgage credit, especially during the housing boom period.

We test H1 and H2 at the national level by examining the correlation between a loan's acceptance rate and the credit standard measure, controlling for other factors that influence the loan decision. We expect acceptance rates to rise with more lax credit standards, and we also expect the CF Ratio to be more highly correlated with loan acceptance than SLOOS. We estimate equation (1) for the following sample periods: (i) 1995-2000 (ii) 2001-2006 (iii) 2007-2013 and (iv) 1995-2013.

$$Loan\ Decision_{ikt} = \beta_0 + \beta_1\ Loan\ Demand_{kt} + \boldsymbol{\beta_2\ Borrower_{it}} + \boldsymbol{\beta_3\ Economy_{kt}} + \beta_4\ Lending\ Standard_t + County_k + \varepsilon_{ikt} \quad (1)$$

We run equation (1) at the loan level using a linear probability model[6] where each loan application is matched with the relevant county to control for county factors that might influence the acceptance decision. *Loan Decision* is a binary variable for loan applicant *i* in county *k* and year *t*, that equals 1 if the loan is accepted by the lender, and 0 if rejected. *Loan Demand* is the log of loan applications in the

[6] We contemplated using a logit model with fixed effects, but it has issues arriving at a solution, since we do not observe the same applicants over the years.

county. *Borrower* is a vector of loan-level variables that controls for the quality of the loan applicant. *Economy* is a vector of county variables that controls for county housing and economic conditions. *Lending Standard* is the national measure of credit standards in year *t*, measured either using the CF Ratio or SLOOS. Multicollinearity prevents us from including both variables in the same regression. *County* represents county fixed effects, and ε is the i.i.d error term. Greater statistical and economic significance from β_4 in the regression when the CF Ratio is the credit standards measure would be consistent with H1 and H2.

An important advantage of the CF Ratio is that we can disaggregate the data by geography and relax the constraint of running tests using an annual time series with few observations. We use a panel framework to test Hypotheses 1 and 3 at the county level to examine the effect of credit standards on loan acceptance rates. Using Equation (2), we regress the county-aggregated loan acceptance rate on the CF Ratio between 2001 and 2006.

$$Loan\ Acceptance\ Rate_{kt} = \beta_0 + \beta_1\ Loan\ Demand_{kt} + \boldsymbol{\beta_2\ Borrower_{kt}} + \boldsymbol{\beta_3\ Economy_{kt}} + \beta_4\ CF\ Ratio_{kt} + Year_t + County_k + \varepsilon_{kt} \qquad (2)$$

The dependent variable, *Loan Acceptance Rate,* is the aggregated loan acceptance rate in county *k* in year *t*. *Loan Demand* is the log of loan applications at the county level. *Borrower* is a vector of variables that controls for the quality of the county loan applicant pool. *Economy* is a vector of variables that controls for county economic conditions. *CF Ratio* is the credit standard measure, and *Year* and *County* represent year and county fixed effects, respectively. A statistically and economically significant β_4 would be consistent with H1 and H3. We also run equation (2) substituting the log of the dollar volume of county loan originations as the dependent variable to more directly test H3.

We theorize that the CF Ratio is a valid measure of mortgage credit standards because it primarily captures changes in acceptance rates and loan volume from subprime and jumbo loans, which are likely to have higher variances than acceptance rates and originations of FHA and conforming loans where minimum credit standards are enforced externally on the lenders. We test the sensitivity of the CF Ratio directly on the components of conventional loans in two different ways. First, at the county level we separately regress prime (including jumbo) acceptance rates and subprime acceptance rates on the CF Ratio and control variables. We repeat the process with the logs of prime and subprime loan originations as the dependent variables. We expect the economic significance of the CF Ratio coefficients to be larger in the subprime regressions than in the prime regressions. Second, we regress county loan acceptance rates and loan originations on the three components of the CF Ratio: Subprime to FHA, Jumbo to FHA, and Prime to FHA. Again, we expect to find greater sensitivity of acceptance rates and originations to the subprime and jumbo components relative to the prime components, which would support H1 and H3.

We need to elaborate on two of our variables. *Economy* controls for housing and economic factors because they can affect bank lending behavior (Ruckes, 2004; Dell'Ariccia et al. 2006). Variables in this vector include growth in the median home price between year *t-1* and *t*, growth in median household income between year *t-1* and *t*, log of county median household income in year *t*, poverty rate in year *t*, and log of population in year *t*. *Borrower* includes the income levels of conventional (CNV) loan applicants and FHA applicants ($Log\ of\ INC_{CNV}$ and $Log\ of\ INC_{FHA}$), loan-to-income ratios (LTI_{CNV} and LTI_{FHA}), and the loan-to-income ratios squared (LTI_{CNV} *squared* and LTI_{FHA} *squared*).

C. Data and Summary Statistics

In this section, we discuss the county and loan application data and present summary statistics. Most financial institutions in the U.S. report loan applications for residential mortgages under the Home Mortgage Disclosure Act (HMDA). The HMDA data are publicly available from the Federal Financial Institutions Examination Council (FFIEC) and from the National Archives. The dataset is reported on an annual basis and comprises all loan applications received by the reporting lenders. It includes the decision on whether the loan was granted or denied, which allows us to examine the effect of bank lending standards on the loan approval decision. HMDA data include loan applications to banks, credit unions, savings institutions, and other non-depository lenders.[7] We keep the home purchase and refinancing loan applications from the HMDA dataset. Applications to non-banks are dropped since our study focuses on bank lending standards. We retain applications only for conventional loans and FHA loans, and exclude applications for other loans that are explicitly guaranteed or subsidized by the federal government such as VA (Veterans Administration), FSA (Farm Service Agency) and RHS (Rural Housing Service) loans. We focus on conventional loans because a portion of these loans such as subprime and jumbo loans do not qualify for purchase by the GSEs; lenders have more flexibility over the credit standards of these loans than that of FHA loans because minimum underwriting standards for FHA loans are decided externally. We include FHA loans in our sample as a benchmark for measuring lending standards.

We include county-level variables to control for socioeconomic trends in U.S. counties. Median household income, poverty rate, and population data come from the U.S. Census Bureau. Unemployment rate data are collected from the Bureau of Labor Statistics, and home price data are from Zillow.com.

In Table 1 Panel A, we list the number of HMDA loan applications in our dataset by year between 2001 and 2006. There are 87.4 million loan applications in our sample, and the number of applications increases from 12 million in 2001 to 14.8 million in 2006, reflecting the rise in loan

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[7] Visit http://www.ffiec.gov/hmda/hmdaproducts.htm for access to the data. HMDA covers depository institutions that meet the following criteria: (i) Its total assets are more than a certain threshold, (ii) It has a presence in an MSA, and (iii) It is federally insured or regulated. HMDA covers non-depository institutions that meet the following criteria: (i) It is a for-profit institution (ii) its mortgage loan originations are at least 10 percent of its total loan originations or at least $25 million (iii) It has a presence in an MSA, and (iv) either its total assets or the number of mortgage loan originations exceed a certain threshold. For detailed information on the HMDA coverage criteria, please visit www.ffiec.gov/hmda.

demand. The mean acceptance rate for conventional loans declined from 77% in 2001 to 72% in 2006; on the other hand, the mean acceptance rate for FHA loans decreased from 92% in 2001 to 82% in 2006. Even though, acceptance rates for both conventional loans and FHA loans declined between 2001 and 2006, the ratio of their acceptance rates (the CF Ratio) increased during the same period. Income of applicants for both conventional and FHA loans increased between 2001 and 2006. The mean loan to income ratio for conventional loans increased from 2.0 in 2001 to 2.43 in 2006; the ratio for FHA loans also increased from 2.59 to 3.0 during the same period. This trend in loan to income is probably a reflection of loosening lending standards.

Table 2 presents the county-level variables used in our study. In Panel A, we show the complete list of variables and their definitions and sources. We categorize them into credit supply, credit standards, loan demand, applicant borrower characteristics and county economic variables. In Panel B, we present summary statistics at the county-level from 2001 to 2006. We exclude counties with less than 31 FHA loan applications and missing county economic data; this drops the number of counties in our sample to 904. Mean lending standard, as measured by the ratio of conventional to FHA loan acceptance rates, was 0.865 between 2001 and 2006. Overall, there was an improvement in the county-level economic conditions as evidenced by the mean growth in home price and household income; mean household income growth and home price growth between 2001 and 2006 was 2% and 8.4%, respectively.

D. Results

Our goal is to introduce a direct measure of mortgage lending standards, and use that measure to examine the correlation with residential mortgage credit expansion. In Table 3, we report the regression results at the national level with loan acceptance decision as the dependent variable on the following sample periods: 1995 to 2000, 2001 to 2006, 2007 to 2013 and 1995 to 2013. We regress loan acceptance decision separately on the CF Ratio and SLOOS, controlling for factors that might affect lending decision. We expect acceptance decision to be positively correlated with the CF Ratio, since easing credit standards will lead to an increase in both the variables. We find that the CF Ratio has a positive and statistically and economically significant coefficient in all the sample periods. A one standard deviation increase in the CF Ratio explains 3.3%, 1%, 2.2% and 0.9% increase in acceptance decisions in the years 1995 to 2000, 2001 to 2006, 2007 to 2013, and 1995 to 2013, which accounts for 7.6%, 2.4%, 5% and 2% of the standard deviation in loan acceptance decisions, respectively.

We report the results regressing loan acceptance decision on SLOOS in the columns 5 through 8 of Table 3. The SLOOS coefficient is statistically significant and positive in the years 1995 to 2000 and 2001 to 2007, and statistically significant and negative in the years 2007 to 2013 and 1995 to 2013. The positive sign of the coefficients in the periods 1995 to 2000 and 2001 to 2007 is unexpected because it implies that the tightening of credit standards led to an increase in loan acceptance. Even though the SLOOS coefficient is statistically significant and negative in the periods 2007 to 2013 and 1995 to 2013, its effect is negligible. The lack of a meaningful relationship between SLOOS and loan acceptance decision is consistent with Cunningham (2006), who finds that SLOOS does not predict well the changes in residential mortgage loans. The results from Table 3 support H1 and H2, since the CF Ratio coefficient is statistically significant and positive in all the sample periods, and is more consistent than SLOOS.

In Table 4, we report county level regression results with loan acceptance rate as the dependent variable. We validate the CF Ratio as a measure of credit standards at the county level by regressing loan acceptance rates on the CF Ratio, loan demand, borrower characteristics, and county conditions. We expect the CF Ratio coefficient to be positive, since counties with easing credit standard would experience an increase in both the loan acceptance rate and CF Ratio. The coefficient for the CF Ratio has the expected positive sign, and it is statistically and economically significant. We find that a one standard deviation increase in the CF Ratio between 2001 and 2006 can explain an 1.4% increase in loan acceptance rate, which accounts for 18.5% of the standard deviation in loan acceptance rate.

We present the regression results with prime and subprime loan acceptance rates as the dependent variables in columns 2 and 3 of Table 4. To study the effect of the CF Ratio on the different types of conventional loans, we separately regress prime and subprime acceptance rates on the CF Ratio and control variables. We find that the CF Ratio has a stronger effect on subprime than prime loan acceptance rates. A one standard deviation increase in the ratio can explain 3% increase in subprime and 0.8% increase in prime acceptance rate, which accounts for 38.2% and 10.6% of their standard deviation, respectively. The results from Table 4 are consistent with H1, since it shows the validity of the CF Ratio a measure of credit standards at the county level. The results also support H3 by showing that the CF Ratio has a robust positive correlation with loan acceptance rate during the housing boom years.

In Table 5, we use the same specification as in Table 4, except we use the log of county loan originations as the dependent variable to study H3 more directly. We regress log of loan originations on the CF Ratio, loan demand, borrower characteristics, and county conditions. Counties with easing credit standard will experience an increase in loan originations, thus we expect the CF Ratio coefficients to be positive. The coefficients of the CF Ratio have the expected positive sign, and they are statistically and economically significant. We find that a one standard deviation increase in the CF Ratio between 2001 and 2006 can explain a 2.7% increase in loan originations. Similar to the results in Table 4, the coefficient of the CF Ratio is bigger for subprime than prime loan originations; a one standard deviation increase in the CF Ratio can explain an 8.5% increase in subprime and a 2.6% increase in prime loan originations.

In Table 6, we report the regression results with loan acceptance rate and origination as the dependent variables. We study the influence of the three components of the CF Ratio (Subprime, Jumbo and Prime) by regressing the county loan acceptance rates and loan originations on the ratio of Subprime to FHA, Jumbo to FHA, and Prime to FHA loan acceptance rates. We expect the subprime and jumbo components to have a bigger effect on the dependent variables compared to the prime component, which would support H1 and H3. The coefficients of all three ratios are statistically significant and positive; they are also economically significant. We find that a one standard deviation increase in the ratio of Subprime to FHA, Prime to FHA, and Jumbo to FHA, between 2001 and 2006, can explain 1.7%, 0.5%, and 0.2% of the increase in loan acceptance rate, which accounts for 22.2%, 6.9%, and 2.4% of the standard deviation in loan acceptance rate, respectively.

We present the regression results with log of loan origination as the dependent variable in columns 4 through 6 of Table 6. We find that a one standard deviation increase in the ratio of Subprime to FHA, Prime to FHA, and Jumbo to FHA, between 2001 and 2006, can explain 2.8%, 1%, and 0.4% of the increase in loan origination, respectively. The fact that the jumbo component has s smaller effect compared to the prime component on the county loan acceptance rate and origination is unexpected, since jumbo loan acceptance rates are likely to have higher variances than that of prime loans where minimum credit standards are enforced externally on the lenders by the GSEs.

Table 7 presents the regression results for the years 1995 to 2000, 2007 to 2013 and 1995 to 2013, with loan acceptance rate and loan origination as the dependent variables. To examine whether the CF Ratio is a valid measure of credit standard in years other than the housing boom years (2001 to 2006), we regress loan acceptance rate and loan origination on the CF Ratio and control variables in the three sample periods; we expect the CF Ratio coefficients to be statistically significant and positive, which would support H1. We find that the CF Ratio coefficients are positive and statistically significant. A one standard deviation increase in the CF Ratio in the years 1995 to 2000, 2007 to 2013, and 1995 to 2013 can explain 2.3%, 0.7%, and 1.9% increase in loan acceptance rate, which accounts for 28.9%, 10%, and 26.4% of the standard deviation in loan acceptance rate, respectively. Similarly, a one standard deviation increase in the CF Ratio in the years 1995 to 2000, 2007 to 2013, and 1995 to 2013 can explain 3.8%, 0.9%, and 2.8% increase in loan origination, respectively. The results in Table 7 support H1 by showing that the CF Ratio is a valid measure of credit standard not just in the housing boom years but also in other sample periods.

E. Conclusion

Subprime securitization and rapidly rising home prices, among other factors, combined to loosen residential mortgage credit standards during the housing boom of 2001 to 2006. Before now, SLOOS was the only measure of mortgage credit standards, but its reliability is suspect. We introduce a more accurate measure of credit standard, which we call the CF Ratio. It is the ratio of the acceptance rate of conventional loans to FHA loans. We show that the CF Ratio is positively correlated with loan acceptance rates and originations, both at the national and county levels. SLOOS, in contrast, largely missed the deterioration in credit standards during the housing boom. During our sample period 1995-2013, the CF Ratio is most sensitive to a rise in subprime originations, though it is also robust to periods when subprime originations are small.

After controlling for loan demand, borrower characteristics and county conditions, we find that a one standard deviation easing of the CF Ratio in a given county between 2001 and 2006 explains a 1.4 percentage point increase in the county loan acceptance rate, which represents 18.5% of the standard deviation in loan acceptance rate between 2001 and 2006. The same increase in the CF Ratio also boosts loan originations in a county by 2.7%. Our contributions are to provide a new measure of credit standards and to show that lax lending standards explain a good portion of the mortgage credit boom between 2001 and 2006.

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Figure 1. The CF ratio and SLOOS between 1995 and 2013

This figure plots the CF ratio (left axis) and the inverted values of SLOOS (right axis) between 1995 and 2013. The CF ratio is the ratio of conventional loan acceptance rates to FHA loan acceptance rates. The SLOOS (Senior Loan Officer Opinion Survey) measure of residential mortgage credit standards asks loan officers whether they have changed credit standards and terms on residential mortgage loans. The SLOOS measure is reported as the fraction of banks that disclosed tighter lending standards minus the fraction that disclosed looser standards. SLOOS is inverted in this figure so that an increase in each measure represents easing credit standards.

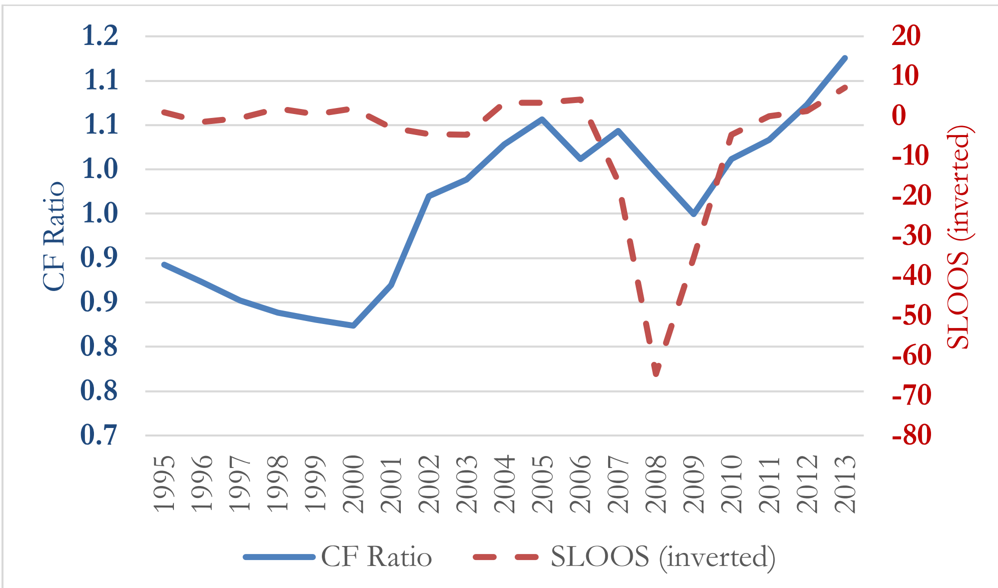

Table 1. Summary Statistics for Loan Applications

Panel A. HMDA Loan Applications

This panel presents our sample of HMDA data for the years 2000 to 2006. We begin with all HMDA home purchase and refinancing loan applications to institutions that are depository or are affiliated with depository institutions. Home purchase loans are those that are used to purchase a dwelling. Refinancing loans are used to replace existing home loans. We only include conventional and FHA applications. Finally, we drop those applications with missing county economic variables to derive our sample. Our sample includes subprime and jumbo loans. Jumbo loans are those that do not meet the purchase requirements by the mortgage GSEs because they exceed the loan size limit.

Application Variables	2000	2001	2002	2003	2004	2005	2006
Total loan applications in our samp	6,934,454	12,000,000	14,200,000	19,300,000	13,300,000	13,800,000	14,800,000
				Conventional			
Loan acceptance rate (sample mear	0.69	0.77	0.82	0.82	0.75	0.74	0.72
Loan amount requested (mean in $(	115	140	161	165	184	202	210
Loan-to-income ratio (mean)	1.83	2.00	2.11	2.23	2.47	2.52	2.43
Income of applicant (mean in $000	77.01	86.79	91.85	92.99	90.42	96.57	105.42
				FHA			
Loan acceptance rate (sample mear	0.88	0.92	0.91	0.90	0.85	0.82	0.82
Loan amount requested (mean in $(	106	117	120	123	126	129	154
Loan-to-income ratio (mean)	2.40	2.59	2.68	2.84	2.81	2.80	3.00
Income of applicant (mean in $000	48.47	51.93	51.60	52.89	52.07	52.29	57.40
FHA application share	0.06	0.06	0.05	0.04	0.03	0.02	0.02
FHA loan volume origination share	0.07	0.06	0.04	0.03	0.02	0.01	0.02
				HUD Subprime			
Loan acceptance rate (sample mear	0.44	0.40	0.47	0.47	0.46	0.47	0.45
Loan amount requested (mean in $(	181875	262671	328997	547177	633136	618968	533745
Loan-to-income ratio (mean)	1.93	2.00	2.16	2.40	2.47	2.55	2.54
Income of applicant (mean in $000	51.45	56.23	57.17	61.80	63.60	67.33	70.99
HUD application share	0.25	0.19	0.19	0.18	0.27	0.23	0.17
HUD loan volume origination shar	0.11	0.07	0.07	0.08	0.13	0.12	0.09

Table 2. Summary statistics of county economic indicators

Panel A presents definitions and sources for variables in our sample. Panel B shows county-level summary statistics for these variables.

Panel A. Definitions		
Category	Variable	Definition
		Dependent Variables
Credit Supply	Loan Acceptance -All	County-level acceptance rate of all sample loan applications. HMDA Data are from the Federal Financial Institutions Examination Council (FFIEC).
	Loan Acceptance -Prime	County-level acceptance rate of all sample loan applications to prime lenders. Prime lenders are those institutions that are not identified as subprime lenders in the HUD lender lsit.
	Loan Acceptance - Subprime	County-level acceptance rate of all sample loan applications to subprime lenders. Subprime lenders are those institutions that are identified as subprime lenders in the HUD lender lsit.
	Log(Loan Origination)	Log of county-level loan originations of all sanple loan applications.
	Log(Loan Origination) - Prime	Log of county-level loan originations of all sanple loan applications to prime lenders.
	Log(Loan Origination) - Subprime	Log of county-level loan originations of all sanple loan applications to subprime lenders.
		Explanatory Variables
Credit Standards	Conventional to FHA Ratio	County-level acceptance rate of conventional loan applications divided by the acceptance rate of FHA loan applications. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	Subprime to FHA Ratio	County-level acceptance rate of subprime loan applications divided by the acceptance rate of FHA loan applications. Subprime lenders are those institutions that are identified as subprime lenders in the HUD lender lsit. List of subprime lenders are from the U.S. Department of Housing and Urban Development. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	Prime to FHA Ratio	County-level acceptance rate of prime loan applications divided by the acceptance rate of FHA loan applications. Prime lenders are those institutions that are not identified as subprime lenders in the HUD lender lsit. List of subprime lenders are from the U.S. Department of Housing and Urban Development. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	Jumbo to FHA Ratio	County-level acceptance rate of jumbo loan applications divided by the acceptance rate of FHA loan applications. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	SLOOS	The Senior Loan Officer Opinion Survey (SLOOS), conducted by the Federal Reserve, asks loan officers whether they have changed credit standards and terms on different loan types. We use the survey about residential real estate loans. It is reported as the fraction of banks that disclosed tighter lending standards minus the fraction that disclosed looser standards. Data are available from the Federal Reserve.

Table 2 (Cont.). Summary statistics of county economic indicators

Panel A (cont.).

Category	Variable	Definition
Loan Demand	Log(Number of Applications)	Log of the total number of home purchase and refinancing loan applications at the county level. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
Borrower Characteristics	LTI_{CNV}	County-level loan-to-income ratio of conventional loan applications. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
	LTI_{CNV} squared	Square of LTI_{CNV} ratio.
	Log(INC_{CNV})	Log of mean income of conventional loan applicants at the county level. HMDA Data are available from the Federal Financial Institutions Examination Council (FFIEC).
	LTI_{FHA}	County-level loan-to-income ratio of FHA loan applications. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	LTI_{FHA} squared	Square of LTI_{FHA} ratio.
	Log(INC_{FHA})	Log of mean income of FHA loan applicants at the county level. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
County Characteristics	FHA Loan Share	County-level ratio of the loan origination amount of FHA loans to the loan origination amount of all loans. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	Prime Jumbo Loan Share	County-level ratio of the loan origination amount of prime jumbo loans to the loan origination amount of all loans. Prime loans are loan applications to prime lenders based on the HUD Subprime and Manufactured Home Lender List. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	HUD Subprime Loan Share	County-level ratio of the loan origination amount of subprime lenders to the loan origination amount of all lenders. Subprime lenders are identified using HUD Subprime and Manufactured Home Lender List. HMDA data are from the Federal Financial Institutions Examination Council (FFIEC).
	Log(Household Income)	Log of median household income at the county level. Household Income data are collected from U.S. Census Bureau.
	Household Income Growth	Growth rate in county median household income between year *t-1* and *t* Household Income data are collected from the U.S. Census Bureau.
	Home Price Growth	Growth rate in county median home price between year *t-1* and *t*. Home Price data are collected from Zillow.com.
	Unemployment Rate	County unemployment rate. Unemployment data are from the Bureau of Labor Statistics.
	Poverty Rate	Proportion of a county population living below the poverty line. Poverty fraction data are collected from the U.S. Census Bureau.
	Log(Population)	Log of the county-level population. Data are collected from the U.S. Census Bureau.

Table 2 (Cont.). Summary statistics of county level variables between 2001 and 2006
Panel B. County-Level Variables

Variable	N	Mean	Std. Dev.	Min	Max	Median
Dependent Variables						
Loan Acceptance	4687	0.746	0.077	0.457	0.940	0.750
Loan Acceptance -Prime	4687	0.809	0.077	0.506	0.959	0.823
Loan Acceptance - Subprime	4687	0.453	0.079	0.217	0.722	0.446
Log(Loan Origination)	4687	13.371	1.535	9.563	18.220	13.301
Log(Loan Origination) - Prime	4687	13.309	1.533	9.497	18.205	13.232
Log(Loan Origination) - Subprime	4687	10.867	1.546	6.958	15.769	10.700
Explanatory Variables						
Conventional to FHA Ratio	4687	0.865	0.097	0.490	1.528	0.868
Subprime to FHA Ratio	4687	0.533	0.105	0.256	1.129	0.524
Prime to FHA Ratio	4687	0.964	0.081	0.632	1.588	0.964
Jumbo to FHA Ratio	4658	0.913	0.168	0.000	2.053	0.928
Log(Number of Applications)	4687	8.980	1.247	5.986	12.945	8.882
FHA Loan Share	4687	0.038	0.028	0.000	0.354	0.032
Prime Jumbo Loan Share	4658	0.113	0.114	0.000	0.763	0.076
HUD Subprime Loan Share	4687	0.186	0.070	0.019	0.488	0.181
LTI_{CNV}	4687	2.067	0.365	1.207	6.421	2.027
LTI_{CNV} squared	4687	5.591	1.813	2.017	13.880	5.284
$Log(INC_{CNV})$	4687	4.332	0.244	3.752	5.679	4.299
LTI_{FHA}	4687	2.657	0.711	1.353	23.610	2.585
LTI_{FHA} squared	4687	7.648	2.687	2.067	33.004	7.311
$Log(INC_{FHA})$	4687	3.914	0.184	3.443	5.155	3.885
Log(Household Income)	4687	3.777	0.237	3.219	4.605	3.752
Household Income Growth	4687	0.020	0.034	-0.125	0.260	0.018
Home Price Growth	4687	0.084	0.074	-0.149	0.238	0.076
Unemployment Rate	4687	0.052	0.016	0.016	0.170	0.050
Poverty Rate	4687	0.114	0.042	0.022	0.347	0.111
Log(Population)	4687	11.748	1.093	9.121	15.108	11.632

Table 3. Effect of lending standards on loan acceptance decisions

This table regresses loan acceptance decision on lending standard between (i) 1995 and 2000 (ii) 2001 and 2006 (iii) 2007 and 2013, and (iv) 1995 and 2013 using a linear probability model. The dependent variable is a binary variable that equals 1 if the loan application is accepted and zero otherwise. Conforming to FHA (CF) ratio measures lending standard, and it is aggregated at the national level. Other explanatory variables include borrower characteristics and county-level variables that could impact loan acceptance decision. Home price growth and household income growth are the growth in median home price and median household income, respectively, between year t-1 and t. All other variables, including the dependent variables are in year t. We run the regressions at the loan level using a 1% subsample (stratified by year and county) of our sample. We hypothesize that the CF ratio is a better measure of lending standards than SLOOS. The SLOOS variable captures bank lending standards for all banks in the country. It is reported as the fraction of banks that disclosed tighter lending standards minus the fraction that disclosed looser standards, thus we expect a negative relationship between SLOOS and loan acceptance decision. However, we find a statistically significant positive effect of SLOOS on the dependent variable from 1995 to 2000 and 2001 to 2006, implying that tightening standards led to an increase in loan acceptance decisions. SLOOS has the correct sign from 2007 to 2013 and 1995 to 2013. We find that the CF ratio a statistically significant positive effect on loan acceptance decision in all the four sample periods. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	Acceptance Decision 1995-00	Acceptance Decision 2001-06	Acceptance Decision 2007-13	Acceptance Decision 1995-13	Acceptance Decision 1995-00	Acceptance Decision 2001-06	Acceptance Decision 2007-13	Acceptance Decision 1995-13
Conforming to FHA Ratio	0.851***	0.480***	0.359***	0.103***				
	(0.02)	(0.02)	(0.02)	(0.01)				
SLOOS					0.008***	0.008***	-0.000***	-0.000***
					(0.00)	(0.00)	(0.00)	(0.00)
Log(Applications)	0.005***	0.051***	0.063***	0.031***	0.016***	0.035***	0.059***	0.031***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Loan FHA Share	-0.143***	0.028*	-0.138***	-0.050***	-0.212***	-0.136***	-0.066***	0.001
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Loan Prime-Jumbo Share	-0.144***	0.024***	-0.031***	0.014***	-0.159***	0.010**	-0.051***	0.008***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Loan SubPrime Share	-0.532***	-0.601***	-0.721***	-0.822***	-0.851***	-0.348***	-0.909***	-0.822***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)

Table 3 (Cont.). Effect of lending standards on loan acceptance decisions

VARIABLES	Acceptance Decision 1995-00	Acceptance Decision 2001-06	Acceptance Decision 2007-13	Acceptance Decision 1995-13	Acceptance Decision 1995-00	Acceptance Decision 2001-06	Acceptance Decision 2007-13	Acceptance Decision 1995-13
LTI_{CNV} squared	0.001***	-0.003***	-0.006***	-0.004***	0.001***	-0.003***	-0.006***	-0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTI_{CNV}	0.001***	0.002***	0.000*	0.000***	0.001***	0.002***	0.000*	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$LogINC_{CNV}$	0.113***	0.079***	0.039***	0.069***	0.113***	0.079***	0.040***	0.071***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Household Income)	0.005	-0.059***	0.012**	-0.102***	-0.022***	0.016***	0.016***	-0.074***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Household Income Growth	0.101***	-0.244***	-0.050***	-0.059***	-0.038*	-0.094***	-0.104***	-0.070***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Home Price Growth	0.003***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	-0.002***	0.004***	-0.002***	-0.000	-0.000	0.001***	-0.002***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Poverty Level	-0.382***	-0.722***	0.048*	-0.730***	-0.380***	-0.383***	0.062**	-0.620***
	(0.03)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)
Log (Total Population)	-0.004**	-0.046***	-0.067***	-0.027***	-0.012***	-0.035***	-0.063***	-0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.314***	0.437***	0.531***	0.988***	0.560***	0.554***	0.878***	0.967***
	(0.04)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)
Observations	448,095	964,963	627,456	2,040,514	448,095	964,963	627,456	2,040,514
R-squared	0.047	0.040	0.047	0.040	0.045	0.042	0.047	0.040
Adjusted R-squared	0.0474	0.0404	0.0469	0.0398	0.0446	0.0420	0.0467	0.0399

Table 4. Effect of lending standards on loan acceptance rate at the county level

This table regresses county-level loan acceptance rate on lending standard from the year 2001 to 2006. The dependent variable is loan acceptance rate aggregated at the county level. Conventional to FHA (CF) ratio measures lending standard, and it is aggregated at the county level. Other explanatory variables include borrower characteristics and county-level variables that could impact the loan acceptance rate. Home price growth and household income growth are the growth in median home price and median household income, respectively, between year t-1 and t. All other variables, including the dependent variables are in year t. The regressions include county and year fixed effects. We hypothesize that CF ratio captures lending standards and can thus explain loan acceptance rates at the county level. In column 1, we find that loosening lending standards has a statistically significant effect on loan acceptance rate. Since, we know that lending standards loosened significantly for subprime mortgages between 2001 and 2006, we examine the effect of CF ratio separately on prime and subprime loan acceptance rate; we separate loans into prime and subprime based on the HUD list for subprime lenders. We expect the ratio to have a stronger effect on subprime loan acceptance rate. We present the regression results for prime and subprime loans in columns 2 and 3, respectively. We find that the CF ratio has a statistically significant effect on the loan acceptance rate for both prime and subprime loans. As expected, it has a stronger effect on subprime acceptance rate. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	All Acceptance Rate 2001-06	Prime Acceptance Rate 2001-06	Subprime Acceptance Rate 2001-06
Conventional to FHA Ratio	0.147***	0.084***	0.312***
	(0.01)	(0.01)	(0.02)
Log(Applications)	0.049***	0.013***	-0.090***
	(0.00)	(0.00)	(0.01)
Loan FHA Share	0.000	-0.007	-0.236***
	(0.02)	(0.02)	(0.05)
Loan Prime-Jumbo Share	-0.061***	-0.060***	0.131***
	(0.01)	(0.01)	(0.02)
Loan SubPrime Share	-0.262***	-0.105***	1.522***
	(0.02)	(0.02)	(0.08)

Table 4 (Cont.). Effect of lending standards on loan acceptance rate at the county level

VARIABLES	All Acceptance Rate 2001-06	Prime Acceptance Rate 2001-06	Subprime Acceptance Rate 2001-06
LTI_{CNV} squared	-0.002**	-0.004***	-0.015***
	(0.00)	(0.00)	(0.00)
LTI_{CNV}	0.020***	0.009***	0.083***
	(0.00)	(0.00)	(0.02)
$LogINC_{CNV}$	0.081***	0.106***	-0.110***
	(0.01)	(0.01)	(0.02)
LTI_{FHA} squared	-0.002***	0.001	0.000
	(0.00)	(0.00)	(0.00)
LTI_{FHA}	0.001*	0.002**	-0.000
	(0.00)	(0.00)	(0.00)
$LogINC_{FHA}$	0.003	0.019***	-0.003
	(0.00)	(0.00)	(0.00)
Log(Household Income)	0.048***	0.066***	0.279***
	(0.02)	(0.02)	(0.05)
Household Income Growth	0.003	-0.015	-0.206***
	(0.01)	(0.02)	(0.05)
Home Price Growth	0.037***	0.024***	0.154***
	(0.00)	(0.01)	(0.02)
Unemployment Rate	-0.172***	-0.128*	-0.706***
	(0.07)	(0.07)	(0.20)
Poverty Level	-0.069*	-0.120***	-0.123
	(0.04)	(0.04)	(0.13)
Log (Total Population)	-0.075***	0.013	0.236***
	(0.01)	(0.01)	(0.04)
Constant	0.557***	-0.256	-2.792***
	(0.16)	(0.17)	(0.48)
Observations	4,687	4,687	2,207
R-squared	0.804	0.896	0.640
Adjusted R-squared	0.756	0.870	0.461

Table 5. Effect of lending standards on mortgage credit expansion at the county level

This table regresses county-level loan origination on lending standard from the year 2001 to 2006. The dependent variable is the log of loan originations aggregated at the county level. Conforming to FHA (CF) ratio measures lending standard, and it is aggregated at the county level. Other explanatory variables include borrower characteristics and county-level variables that could impact loan originations. Home price growth and household income growth are the growth in median home price and median household income, respectively, between year t-1 and t. All other variables, including the dependent variables are in year t. The regressions include county and year fixed effects. We hypothesize that loosening lending standards between 2001 and 2006 contributed to the mortgage credit expansion at the county level. In column 1, we find that loosening lending standards has a statistically significant effect on loan originations. Since, we know that lending standards loosened significantly for subprime mortgages between 2001 and 2006, we examine the effect of the CF ratio separately on prime and subprime loan originations. We present the regression results for prime and subprime loans in columns 2 and 3, respectively. We find that loosening lending standards, as measured by the CF ratio, led to an increase in loan originations for all, prime and subprime loans. However, loosening lending standards had a stronger effect on subprime loan originations. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	All	Prime	Subprime
	Log(Loan Origination)	Log(Loan Origination)	Log(Loan Origination)
VARIABLES	2001-06	2001-06	2001-06
Conventional to FHA Ratio	0.278***	0.260***	0.845***
	(0.02)	(0.02)	(0.07)
Log(Applications)	1.137***	1.156***	0.670***
	(0.01)	(0.01)	(0.03)
FHA Loan Share	0.223***	-0.227***	-0.707***
	(0.06)	(0.06)	(0.15)
Prime-Jumbo Loan Share	0.967***	0.688***	0.358***
	(0.03)	(0.03)	(0.07)
SubPrime Loan Share	-0.554***	-1.559***	4.907***
	(0.06)	(0.06)	(0.22)

Table 5 (Cont.). Effect of lending standards on mortgage credit expansion at the county level

VARIABLES	All Log(Loan Origination) 2001-06	Prime Log(Loan Origination) 2001-06	Subprime Log(Loan Origination) 2001-06
LTI_{CNV} squared	0.021***	0.046***	-0.013
	(0.00)	(0.00)	(0.01)
LTI_{CNV}	0.177***	0.144***	0.302***
	(0.01)	(0.01)	(0.05)
$LogINC_{CNV}$	0.487***	0.394***	0.295***
	(0.02)	(0.02)	(0.06)
LTI_{FHA} squared	-0.002*	-0.005***	-0.000
	(0.00)	(0.00)	(0.00)
LTI_{FHA}	0.005**	0.010***	0.000
	(0.00)	(0.00)	(0.00)
$LogINC_{FHA}$	0.057***	0.054***	-0.005
	(0.01)	(0.01)	(0.01)
Log(Household Income)	0.506***	0.572***	1.848***
	(0.05)	(0.05)	(0.14)
Household Income Growth	-0.205***	-0.305***	-1.163***
	(0.04)	(0.04)	(0.14)
Home Price Growth	0.115***	0.122***	0.571***
	(0.01)	(0.01)	(0.06)
Unemployment Rate	-1.111***	-0.815***	-4.262***
	(0.19)	(0.19)	(0.59)
Poverty Level	-0.338***	-0.465***	-0.519
	(0.11)	(0.11)	(0.38)
Log (Total Population)	-0.303***	-0.302***	0.538***
	(0.04)	(0.04)	(0.11)
Constant	1.799***	1.794***	-10.299***
	(0.47)	(0.48)	(1.38)
Observations	4,687	4,687	2,207
R-squared	0.962	0.961	0.960
Adjusted R-squared	0.952	0.952	0.940

Table 6. Effect of lending standards on loan acceptance rate and loan origination at the county level using alternative measures

This table regresses county-level loan acceptance rate (columns 1, 2 and 3) and loan origination (columns 4, 5 and 6) on lending standard between year 2001 and 2006. The dependent variables are loan acceptance rate and log of loan origination aggregated at the county level. As robustness to our main lending standard measure, conventional to FHA ratio, we use three additional measures of lending standard: (i) Subprime to FHA loan acceptance rate, (ii) Prime to FHA loan acceptance rate, and (iii) Jumbo to FHA loan acceptance rate. Subprime and prime loans are identified using the HUD lender list. Loan applications received by subprime and non-subprime lenders are categorized as subprime and prime loans, respectively. This method of identification has limitations, since all loans received by a subprime lender are unlikely to be subprime loans. However, since HMDA data does not identify subprime loan applications (subprime loans originated can be identified starting 2004), we use the HUD lender list for the purpose. Jumbo loans are those loans that are above the conforming loan limit. The regressions control for borrower characteristics and county-level variables. Home price growth and household income growth are the growth in median home price and median household income, respectively, between year t-1 and t. All other variables, including the dependent variables are in year t. They also include county and year fixed effects. We hypothesize that (i) Subprime to FHA loan acceptance rate, (ii) Prime to FHA loan acceptance rate, and (iii) Jumbo to FHA loan acceptance rate capture lending standards and can thus explain loan acceptance rate and loan origination at the county level. We find that loosening lending standards has a statistically significant effect on loan acceptance rate and loan origination. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	Acceptance Rate 2001-06	Acceptance Rate 2001-06	Acceptance Rate 2001-06	Log(Loan Origination) 2001-06	Log(Loan Origination) 2001-06	Log(Loan Origination) 2001-06
Subprime to FHA Ratio	0.163***			0.262***		
	(0.01)			(0.02)		
Prime to FHA Ratio		0.066***			0.129***	
		(0.01)			(0.02)	
Jumbo to FHA Ratio			0.011***			0.021**
			(0.00)			(0.01)
Log(Applications)	0.044***	0.057***	0.057***	1.131***	1.155***	1.179***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
FHA Loan Share	-0.034*	-0.061***	-0.065***	0.147***	0.106*	-0.039
	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.07)
Prime-Jumbo Loan Share	-0.084***	-0.066***	-0.010	0.927***	0.960***	1.427***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
SubPrime Loan Share	-0.467***	-0.301***	-0.310***	-0.897***	-0.629***	-0.269***
	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.07)

Table 6 (Cont.). Effect of lending standards on loan acceptance rate and loan origination at the county level using alternative measures

VARIABLES	Acceptance Rate 2001-06	Acceptance Rate 2001-06	Acceptance Rate 2001-06	Log(Loan Origination) 2001-06	Log(Loan Origination) 2001-06	Log(Loan Origination) 2001-06
LTI_{CNV} squared	-0.003***	-0.001	-0.000	0.020***	0.024***	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTI_{CNV}	0.018***	0.020***	-0.000	0.174***	0.177***	0.000**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
$LogINC_{CNV}$	0.099***	0.100***	0.001	0.525***	0.522***	-0.006
	(0.01)	(0.01)	(0.00)	(0.02)	(0.02)	(0.01)
LTI_{FHA} squared	-0.002***	-0.002***	-0.001	-0.003**	-0.003**	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTI_{FHA}	0.002**	0.001	0.000	0.005**	0.004*	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$LogINC_{FHA}$	0.005	0.003	0.013***	0.061***	0.057***	0.151***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Log(Household Income)	0.045***	0.036*	0.104***	0.497***	0.478***	0.978***
	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.06)
Household Income Growth	0.013	0.022	-0.005	-0.181***	-0.166***	-0.411***
	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)
Home Price Growth	0.027***	0.019***	0.050***	0.102***	0.060***	0.145***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Unemployment Rate	-0.026	-0.003***	-0.399***	-0.897***	-0.013***	-2.293***
	(0.06)	(0.00)	(0.07)	(0.19)	(0.00)	(0.23)
Poverty Level	-0.076**	-0.059	-0.111***	-0.346***	-0.317***	-0.644***
	(0.04)	(0.04)	(0.04)	(0.11)	(0.11)	(0.13)
Log (Total Population)	-0.100***	-0.083***	-0.045***	-0.345***	-0.317***	-0.165***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.05)
Constant	0.887***	0.607***	0.372**	2.351***	1.883***	0.390
	(0.16)	(0.17)	(0.18)	(0.47)	(0.48)	(0.57)
Observations	4,687	4,687	4,640	4,687	4,687	4,640
R-squared	0.816	0.778	0.766	0.962	0.960	0.945
Adjusted R-squared	0.771	0.724	0.707	0.952	0.950	0.931

Table 7. Effect of lending standards on loan acceptance rate and loan origination at the county level using alternate sample periods

This table regresses county-level loan acceptance rate and loan origination on lending standard between (i) 1995 and 2000, (ii) 2007 and 2013, and (iii) 1995 and 2013. The dependent variables are loan acceptance rate and log of loan origination aggregated at the county level. In this table, we examine whether our lending standard measure, CF ratio, can explain loan acceptance rate and loan origination in years other than the housing boom years (2001 to 2006). The regressions control for borrower characteristics and county-level variables. Household income growth is the growth in median household income between year t-1 and t. Change in home price index is the change in FHFA Home Price Index between t-1 and t; we use this index instead of the median home price from Zillow due to data availability. All other variables, including the dependent variables are in year t. We also include county and year fixed effects. We find that loosening lending standards have a statistically significant effect on loan acceptance rate and loan origination in all three sample periods. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	Acceptance Rate	Acceptance Rate	Acceptance Rate	Log(Loan Origination)	Log(Loan Origination)	Log(Loan Origination)
VARIABLES	1995-2000	2007-2013	1995-2013	1995-2000	2007-2013	1995-2013
Conventional to FHA Ratio	0.232***	0.046***	0.115***	0.375***	0.063***	0.166***
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
Log(Applications)	0.011***	0.018***	0.027***	0.964***	0.981***	1.047***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
FHA Loan Share	0.116***	-0.042***	0.018***	0.136***	-0.218***	-0.018
	(0.02)	(0.01)	(0.01)	(0.05)	(0.02)	(0.02)
Prime-Jumbo Loan Share	-0.077***	-0.003	-0.037***	0.586***	0.657***	0.618***
	(0.02)	(0.01)	(0.00)	(0.04)	(0.02)	(0.01)
Subprime Loan Share	-0.085***	-0.128***	-0.293***	0.104***	-0.227***	-0.779***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)

Table 7 (Cont.). Effect of lending standards on loan acceptance rate and loan origination at the county level using alternate sample periods

VARIABLES	Acceptance Rate 1995-2000	Acceptance Rate 2007-2013	Acceptance Rate 1995-2013	Log(Loan Origination) 1995-2000	Log(Loan Origination) 2007-2013	Log(Loan Origination) 1995-2013
LTI_{CNV} squared	-0.014***	-0.007***	-0.003***	0.030***	0.011***	0.026***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
LTI_{CNV}	0.031***	0.001	0.005***	0.132***	0.048***	0.144***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
$LogINC_{CNV}$	0.100***	0.030***	0.055***	0.497***	0.336***	0.545***
	(0.01)	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)
LTI_{FHA} squared	-0.003***	-0.003***	-0.002***	0.001	-0.002*	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LTI_{FHA}	0.005***	0.003**	0.004***	0.011***	0.019***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$LogINC_{FHA}$	-0.006***	-0.011***	-0.003*	-0.007	0.070***	0.057***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Log(Household Income)	-0.031*	0.011	0.049***	0.147***	0.123***	0.386***
	(0.02)	(0.01)	(0.00)	(0.04)	(0.03)	(0.01)
Household Income Growth	0.029*	-0.007	-0.030***	-0.100**	-0.027	-0.132***
	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)	(0.02)
Change Home Price Index	0.001***	0.001***	0.001***	0.003***	0.003***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Unemployment Rate	-0.000	0.000	-0.004***	0.001	-0.001	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Poverty Level	0.006	0.021	-0.073***	0.180	-0.224***	0.180***
	(0.05)	(0.02)	(0.01)	(0.12)	(0.06)	(0.04)
Log (Total Population)	0.063***	-0.086***	-0.023***	0.390***	0.407***	-0.031***
	(0.02)	(0.01)	(0.00)	(0.04)	(0.04)	(0.00)
Constant	-0.497***	1.417***	0.409***	-3.489***	-2.702***	-0.291***
	(0.18)	(0.15)	(0.01)	(0.46)	(0.41)	(0.04)
Observations	5,284	9,775	22,279	5,284	9,775	22,279
R-squared	0.832	0.770	0.725	0.973	0.910	0.991
Adjusted R-squared	0.781	0.730	0.688	0.966	0.894	0.990

IV. Conclusion

We examine the relationship between bank conditions and the residential mortgage market before and during the 2007-09 financial crisis. In essay 1, we document a residential bank lending channel by showing the effect of bank distress on the residential housing market and employment between 2007 and 2009. Borrowers had difficulty obtaining credit in counties where banks were more distressed, since banks were reluctant to make residential loans that were harder to sell. We find that a median increase in bank distress, measured using the change in the ratio of jumbo loan acceptance rate to nonjumbo loan acceptance rate, explains an additional decline in county home prices of 1.5%, and an additional increase in county unemployment rate of 20 basis points; these changes explain 15% and 5%, respectively, of the median changes in these variables between 2007 and 2009.

In essay 2, we investigate the relationship between bank credit standards and residential mortgage expansion between 2001 and 2006. Easing credit standards increased mortgage supply to relatively lower creditworthy borrowers, which contributed to the housing boom. Until now, SLOOS was the only measure of mortgage credit standards. We introduce a more reliable measure of credit standard, the CF Ratio, which is the ratio of conventional loan acceptance rate to FHA loan acceptance rate. It has a positive correlation with loan acceptance rates between 1995 and 2013, both at the national and county levels, whereas, SLOOS fails to explain the sharp decline in credit standards during the housing boom years. After controlling for loan demand, applicant characteristics and county factors, we find that a one standard deviation weakening in credit standard accounts for 1.4% increase in loan acceptance rate, which represents 18.5% of the standard deviation in loan acceptance rate between 2001 and 2006.