The Industry Expertise Channel of Mortgage Lending

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Abstract

We show that banks use industry knowledge acquired through corporate lending in mortgage lending, a phenomenon we refer to as the "industry expertise channel." Specifically, banks specializing in particular industries increase their mortgage lending activity in regions where those industries are concentrated. The impact of industry expertise increases with information asymmetry and borrower risk. In addition, mortgages originated from this channel contain more soft information and perform better. The effect of the channel increases after unexpected industry distress and the 2008 financial crisis, suggesting that the effect is likely causal.

Keywords: Lending Specialization; Industry Expertise; Mortgage; Syndicated Loans.

JEL Codes: G21, G30, D82.

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I Introduction

Banks acquire information through their interactions with borrowers. Research on lending relationships shows that banks use borrower-specific information to screen and monitor future borrowers (Berger and Udell (1995), Petersen and Rajan (1995)). The recent literature further suggests that banks develop industry-specific knowledge by concentrating their lending activities within particular sectors (Acharya, Hasan, and Saunders (2006), Berger, Minnis, and Sutherland (2017), Blickle, Parlatore, and Saunders (2025)). In this paper, we explore whether the influence of such specialized knowledge extends beyond commercial lending by examining how banks' industry-specific expertise affects their residential mortgage lending practices.

Specifically, we investigate the impact of banks' industry expertise on their mortgage lending in areas where those industries are concentrated. We hypothesize that banks' industry expertise could mitigate the information asymmetry between borrowers and lenders, thereby alleviating credit rationing. We develop the hypothesis on the basis of two arguments. First, household income growth is positively correlated with the performance of the leading industries in a county. This relation holds for both households working in those industries and those in other industries due to spillover effects.[1] Second, industry expertise helps banks gain a deeper understanding of the local economy in areas where these industries are concentrated. Considering the importance of regular income in mortgage repayment (Elul, Souleles, Chomsisengphet, Glennon,

[1]For example, a collapse of the auto industry in Detroit negatively affects both auto workers and non-auto workers (e.g., workers in the service industry like restaurants or the retail industry like shopping malls).

and Hunt (2010)), the industry-specific knowledge allows banks to better assess borrowers' income risk and therefore mortgage affordability. As articulated by Stiglitz and Weiss (1981), the reduction in information asymmetry could curtail credit rationing, thereby increasing credit supply.[2]

To empirically test the effects of industry expertise on mortgage lending, we construct a measure of industry specialization using DealScan syndicated loan data. A bank is classified as specialized in a given industry if its loan share in that industry is an outlier relative to the portfolio shares of other banks lending to the same industry. This classification approach accounts for heterogeneity in both bank size and industry size. We define a bank and a county as connected through the industry expertise channel if the bank has specialized industries that provide at least 5% of jobs in the county.

We compare mortgages to borrowers in a county by banks connected through the industry expertise channel relative to those by banks that are not. We find that industry expertise significantly increases mortgage lending. The results hold after adding county-by-year fixed effects to control for county-specific time-varying trends and bank-by-state fixed effects to control for links between banks and states. The economic magnitude is also significant. The channel increases banks' mortgage lending by 6.3% in the number of mortgages and 6.5% in dollar volumes. The findings highlight the importance of the information embedded in the industry expertise channel in banks' mortgage decisions.

[2]Another underlying assumption is that information could transfer across different lending arms within a financial institution, which is demonstrated by prior studies showing that asset management arms under the same roof strategically exploit information that banks gain from the corporate loan market in stock trading and earn abnormal returns (e.g., Massa and Rehman (2008), Ivashina and Sun (2011)).

We also examine the effects on banks' mortgage approval rates, which reflect lending decisions conditional on received applications and therefore isolate demand-side factors from contaminating our estimates. We find that industry expertise increases banks' approval rates by 40 basis points. The evidence suggests that our findings are likely driven by banks' supply decisions, rather than by demand-side forces.

Next, we provide seven sets of evidence supporting the information mechanism of the industry expertise channel. First, a prerequisite for the channel is that household income growth and mortgage affordability positively correlate with the performance of the leading industries in a county. Therefore, industry expertise allows banks to assess local borrowers' income dynamics and mortgage risks after origination. Consistent with this conjecture, we find that sales growth of a county's key industries positively affects household income growth and negatively affects mortgage delinquency rates. The economic effect is large — a one standard deviation increase in sales growth is associated with a 14.9% increase in household income growth.

Second, we examine the information asymmetry between banks and mortgage borrowers. We find that banks' use of industry expertise increases with the distance between their headquarters and borrowers' home counties, suggesting that industry expertise can mitigate distance-generated information frictions. Moreover, social connections between banks and borrowers reduce banks' reliance on industry expertise, indicating that the soft information from industry expertise can substitute for that from social connections.

Third, banks' information needs in mortgage origination are greater for borrowers with higher default risk. Our first proxy for borrower risk is county-level house price volatility, which increases downside risk and the likelihood of negative equity. We find that banks rely more on the channel when local house prices are more volatile. In addition, we use loan-to-income ratios (LTI) as a proxy for borrower risk and find that banks rely more on industry expertise when lending to high-LTI borrowers.

Fourth, we explore the heterogeneity in banks' asset size and real estate (RE) lending. We find that larger banks rely more on information acquired through the industry expertise channel for mortgage lending, consistent with prior studies showing that small and concentrated banks have a comparative advantage in collecting and acting on local soft information and therefore depend less on the industry expertise channel (e.g., Berger, Miller, Petersen, Rajan, and Stein (2005), Loutskina and Strahan (2011)). The lending effects are also more pronounced among banks with higher shares of RE loans, as their revenues are more tied to mortgage performance and they are less aggressive in shifting risks through securitization.

Fifth, we analyze the soft information embedded in mortgage contracts to provide more direct evidence of the information mechanism. The screening model in Cornell and Welch (1996) shows that lower information frictions lead to larger loan term dispersion, as better-informed banks can more effectively distinguish between "good" and "bad" borrowers. Consequently, banks can offer favorable terms to low-risk borrowers and stricter terms to high-risk ones (Fisman, Paravisini, and Vig (2017), Lim and Nguyen (2021)). Consistent with this model, we find that industry expertise significantly increases the dispersion in mortgage amounts, LTI ratios, interest rates, and loan-to-value ratios.

Sixth, we examine the differential impact of industry expertise on conventional versus government-insured mortgages. Government insurance provided by the Federal Housing Administration (FHA) and Veterans Affairs (VA) makes lenders' mortgage exposure less information-sensitive, and hence, underwriting government-insured mortgages is less subject to information asymmetry and credit rationing. We find that banks with industry expertise originate more conventional mortgages than government-insured mortgages.

Lastly, we test the performance implications of the industry expertise channel. If the channel improves banks' screening and monitoring in mortgage decisions, it should lead to better mortgage performance. Using HMDA data matched with Fannie Mae, Freddie Mac, and McDash loan performance data, we find that mortgages originated through the industry expertise channel have lower delinquency and foreclosure rates.

Our results may be influenced by omitted bank-county factors or reverse causality. For example, banks might allocate credit to certain industries based on mortgage demand. To address these concerns, we use a difference-in-differences design around unexpected industry-wide distress. We compare the impact of industry distress on mortgage lending across banks with different ex-ante industry specializations. This test examines whether the industry expertise channel is most valuable in sectors with high uncertainty and downside income risk. Industry expertise can help banks better price borrower risk and reduce defaults by offloading risky mortgages to entities like Fannie Mae and Freddie Mac. Importantly, industry-level shocks are plausibly exogenous to individual banks, counties, and borrowers, helping to address endogeneity concerns. Our empirical results show that the industry expertise channel becomes more important during periods of industry distress. Its effect on mortgage lending increases from 2% in non-distress periods to 6.4% in distress periods. Additionally, using the 2008 financial crisis as an alternative shock in a difference-in-differences setting, we find that industry expertise becomes more valuable for mortgage underwriting during the crisis.

In the final analysis, we study how banks adjust mortgage terms to limit losses during downturns, given their exposure to less opaque borrowers through the industry expertise channel. Our analysis reveals that banks impose stricter terms at the onset of industry distress, that is, lower LTV ratios and higher interest rates, and shift toward insured mortgages. These results suggest that banks tighten terms and favor safer loans to reduce defaults in lending related to their industry expertise, providing further evidence of how they achieve lower default rates in these mortgages.

Our paper contributes to the growing literature on banks' lending specialization, which finds that concentrated lending enables banks to develop industry expertise. This expertise enhances information collection and monitoring of corporate borrowers, leading to lower risk and higher bank value (Acharya et al. (2006), Loutskina and Strahan (2011), Berger et al. (2017), Blickle et al. (2025)). We examine the role of industry expertise in banks' mortgage lending. We show that banks use the knowledge gained from corporate lending to better screen and monitor mortgage borrowers, suggesting that cross-market expertise improves lending efficiency.[3]

Our paper also contributes to the literature on information asymmetry and credit access in the mortgage market. While hard information such as credit reports and

[3]It is important to note that our sample, by design, focuses on relatively large banks that are active in both the corporate loan and mortgage markets. As a result, our findings reflect primarily the mortgage decisions of these large banks and may not represent the perspectives of smaller banks on the industry expertise channel of mortgage lending. Furthermore, our sample does not include non-bank mortgage lenders, so our results also do not reflect their use of the industry expertise channel in mortgage lending.

employment records alleviates information frictions in mortgage origination (Ergungor (2010), Gilje, Loutskina, and Strahan (2016)), widespread mortgage fraud exists (Garmaise (2015), Mian and Sufi (2017)). We uncover a new soft information channel, the industry expertise channel, that helps banks overcome information frictions by improving screening and monitoring through credible insights into borrowers' income dynamics.

Several studies investigate how banks allocate mortgage credit across regions based on local demand (Cortés and Strahan (2017)), political factors (Chavaz and Rose (2019), Chu and Zhang (2022)), and social connectedness (Lim and Nguyen (2021), Rehbein and Rother (2020)). Our paper complements these studies by showing that banks extend more mortgage credit to counties with shared industry concentrations.

Lastly, our paper adds to the literature on income risk and mortgage default (Elul et al. (2010), Gerardi, Herkenhoff, Ohanian, and Willen (2018)). While income is a critical factor in standard models of mortgage default, empirical estimates of its effects are small. For example, Foote, Gerardi, Goette, and Willen (2010) find that the debt-to-income ratio (DTI) is a weak predictor of future defaults, particularly as the loan ages. We show that the industry expertise channel complements hard income information collected at origination by helping banks predict borrowers' future income dynamics. This, in turn, improves their ability to assess income risk.

II Data and Measures

A Sample Construction

We use the LPC DealScan data to measure banks' specialization in corporate lending. Using link tables from Schwert (2018) and Gomez, Landier, Sraer, and Thesmar (2021), we merge DealScan lenders with bank call report data.[4] We also use the link table from Chava and Roberts (2008) to match borrowers with their accounting and industry data from Compustat.

Data on banks' branch characteristics (e.g., name, address, BHC, deposits, etc.) are from the Summary of Deposits (SOD), which covers the universe of banks' depository branches annually from 1994. Small business lending is measured using the Community and Reinvestment Act (CRA) small business loans database from the Federal Financial Institutions Examination Council (FFIEC), which reports the number and volume of loans originated by each reporting bank at the county level since 1996.

Mortgage data are collected from the Home Mortgage Disclosure Act (HMDA) database. We follow the prior literature and drop non-conventional loans and loans for manufactured housing and multifamily dwellings to remove the impact of government subsidies on banks' lending decisions.[5] We also exclude other non-standard mortgages, such as mortgages for home improvement and non-owner-occupied dwellings. We further exclude counties in which a bank has fewer than five mortgage applications per

[4]Banks are aggregated at the bank holding company (BHC) level in link tables. Throughout the paper, we use the term "bank" to refer to BHCs.

[5]Non-conventional loans include the Federal Housing Administration (FHA)-insured loans, Veterans Affairs (VA)-guaranteed loans, Farm Service Agency (FSA) loans, and Rural Housing Service (RHS) loans.

year to ensure that our results are not driven by outliers.[6] We merge the HMDA data with banks in the call reports by matching agency-specific IDs in HMDA (e.g., Federal Reserve RSSD-ID, FDIC Certificate Number, and OCC Charter Number) to RSSD IDs.

We complement the HMDA data with information on monthly loan-level performance from three sources: Fannie Mae and Freddie Mac single-family loan-level datasets and McDash loan-level data. The Fannie Mae data cover the fixed-rate single-family mortgage loans acquired by Fannie Mae from January 2000 to December 2022, with the origination year starting from 1999. The Freddie Mac data cover approximately 52.2 million fixed-rate single-family mortgage loans originated between January 1, 1999 and September 30, 2022 that are acquired by Freddie Mac. The McDash data are a proprietary database compiled by Black Knight, which tracks the dynamic performance of both agency and non-agency loans. Depending on the years, the McDash data cover 60% to 80% of the US mortgage market. Important to our study, all three datasets include a rich set of information not available in HMDA, including borrowers' credit scores, loan-to-value (LTV) ratios, interest rates, and ex-post monthly loan performance. We follow Chu, Ma, and Zhang (2022) and match the three datasets to HMDA. The matched government-sponsored enterprise (GSE) mortgage sample is based on Fannie Mae and Freddie Mac data, and the non-GSE mortgage sample is based on the McDash data. We combine GSE and non-GSE mortgages and focus on the period 1999 to 2017.

To quantify the distribution of employment across industries within a county, we

[6] Results are robust to requiring at least ten or twenty mortgage applications, or to removing the requirement.

use data from the Quarterly Census of Employment and Wages (QCEW), which provides annual employment figures from 1990 to 2018 for all six-digit NAICS industries across more than 3,000 U.S. counties. In addition, data on county-to-county distances and county-level characteristics, such as income, housing price index, population, race, and age, are obtained from the Bureau of Economic Analysis (BEA), the Federal Housing Finance Agency (FHFA), and the NBER database. County-level mortgage delinquency rates are from the Consumer Financial Protection Bureau (CFPB), and the county-to-county Social Connectedness Index (SCI), based on Facebook friendship links in 2016, is from Bailey, Cao, Kuchler, Stroebel, and Wong (2018). Data on establishment-level locations and employment for U.S. firms are from the Your Economy Time Series (YTS), provided by the Business Dynamics Research Consortium (BDRC).

B Measuring a Bank's Industry Specialization

We measure each bank's industry specialization using DealScan data. Borrowers in DealScan are relatively large firms, and interactions with them enable banks to acquire advanced and comprehensive industry knowledge. We use origination dates and maturities to create a panel that tracks each bank's lending portfolio at any given time.

Most of the loans in DealScan are syndicated and thus have multiple lenders. However, only lead lenders assume the monitoring responsibilities (Sufi (2007), Gustafson, Ivanov, and Meisenzahl (2021)). In addition, the lead lenders have stronger incentives and better opportunities than participating lenders to acquire information about the borrowers and accumulate industry expertise. As a result, lending specialization matters more for lead lenders than for participating lenders (Blickle et al.

(2025)). Lead lenders are also less likely to sell all of their loan shares in the secondary market (Irani, Iyer, Meisenzahl, and Peydro (2021)). We therefore focus on the lead lenders of syndicated loans.[7]

We assume that the lead lenders commit all capital in a loan because the allocation of loan shares is missing for most loans in DealScan, and the lead lenders obtain industry knowledge by monitoring the total loan amount rather than their own capital (e.g., Giannetti and Saidi (2019), Saidi and Streitz (2021)). For loans with multiple lead lenders, we divide the loan amount equally among all lead lenders.[8]

We aggregate banks' outstanding loans at the three-digit NAICS industry level each year. Our choice of the three-digit NAICS code level ensures sufficient precision of industry breakdowns and a reasonable number of firms and loans in each industry. We exclude firms in the financial industry. Following Paravisini, Rappoport, and Schnabl (2023), we classify a bank as specialized in an industry if its loan share in that industry is an outlier relative to the portfolio shares of other banks.

$$Specialization^b_{i,t} = \begin{cases} 1 & L^b_{i,t} \geqq L^*_{i,t} \\ 0 & otherwise \end{cases} \tag{1}$$

where b denotes bank, i denotes industry, and t denotes year. $L^b_{i,t} = \frac{Loan^b_{i,t}}{\sum_{i=1}^{I} Loan^b_{i,t}}$ is bank b's portfolio share of syndicated loans towards industry i in the list of industries from 1 to I, at time t. $L^*_{i,t}$ is the threshold to identify outliers in the distribution of $L^b_{i,t}$ among all

[7] We define lead lenders in each syndicated loan following the procedure outlined in Chakraborty, Goldstein, and MacKinlay (2018).

[8] We get similar results if we set loan shares retained by lead lenders equal to the median of the sample with non-missing information on the syndicate allocation (Chodorow-Reich (2014), Giannetti and Saidi (2019)).

banks in industry i. For each industry, the threshold is the 75^{th} percentile plus one and a half times the interquartile range of the distribution of all banks' portfolio shares in the industry (Hodge and Austin (2004)).

There are at least two advantages to measuring lending specialization in a relative way. First, this method accounts for the heterogeneity in the size of different banks and industries. Specifically, scaling a bank's loans to a given industry by the bank's total loans makes the measure impervious to bank size. Comparing different banks' loan shares within the same industry makes the measure impervious to industry size. Second, as we will discuss later, we include county-by-year fixed effects in our main empirical specifications to compare different banks' mortgage lending in the same county. A relative measure enables us to focus on banks' relative industry advantages in a county.

C Measuring a County's Industry Specialization

We use the employment information provided by the QCEW to identify key industries in a county. We exclude employment by government-owned entities and the financial industry and aggregate employment at the three-digit NAICS level. An average county has 59 three-digit NAICS industries.[9] Figure 1 presents the employment shares by the top 20 industries in a county, which range from 1.12% to 19.35%. We classify industries that provide at least 5% of jobs in a county as the county's specialized industries. Our choice of 5% ensures that an industry has a material impact on the local economy and household income. In total, these industries provide about 58% of jobs in an average county.

[Insert Figure 1 here]

[9] The 25^{th} percentile, the median, and the 75^{th} percentile are 50, 62, and 72, respectively.

D Measuring the Industry Expertise Channel

Using industry specialization measures for each bank and county, we classify a bank and a county as connected through the industry expertise channel if the bank has one or more specialized industries that provide at least 5% of jobs in the county. Banks can use their industry expertise to better screen eligible mortgage borrowers and monitor their income risks, allowing them to extend more mortgage credits to local residents. By construction, variations in this channel come mostly from changes in the bank's loan portfolio and the distribution of portfolio shares of other banks in the industry.[10]

E Sample and Summary Statistics

We aggregate mortgage data at the bank-by-county-by-year level. The sample consists of 78 unique banks with mortgage business in 3,165 counties from 1999 to 2017.[11] Table 1 reports the summary statistics of the variables used in our empirical analyzes. Panel A presents the county-level statistics; Panel B presents the bank-level statistics; Panel C presents the HMDA-based main sample at the bank-county level; and Panel D presents the matched bank-county-level sample between HMDA and monthly loan-level performance from the Fannie Mae, the Freddie Mac and the McDash datasets. The sample period is 1999 to 2017, except that the county-level mortgage delinquency in panel A is only available from 2008 to 2017.

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[10]Internet Appendix Figure IA.1 presents the distribution of counties that are connected to at least one bank in our sample through the industry expertise channel in 1999, 2004, 2009, and 2014. The maps suggest that connected counties are evenly distributed throughout the US during the sample period.

[11]We do not require a minimum number of outstanding loans for a bank to be included in our sample. However, our sample mainly covers large banks active in both the corporate loan and mortgage markets, because the link tables by Schwert (2018) and Gomez et al. (2021) focus on large banks in the syndicated loan market. For example, Schwert (2018) requires that each DealScan lender have at least 50 loans or $10 billion in loan volume.

The average asset size of the banks in our sample is $174 billion and the median is $51 billion, indicating that our sample predominantly covers large banks. The number of mortgages a bank approves in a county has a mean of 88.0 and a median of 19.0. The standard deviation is 193.8, suggesting large variations across bank-county pairs. The mean dollar volume (in millions) of approved mortgages is 14.4, and the median is 2.3. The average number-based mortgage approval rate is 74.6%, and the average volume-based mortgage approval rate is 75.6%. 16.5% of the 316,552 bank-county pairs are connected through the industry expertise channel.

[Insert Table 1 here]

III The Industry Expertise Channel and Mortgage Lending

A The Number and Volume of Approved Mortgages

We conjecture that industry expertise enhances banks' abilities to assess household income risk and therefore reduces information frictions in mortgage decisions. The lower information asymmetry mitigates credit rationing, leading to more credit supply. We test this conjecture using the following empirical specification:

$$Y_{bct} = \pi_{ct} + \mu_{bs} + \beta \, \mathit{Industry\ Expertise}_{bct} + \delta \mathbf{X}_{bct} + \varepsilon_{bct} \tag{2}$$

where b denotes bank, c denotes home county of the borrower, s denotes home state of the borrower, and t denotes year. Y_{bct} is the natural logarithm of the number or dollar volume (in millions) of the mortgages bank b approves to borrowers in county c in year t. $\mathit{Industry\ Expertise}_{bct}$ is a dummy equal to one for a bank-county pair if there exists at least one industry in which the bank b specializes and provides at least 5% of jobs in county c in year t. X_{bct} is a vector of controls, including the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans that a bank originates in the borrower's home county, the average fraction of mortgages retained in the balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. π_{ct} is county-by-year fixed effects, which allows us to compare different banks' mortgage lending in the same county. μ_{bs} is bank-by-state fixed effects, which controls for hidden links between banks and states, such as political rent-seeking (Chu and Zhang (2022)).

We present the results of estimating equation (2) in Table 2. In column 1, the coefficient estimate on *Industry Expertise* is positive and statistically significant, indicating that industry expertise increases banks' mortgage lending. The significance remains after adding mortgage-level or bank-level controls in columns 2 and 3. We use county-by-year fixed effects to replace borrower home county and year fixed effects in column 4 and further use bank-by-state fixed effects to replace bank fixed effects in column 5. The results continue to hold, and the estimated effect is economically significant. The result in column 5 suggests that industry expertise increases banks' mortgage lending by 6.3%. Columns 6 - 10 repeat the analyses using the dollar volume of approved mortgages as the dependent variable. The findings are consistent with those in columns 1 - 5.

[Insert Table 2 here]

B Robustness

In Internet Appendix IA.II, we conduct a series of additional tests to demonstrate the robustness of our results. First, we reconstruct the industry expertise channel by accounting for each borrowing firm's market position, assuming that lending to industry leaders enhances banks' expertise. Second, we develop two continuous measures that capture the intensity of connections between banks and counties through the channel: one based on the share of residents working in bank-specialized industries that provide at least 5% of county jobs, and the other based on the share working in any bank-specialized industry. Third, we revise our expertise measure as the difference between a bank's industry loan share and the threshold $L^*_{i,t}$ used to identify outliers in equation (1). Fourth, we include bank-by-year and bank-by-county fixed effects to control for time-varying bank characteristics and time-invariant bank-county links. The results remain robust. Fifth, we use both linear regressions and the fixed effects Poisson model (Cohn, Liu, and Wardlaw (2022) to address concerns with log-transformed dependent variables; the results are statistically significant and economically stronger. Sixth, we follow Blickle, Fleckenstein, Hillenbrand, and Saunders (2022) to estimate loan shares and reconstruct the industry expertise measure. Our findings remain robust.

C Mortgage Approval Rates

Although the results hold after controlling for county-by-year and bank-by-state fixed effects, they could still be driven by demand-side factors. For example, certain households may prefer to borrow from a bank due to brand preferences or access to mobile apps. To alleviate this concern, we examine banks' mortgage approval decisions conditional on received applications using approval rates, defined as approved mortgages (by number or volume) divided by applications received, as the dependent variable. The results are reported in Table 3. We find that, conditional on received applications, industry expertise increases both number- and volume-based approval rates by 40 basis points, implying that the findings in Table 2 are unlikely to be driven by demand-side factors.

[Insert Table 3 here]

Overall, the results in Section III support the conjecture that the industry expertise channel mitigates information asymmetry, and hence credit rationing.

IV The Information Mechanism

We hypothesize that banks use industry expertise in mortgage lending to obtain credible soft information that improves their assessment of income risk at origination. This section presents seven pieces of evidence that support this information channel mechanism.

A Industry Growth and Household Income and Mortgage Delinquency

A prerequisite for the industry expertise channel is that the conditions of the key industries in a county are useful in assessing borrower credit quality; that is, banks can use their industry expertise to assess local borrowers' income dynamics and mortgage default probabilities. We test whether this is true using the following empirical model:

$$Y_{ct} = \theta_c + \tau_t + \beta \, \textit{Sales Growth}_{ct} + \delta \mathbf{X}_{ct} + \varepsilon_{ct} \tag{3}$$

where c denotes county and t denotes year. Y_{ct} is the dependent variable, the income growth rate or the annual change in the mortgage delinquency rate. $Sales\ Growth_{ct}$ is the standardized employment-weighted industry sales growth rate in a county. The weights are the fractions of local residents working in a given industry. The sales growth rates for each industry are estimated using the sales of all U.S. public firms in that industry. $\boldsymbol{X}_{ct}$ is a vector of county-level controls, including the natural logarithm of the population, the percentage of the population over 65, the percentage of the male population, the percentage of the minority population, and the percentage of the population with a bachelor's degree or above. θ_c is county fixed effects and τ_t is year fixed effects.

The results are presented in Table 4. The dependent variable in columns 1 - 3 is the income growth rate. The coefficient estimate on sales growth is positive and statistically significant, suggesting that faster industry growth is associated with greater growth in household income. The correlation is also economically significant. In column 3, a one standard deviation increase in sales growth is associated with a 14.9% increase in household income growth. In columns 4 - 6, we examine the mortgage delinquency rate, an indicator of mortgage performance.[12] Consistent with our expectation, the coefficient estimate on sales growth is negative and statistically significant, suggesting that faster industry growth is associated with lower mortgage delinquency rates.

[Insert Table 4 here]

Overall, the findings suggest that growth in a county's key industries is positively correlated with the county's household income growth and negatively correlated with the county's mortgage delinquency rate. The evidence builds the foundation for the key

[12]The sample is much smaller because the data on the mortgage delinquency rate from the CFPB only cover 470 counties per year from 2008. The data are based on a nationally representative five percent sample of closed-end, first-lien, 1–4 family residential mortgages.

argument in this paper: industry expertise enables banks to predict local household income dynamics and, therefore, mortgage default risks after origination.

B Information Asymmetry

We then investigate the effect of information asymmetry on the industry expertise channel in mortgage lending. We start with the geographic distance between banks' headquarters and mortgage borrowers. Previous studies show that long geographic distance erodes banks' ability to acquire information, creating significant barriers for banks to reach distant borrowers (Agarwal and Hauswald (2010)). We expect that industry expertise mitigates information barriers and enables banks to extend mortgage credits to distant borrowers. We test this prediction in columns 1 and 3 of Table 5. Consistent with prior studies, mortgage credit declines with distance between the banks' headquarters and borrowers. More importantly, the effect of industry expertise increases with distance, more than doubling for a one standard deviation increase. This suggests that industry expertise mitigates distance-related information frictions between banks and mortgage borrowers.

We also examine how soft information in the channel interacts with soft information banks collected from other sources. To this end, we use social networks as a proxy for alternative soft information in columns 2 and 4 of Table 5. Consistent with Rehbein and Rother (2020), social connections between a bank's headquarters county and a borrower's home county significantly increase banks' mortgage lending. However, social connections decrease banks' reliance on industry expertise. In column 2, a one standard deviation increase in SCI is associated with a 31.3% decrease in the effect of industry expertise. The evidence further suggests that industry expertise offers additional soft information that can substitute for that from social connections.

[Insert Table 5 here]

C Borrower Risk

Credit rationing caused by information asymmetry should be more severe for ex-ante riskier borrowers. We therefore expect that the impact of industry expertise should be stronger for riskier borrowers. Our first proxy for borrower risk is the local house price volatility (Gerardi et al. (2018)). We report the results in columns 1 and 3 of Table 6. The coefficient estimates on the interaction term between *Industry Expertise* and *HP Volatility*, the standardized county-level housing price volatility, are positive and statistically significant, indicating that banks rely more on industry expertise when local house prices are more volatile. In column 1, the effect of industry expertise on mortgage lending increases from 6.7% to 11.4% for a one standard deviation increase in house price volatility.

Our second proxy for borrower risk is the LTI ratio. A higher LTI ratio indicates higher mortgage leverage and higher borrowing constraints. The results in columns 2 and 4 of Table 6 show that the effect of industry expertise is stronger for borrowers with higher LTI ratios. The estimate in column 2 suggests that the effect of industry expertise increases from 5.3% to 11.1% for a one standard deviation increase in the LTI ratio.

[Insert Table 6 here]

D Bank Size and Real Estate Loan Share

We also explore how banks' asset sizes affect their use of the industry expertise channel in mortgage lending. Despite the limited size variation among the 78 banks in our sample, the results in columns 1 and 3 of Table 7 show that the effect of industry expertise is stronger for larger banks. This suggests that large banks rely more on industry expertise, consistent with prior findings that smaller, more localized banks have a comparative advantage in collecting soft information through other channels (e.g., Berger et al. (2005), Loutskina and Strahan (2011)).

Additionally, we explore heterogeneities in banks' business models, focusing on the importance of real estate (RE) lending within their loan portfolios. We expect the effects to be more pronounced among banks with higher shares of RE loans, as their revenues are more closely tied to mortgage performance, and they are less aggressive in shifting risks through securitization. The results in columns 2 and 4 of Table 7 support our conjecture.

[Insert Table 7 here]

E Soft Information in Mortgage Contracts

To provide more direct evidence, we test soft information contained in mortgage contracts by examining whether mortgages originated through the industry expertise channel are less standardized, that is, greater dispersion in contractual terms. This is because better information allows banks to better distinguish between "good" and "bad" borrowers (Cornell and Welch (1996), Rajan, Seru, and Vig (2015)). As a result, banks can grant mortgages with favorable terms to "good" borrowers and mortgages with strict terms to "bad" borrowers. In contrast, when banks lack sufficient information, they rely on the quality of average borrowers and offer similar mortgage terms to all.

We construct four variables to capture the dispersion in the terms of approved mortgage contracts: the natural logarithm of the standard deviations of the loan amounts, LTI ratios, interest rates, and LTV ratios (Fisman et al. (2017), Lim and Nguyen (2021)). We present the results in Table 8. Consistent with our prediction, mortgages originated through the industry expertise channel have less standardized contractual terms. The standard deviations of loan amounts, LTI ratios, interest rates, and LTV ratios are 0.6%, 0.5%, 2.1%, and 2.2% higher for mortgages originated through the channel.[13]

[Insert Table 8 here]

F Conventional and Government-Insured Mortgages

Government-insured mortgages, i.e., FHA and VA loans, are less subject to credit rationing (Duca and Rosenthal (1991), Ambrose, Pennington-Cross, and Yezer (2002)). Banks should therefore originate more conventional mortgages relative to government-insured mortgages in counties connected by the industry expertise channel if it mitigates credit rationing. To test this, we re-estimate equation (2) by extending the HMDA-based mortgage sample to include government-insured mortgages and replacing the dependent variable with the percentage of conventional loans originated in a county. The results are presented in Table 9, with columns 1 - 3 for the number-based percentage of conventional mortgages and columns 4 - 6 for the volume-based percentage. The coefficient estimates on *Industry Expertise* are all positive and significant, suggesting that banks increase conventional mortgages relative to government-insured mortgages in counties connected by the industry expertise channel, consistent with the argument that banks' industry expertise mitigates credit rationing.

[Insert Table 9 here]

[13] We obtain similar results (untabulated) using the natural logarithm of the inter-quartile ranges of the four contractual terms.

G Mortgage Performance

Lastly, we examine the effect of industry expertise on ex-post mortgage performance. If it helps banks better screen applicants and monitor income risk, we expect improved mortgage outcomes. To test the performance implications, we focus on mortgage delinquency and foreclosure rates using the matched sample between HMDA and monthly loan-level performance from the Fannie Mae, Freddie Mac, and McDash datasets. Specifically, we track each mortgage's monthly payment records to identify whether a mortgage ever had a 60-day-plus delinquency, a 90-day-plus delinquency, or a foreclosure. We aggregate loan-level data to the bank-county-year level and construct three outcome variables: *Delinquency 60 Days*, defined as the share of mortgages more than 60 days past due on monthly payments; *Delinquency 90 Days*, the share more than 90 days past due; and *Foreclosure*, the percentage of mortgages that have entered foreclosure proceedings.

The results are presented in Table 10. The coefficient estimate on *Industry Expertise* suggests a negative effect of industry expertise on subsequent mortgage delinquency and foreclosure rates. On average, mortgages originated by banks with industry expertise have 4.1% lower 60-day-plus delinquency rates, 4.0% lower 90-day-plus delinquency rates, and 4.8% lower foreclosure rates, respectively.

[Insert Table 10 here]

In summary, our analyses show that banks increasingly rely on the industry expertise channel when borrower information is scarce or borrowers are riskier. Mortgages originated through the channel embed more soft information, as reflected in more dispersed terms. Banks also issue more conventional (vs. government-insured) loans in connected counties, consistent with reduced credit rationing. Finally, the channel is associated with lower delinquency and foreclosure rates. Together, these findings provide strong evidence for the information mechanism underlying the industry expertise channel.[14]

V Addressing Endogeneity using Two Types of Shocks

The results above provide consistent evidence that industry expertise offers credible soft information that facilitates mortgage lending. However, they may still be biased by omitted variables at the bank-by-county level or by reverse causality; that is, banks may specialize in certain industries in response to mortgage market expansion. To address these endogeneity concerns, we conduct two empirical tests based on shocks plausibly exogenous to banks' use of industry expertise in mortgage lending.

A Industry Distress

We first design a difference-in-differences test using unexpected industry distress, a sharp downturn in an industry accompanied by significant uncertainty and operational strain. This distress can negatively affect household income, particularly for those employed in the affected industry or living in the counties where it is concentrated. In severe cases, households can face layoffs and complete income loss.

Relevant industry expertise enables banks to better assess the duration and severity of industry distress and its implications for mortgage risk. As a result, these

[14] In Internet Appendix IA.III, we further demonstrate that the industry expertise channel is distinct from a bank's private information regarding local economies, such as that acquired through relationships with local corporate borrowers, geographic specialization, or the presence of local depository branches. In Internet Appendix IA.IV, we exclude the concern regarding "soft rejection" by showing that banks with industry expertise are not more likely to "soft reject" applicants before they submit application documentation.

banks can more accurately price borrowers' income risks and mitigate defaults, for example, by timely selling high-risk mortgages to third parties. Consequently, the positive impact of industry expertise on mortgage lending should be stronger in distressed industries.[15] More importantly, industry-wide shocks are plausibly exogenous for any given bank, county, or mortgage borrower, mitigating the issues of omitted variables and reverse causality (Giannetti and Saidi (2019), Babina (2020)).

We measure industry distress following previous studies (Opler and Titman (1994), Babina (2020)). Specifically, we classify a three-digit NAICS industry as distressed in a year if the industry-level two-year sales growth is negative and the industry-level two-year stock return is less than –10% from the beginning of that year. For robustness checks, we also use two additional stock return thresholds: –20% and –30%. We then compare the effects of industry distress on mortgage lending with differential ex-ante industry specializations using the following model:

$$
\begin{aligned}
Y_{bct} = {} & \pi_{ct} + \mu_{bs} + \tau_{bt} + \beta_1 \, \textit{Industry Expertise}_{bct-2} \times \textit{Distress}_{bct-1} \\
& + \beta_2 \textit{Industry Expertise}_{bct-2} + \delta \boldsymbol{X}_{bct-2} + \varepsilon_{bct}
\end{aligned}
\tag{4}
$$

where b denotes bank, c denotes borrower home county, s denotes borrower home state, and t denotes year. Y_{bct} is the dependent variable: the natural logarithm of the number or the dollar volume of mortgages (in millions) bank b approves to borrowers in county c in year t. $\textit{Industry Expertise}_{bct-2}$ is a dummy variable equal to one for a bank-county pair if there exists at least one industry in which bank b specializes and provides at least 5% jobs in county c, measured at $t-2$. $\textit{Distress}_{bct-1}$ is a dummy that equals one for a

[15] Our reasoning is consistent with Dursun-de Neef (2023), which shows that geographically specialized banks cut their mortgages less in specialized markets during the great financial crisis.

bank-county pair if distress happens in any of the industries in which bank b specializes and provides at least 5% of jobs in county j, measured at $t-1$.[16] In addition to county-by-year fixed effects π_{ct} and bank-by-state fixed effects μ_{bs}, we also add bank-by-year fixed effects τ_{bt} to account for potential negative effects of industry distress on bank capital.

Table 11 presents the results. Columns 1 and 4 use a return threshold of –10%, columns 2 and 5 use –20%, and columns 3 and 6 use –30%. The coefficient estimates on the interaction term between *Industry Expertise* and *Distress* are positive and statistically significant, suggesting that banks rely more on their industry expertise in distress periods. In column 1, the effect of industry expertise on mortgage lending rises from 2% in non-distress periods to 6.4% during distress. The incremental effect grows with distress severity—rising from 4.4% to 5.6% when tightening the return threshold from –10% to –30%, a 27% increase. Similar patterns are observed for mortgage volumes.

[Insert Table 11 here]

B The 2008 Financial Crisis

We use the 2008 financial crisis as an alternative shock, given that mortgages and housing markets were central to the recession. From 2007 to 2009, national house prices fell by more than 10%, and average delinquency rates on single-family mortgages rose from 1.84% (2004–2007) to 7.04% (2008–2009).[17] These widespread defaults resulted in substantial losses for banks. A key driver was the fraudulent overstatement of income in

[16]We intentionally measure the industry expertise channel at $t-2$ and industry distress at $t-1$ to avoid the concern that industry distress may affect banks' loan originations and thus choices of industry specialization.

[17]Estimated using data on housing price indexes and mortgage delinquency rates from the website of the Federal Reserve Bank of St. Louis.

mortgage applications (Mian and Sufi (2017)). Banks should be more cautious in screening mortgage borrowers during and after the crisis. Therefore, industry expertise should become more valuable in mortgage underwriting.

We design a difference-in-differences test to assess how the crisis influenced banks' use of industry expertise in mortgage lending from 2004 to 2010, using the following model:

$$\begin{aligned} Y_{bct} = \pi_{ct} + \mu_{bs} + \tau_{bt} + \beta_1 \, \textit{Industry Expertise}_{bc2003} \times \textit{Crisis}_t \\ + \beta_2 \, \textit{Industry Expertise}_{bc2003} + \delta \mathbf{X}_{bct} + \varepsilon_{bct} \end{aligned} \tag{5}$$

where b denotes bank, c denotes borrower home county, s denotes borrower home state, and t denotes year.[18] Y_{bct} is the dependent variable measuring mortgage lending, and $\textit{Industry Expertise}_{bc2003}$ captures the industry expertise channel as measured in 2003. *Crisis* is an indicator variable equal to zero for the period 2004-2007 and one for the period 2008-2010. π_{ct} denotes county-by-year fixed effects, μ_{bs} denotes bank-by-state fixed effects, and τ_{bt} denotes bank-by-year fixed effects.

Table 12 presents the results. Columns 1 and 3 show that industry expertise positively affects mortgage lending prior to the crisis. Banks' reliance on the channel increases from 3.8% to 12.3% in column 1, and from 4.7% to 12% in column 3. In columns 2 and 4, we break down the *Crisis* dummy into year dummies. Year 2007 is the base year and thus omitted. The coefficient estimates on the interaction terms *Industry Expertise* $\times$ *Year 2004*, *Industry Expertise* $\times$ *Year 2005*, and *Industry Expertise* $\times$ *Year 2006* are not

[18] The crisis ended in 2009. We include 2010 in the sample because our goal is to assess banks' use of the channel before, during, and after the crisis. For simplicity, we use "crisis" to represent the period 2008 - 2010.

statistically significant, suggesting that the effect of industry expertise on mortgage lending is stable before the crisis. In 2009, the effect of industry expertise increases by 14.2% and 12.6% in columns 2 and 4. The effect slightly decreases in 2010 after the peak of the crisis, but is still positive and significant. Figure 2 presents the dynamics of the coefficient estimates.

[Insert Table 12 here]

[Insert Figure 2 here]

In summary, the findings suggest that industry expertise becomes more valuable during periods of greater uncertainty, when income risk is more pronounced. Importantly, these tests help address endogeneity concerns, supporting a causal interpretation of the industry expertise effect on mortgage lending.

VI Negative Lending Practices

Our main analysis shows that industry expertise increases total mortgage lending by reducing information asymmetry and easing credit rationing for otherwise opaque borrowers. However, during severe economic downturns, this additional lending may expose banks to heightened default risk unless risks are accurately priced into mortgage terms, thereby lowering expected losses. We therefore conjecture that banks with industry expertise impose stricter mortgage terms around periods of significant downturns.

We test this conjecture by examining the terms of approved mortgages at the onset of industry-specific distress. Columns 1 and 2 of Table 13 show that at the onset of industry distress, mortgages issued through the industry expertise channel tend to have significantly lower LTV ratios and higher interest rates. Furthermore, columns 3 and 4 suggest that banks reduce their conventional mortgages relative to government-insured mortgages. Collectively, these findings indicate that banks set stricter mortgage terms and shift to safer mortgages to mitigate losses during downturns.

[Insert Table 13 here]

VII Conclusion

This paper shows that the industry knowledge banks gain from corporate lending helps them overcome informational frictions in mortgage markets. In particular, we show that banks specialized in certain industries increase mortgage lending in areas where those industries are concentrated, which we call the industry expertise channel. The effect is more pronounced when information asymmetry is more severe or borrowers are riskier. We also find that mortgages originated through the channel contain more soft information and perform better. Further analyses based on unexpected industry distress and the 2008 crisis suggest that the effects are likely causal. Overall, our work demonstrates a broader impact of banks' lending concentration at the industry level: the industry expertise developed through lending concentration benefits banks in mortgage lending, extending beyond its role in corporate lending. Our paper also shows that information can flow from the corporate lending division to the mortgage lending division within a bank.

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Appendix A. Variable Definitions

Variables	Description
Dependent Variables	
Log(Number of Approved Mortgages)	The natural logarithm of the number of mortgages a bank approves in a county.
Log(Volume of Approved Mortgages)	The natural logarithm of the dollar volume of mortgages (in millions) a bank approves in a county.
Approval Rate - Number	The number of mortgages a bank approves scaled by the number of mortgage applications a bank receives in a county.
Approval Rate - Volume	The dollar volume (in millions) of mortgages a bank approves scaled by the dollar volume of mortgage applications a bank receives in a county.
Income Growth (%)	A county's household income growth rate (%).
Delta Delinquency Rate (%)	The annual change in a county's 1-4 family residential mortgage delinquency rate (%).
Log(STD. Mortgage Size)	The natural logarithm of the standard deviation of the amounts of approved mortgages.
Log(STD. LTI)	The natural logarithm of the standard deviation of the loan-to-income (LTI) ratios of approved mortgages.
Log(STD. Interest Rates)	The natural logarithm of the standard deviation of the interest rates of approved mortgages.
Log(STD. LTV)	The natural logarithm of the standard deviation of the loan-to-value (LTV) ratios of approved mortgages.
Delinquency 60 Days	The percentage of mortgages that are more than 60 days past due on monthly payments.
Delinquency 90 Days	The percentage of mortgages that are more than 90 days past due on monthly payments.
Foreclosure	The percentage of mortgages that have gone through a foreclosure.
% Conventional Mortgages	The number-based (or volume-based) percentage of conventional mortgages a bank approves in a county.
LTV	The average loan-to-value (LTV) ratio of approved mortgages.
Interest Rate	The average interest rate of approved mortgages.
Key Independent Variables	
Industry Expertise	A dummy that equals one for a bank-county pair if there exists at least one industry which a bank specializes in and provides at least 5% of jobs in a county.
Sales Growth	The standardized employment-weighted industry-level sales growth rate in a county. The sales growth rate for each industry is calculated as the average sales growth rate of all public U.S firms in the industry.
Distress	A dummy that equals one for a bank-county pair if distress happens in any of the industries that a bank specializes in and provide at least 5% of jobs in a county.
Crisis	A dummy that equals one for the period 2008 - 2010 and zero for the period 2004 - 2007.

Variables	Description
Other Independent Variables	
LTI	The average of the loan-to-income (LTI) ratios of mortgage applicants.
Male	The fraction of mortgage applicants that are male.
Minority	The fraction of mortgage applicants that are minorities.
Credit Score	The average credit score of approved mortgages.
DTI	The average debt-to-income ratio (DTI) ratio of approved mortgages.
Branch	The logarithm of one plus the number of branches a bank has in a county.
Distance	The natural logarithm of one plus the geographic distance between a mortgage borrower's home county and a bank's headquarter county.
SBL	The natural logarithm of one plus the number of small business loans a bank lends out in a county.
Mortgage Exposure	The average fraction of mortgages retained on balance sheets in the borrower's home county in the past. three years.
SCI	The standardized social connectedness index between a mortgage borrower's home county and a bank's headquarter county.
HP Volatility	The standardized county-level house price volatility, based on a county's housing prices in the past five years.
Log(Assets)	The natural logarithm of bank assets.
Total Loans/Assets	Total loans scaled by assets.
Deposits/Assets	Total deposits scaled by assets.
C&I Loans/Total Loans	Commercial & industrial (C&I) loans scaled by total loans.
RE Loans/Total Loans	Real estate loans scaled by total loans.
ROA	Total income scaled by assets.
Liquidity/Assets	The sum of total investment securities, total assets held in trading accounts, and federal funds sold and securities purchased under agreements to resell scaled by assets.
Population	The natural logarithm of the population in a county.
Above 65	The fraction of the population above 65 in a county.
Male	The fraction of the male population in a county.
Minority	The fraction of the minority population in a county.
Bachelor	The fraction of the population with a bachelor's degree or above in a county.

Figures

FIGURE 1
Average Employment Share by Top-20 Industries in a County

The figure presents the average employment share by top-20 industries in a county.

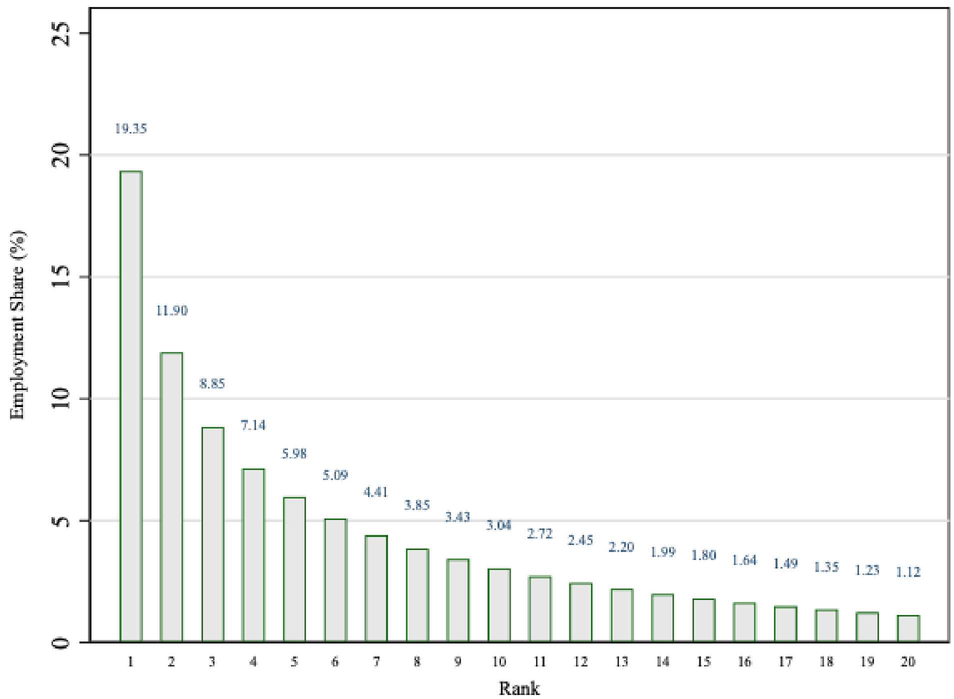
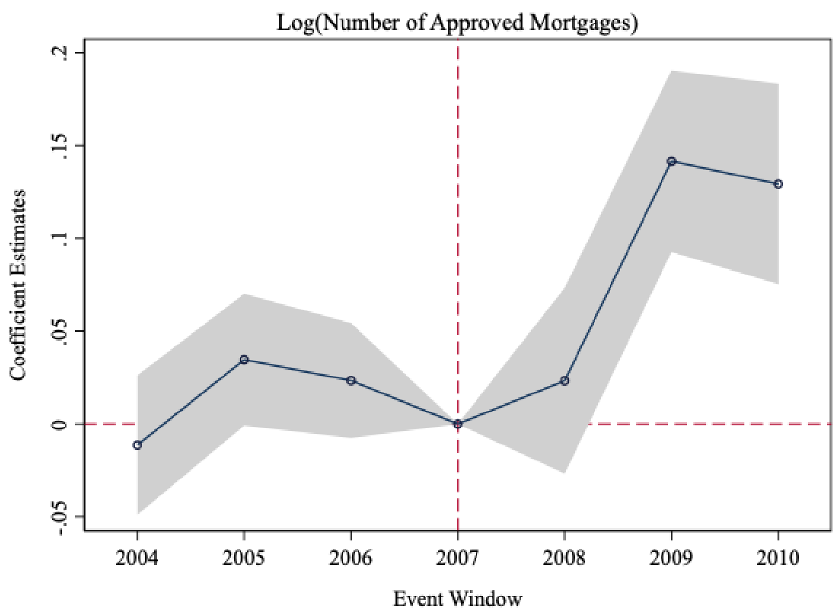


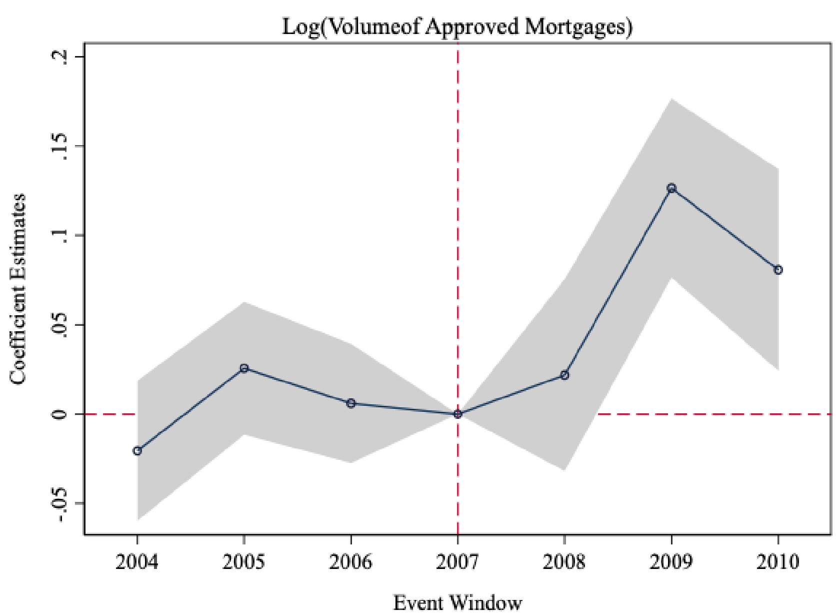
FIGURE 2
The 2008 Financial Crisis and the Industry Expertise Channel

The figures present the dynamic treatment effects of the 2008 financial crisis on banks' use of the industry expertise channel in mortgage lending. Figures (A) and (B) present the effects on the number and volume of approved mortgages, respectively. The regression results behind the figures are reported in columns 2 and 4 of Table 12.

(A) **Number of Approved Mortgages**



(B) **Volume of Approved Mortgages**



Tables

TABLE 1
Summary Statistics

This table presents the summary statistics of variables used in empirical analyses. Panel A presents the county-level statistics. Panel B presents the bank-level statistics. Panel C presents the HMDA-based main sample at the bank by county level. Panel D presents the matched bank-county-level sample between HMDA and monthly loan-level performance from the Fannie Mae, Freddie Mac, and McDash datasets. The sample period is 1999 to 2017, except that the data on county-level mortgage delinquency is from 2008 to 2017. See Appendix A for variable definitions.

	N	Mean	SD	P25	P50	P75
Panel A. County Level						
Income Growth (%)	58,394	3.926	4.809	1.521	3.848	6.205
Delta Mortgage Delinquency (%)	4,230	-0.209	1.088	-0.800	-0.383	0.117
Sale Growth	60,857	-0.003	0.998	-0.496	-0.079	0.449
Population	58,395	10.267	1.381	9.321	10.151	11.097
Above 65	59,322	0.112	0.031	0.090	0.109	0.131
Male	59,322	0.498	0.017	0.488	0.495	0.503
Minority	59,297	0.128	0.152	0.023	0.059	0.173
Bachelor	57,607	0.171	0.077	0.116	0.151	0.205
Panel B. Bank Level						
Log(Assets)	592	11.020	1.333	10.055	10.832	11.838
Total Loans/Assets	592	0.631	0.114	0.562	0.659	0.719
Deposits/Assets	592	0.719	0.076	0.667	0.724	0.772
C&I Loans/Total Loans	592	0.246	0.080	0.188	0.239	0.292
RE Loans/Total Loans	592	0.521	0.141	0.420	0.515	0.649
ROA	592	0.010	0.007	0.008	0.011	0.013
Liquidity/Assets	592	0.230	0.095	0.161	0.211	0.292

	N	Mean	SD	P25	P50	P75
Panel C. Bank-County Level (HMDA)						
Number of Approved Mortgages	316,552	87.987	193.768	7.000	19.000	66.000
Log(Number of Approved Mortgages)	316,552	3.196	1.503	1.946	2.944	4.190
Volume of Approved Mortgages	316,552	14.407	34.847	0.820	2.330	9.142
Log(Volume of Approved Mortgages)	316,552	1.102	1.699	-0.198	0.846	2.213
Approval Rate-Number	316,552	0.746	0.167	0.638	0.775	0.867
Approval Rate-Volume	316,552	0.756	0.174	0.649	0.786	0.889
Log(STD. LTI)	316,551	4.283	0.643	3.859	4.266	4.678
Log(STD. Mortgage Size)	314,818	-0.049	0.377	-0.246	-0.016	0.189
Industry Expertise	316,552	0.165	0.371	0.000	0.000	0.000
LTI	316,552	2.042	0.553	1.653	1.991	2.377
Male	315,054	0.731	0.136	0.653	0.734	0.812
Minority	316,552	0.096	0.128	0.000	0.048	0.143
Branch	316,552	0.400	0.749	0.000	0.000	0.693
Distance	316,552	6.285	0.956	5.659	6.352	7.003
SBL	316,552	2.477	2.096	0.000	2.303	4.094
Mortgage Exposure	270,672	0.390	0.257	0.185	0.348	0.556
Panel D. Bank-County Level (Matched - HMDA, Fannie Mae, Freddie Mac, and McDash)						
Delinquency 60 Days	73,732	0.121	0.154	0.000	0.067	0.194
Delinquency 90 Days	73,732	0.100	0.140	0.000	0.034	0.164
Foreclosure	73,732	0.063	0.107	0.000	0.000	0.100
Log(STD. Interest Rates)	73,726	-0.405	0.597	-0.845	-0.505	0.066
Log(STD. LTV)	73,712	2.845	0.416	2.589	2.897	3.156
Industry Expertise	73,732	0.180	0.385	0.000	0.000	0.000
Credit Score	73,732	729.481	33.914	707.750	733.527	756.667
LTV	73,732	70.848	9.554	64.888	72.044	77.900
DTI	73,354	32.833	5.464	29.545	32.924	36.355
Interest Rate	73,732	5.624	1.432	4.232	5.822	6.744
LTI	73,732	2.221	0.530	1.840	2.182	2.559
Male	73,706	0.736	0.148	0.643	0.750	0.833
Minority	73,686	0.089	0.124	0.000	0.026	0.143
Branch	73,732	1.010	1.041	0.000	0.693	1.792
Distance	73,732	6.326	1.079	5.577	6.407	7.305
SBL	73,732	4.119	2.074	2.944	4.431	5.665
Mortgage Exposure	70,524	0.365	0.200	0.222	0.342	0.477

TABLE 2

Mortgage Lending Through the Industry Expertise Channel: Number and Volume

This table presents the effects of the industry expertise channel on banks' mortgage lending across counties. The dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 5 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 6 - 10. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% jobs in a county. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9	10
	Log(Number of Approved Mortgages)					Log(Volume of Approved Mortgages)				
Industry Expertise	0.024***	0.025***	0.056***	0.067***	0.063***	0.028***	0.028***	0.060***	0.068***	0.065***
	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)
LTI		-0.331***	-0.062***	-0.056***	-0.004		-0.046***	0.202***	0.200***	0.235***
		(0.010)	(0.007)	(0.008)	(0.007)		(0.010)	(0.007)	(0.008)	(0.008)
Male		-0.020	-0.012	-0.011	0.031*		0.315***	0.320***	0.322***	0.322***
		(0.020)	(0.017)	(0.020)	(0.017)		(0.020)	(0.017)	(0.019)	(0.017)
Minority		0.913***	0.392***	0.410***	0.285***		0.669***	0.154***	0.127***	0.064*
		(0.055)	(0.037)	(0.042)	(0.034)		(0.054)	(0.036)	(0.041)	(0.035)
Branch			0.540***	0.548***	0.458***			0.507***	0.513***	0.430***
			(0.010)	(0.010)	(0.010)			(0.010)	(0.010)	(0.010)
Distance			-0.157***	-0.152***	-0.190***			-0.159***	-0.155***	-0.200***
			(0.007)	(0.007)	(0.018)			(0.008)	(0.008)	(0.018)
SBL			0.246***	0.251***	0.206***			0.255***	0.261***	0.213***
			(0.003)	(0.003)	(0.003)			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.172***	0.139***	0.200***			0.082***	0.039**	0.107***
			(0.016)	(0.017)	(0.016)			(0.015)	(0.017)	(0.016)
Log(Assets)			0.138***	0.110***	0.218***			0.151***	0.123***	0.241***
			(0.015)	(0.016)	(0.017)			(0.016)	(0.017)	(0.018)
Total Loans/Assets			1.000***	1.039***	1.080***			1.489***	1.508***	1.547***
			(0.074)	(0.079)	(0.072)			(0.074)	(0.078)	(0.073)
Deposits/Assets			-1.309***	-1.486***	-1.367***			-1.478***	-1.632***	-1.530***
			(0.049)	(0.052)	(0.052)			(0.051)	(0.054)	(0.053)
C&I Loans/Total Loans			3.975***	3.999***	4.090***			3.880***	3.902***	4.000***
			(0.097)	(0.105)	(0.098)			(0.099)	(0.107)	(0.101)
RE Loans/Total Loans			2.270***	2.103***	2.334***			2.346***	2.151***	2.419***
			(0.068)	(0.074)	(0.069)			(0.072)	(0.077)	(0.073)
ROA			-0.187	-1.663***	-2.223***			1.007**	-0.620	-1.045**
			(0.458)	(0.487)	(0.449)			(0.477)	(0.505)	(0.467)
Liquidity/Assets			-1.480***	-1.793***	-1.872***			-0.951***	-1.291***	-1.377***
			(0.076)	(0.082)	(0.086)			(0.079)	(0.084)	(0.089)
Observations	316,524	315,026	265,134	257,492	257,382	316,524	315,026	265,134	257,492	257,382
Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No
Bank FE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
County FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No
County×Year FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Bank×State FE	No	No	No	No	Yes	No	No	No	No	Yes
Adjusted R^2	0.472	0.482	0.718	0.704	0.773	0.580	0.583	0.762	0.750	0.804

TABLE 3

Mortgage Lending Through the Industry Expertise Channel: Approval Rates

This table presents the effects of the industry expertise channel on banks' mortgage approval rates across counties. The dependent variables are the number-based approval rate in columns 1 - 3 and the volume-based approval rate in columns 4 - 6. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6
	Approval Rate-Number			Approval Rate-Volume		
Industry Expertise	0.003***	0.004***	0.004***	0.004***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	265,134	257,492	257,382	265,134	257,492	257,382
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Bank FE	Yes	Yes	No	Yes	Yes	No
County FE	Yes	No	No	Yes	No	No
County×Year FE	No	Yes	Yes	No	Yes	Yes
Bank×State FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.378	0.386	0.436	0.330	0.343	0.389

TABLE 4

Industry Growth and Household Income and Mortgage Delinquency

This table presents the relation between the growth of a county's key industries and the county's household income growth and mortgage delinquency rates. The dependent variable in columns 1 - 3 is a county's average income growth rate (%). The dependent variable in columns 4 - 6 is the annual change in a county's mortgage delinquency rate (%). The key independent variable is a county's employment-weighted industry-level sales growth rate. The weight is the fraction of local residents working in a given industry. The sales growth rate for each industry is estimated using the sales of all U.S. public firms in the industry. Controls include *Population*, *Above 65*, *Male*, *Minority*, *Bachelor*. See Appendix A for variable definitions. The sample that examines the income growth rate is from 1999 to 2017, and the sample that examines the mortgage delinquency rate is from 2008 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6
	Income Growth (%)			Delta Mortgage Delinquency (%)		
Sales Growth	1.257***	1.339***	0.585***	-1.577***	-1.700***	-0.169***
	(0.033)	(0.035)	(0.044)	(0.054)	(0.050)	(0.052)
Population		0.100***	-2.771***		-0.082***	1.840***
		(0.023)	(0.286)		(0.028)	(0.543)
Above 65		-16.116***	23.559***		-2.747***	-9.766**
		(0.999)	(2.801)		(0.668)	(4.778)
Male		-6.025***	-11.616**		-10.751***	68.652***
		(1.268)	(5.023)		(2.927)	(12.013)
Minority		-1.999***	-0.242		0.001	0.253
		(0.125)	(1.597)		(0.167)	(2.373)
Bachelor		3.214***	9.738***		-0.623***	-2.526***
		(0.307)	(1.784)		(0.187)	(0.778)
Observations	58,394	55,212	55,212	4,230	3,728	3,728
County FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.0681	0.0865	0.222	0.355	0.405	0.714

TABLE 5
Information Asymmetry and the Industry Expertise Channel

This table presents the effects of information asymmetry on banks' use of the industry expertise channel in mortgage lending. The dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 2 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 3 - 4. The key independent variable is the interaction term between the *Industry Expertise* and the partition variables. *Industry Expertise* is a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. *Distance* is the standardized distance between a bank's headquarters county and a borrower's home county. *SCI* is the standardized social connectedness index between a bank's headquarters county and a borrower's home county. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Approved Mortgages)		Log(Volume of Approved Mortgages)	
Industry Expertise	0.070***	0.064***	0.072***	0.066***
	(0.006)	(0.006)	(0.006)	(0.006)
Industry Expertise × Distance	0.083***		0.085***	
	(0.006)		(0.006)	
Distance	-0.302***		-0.307***	
	(0.035)		(0.034)	
Industry Expertise × SCI		-0.020***		-0.020***
		(0.006)		(0.006)
SCI		0.045***		0.048***
		(0.009)		(0.009)
Observations	257,382	257,302	257,382	257,302
Controls	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.773	0.773	0.804	0.804

TABLE 6
Borrower Risk and the Industry Expertise Channel

This table presents the effects of borrower risk on banks' use of the industry expertise channel in mortgage lending. The dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 2 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 3 - 4. The key independent variable is the interaction term between *Industry Expertise* and the partition variables. *Industry Expertise* is a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. *HP Volatility* is the standardized county-level house price volatility. *LTI* is the average LTI ratio for all mortgage applicants in a county. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Approved Mortgages)		Log(Volume of Approved Mortgages)	
Industry Expertise	0.067***	0.053***	0.067***	0.055***
	(0.007)	(0.006)	(0.007)	(0.006)
Industry Expertise × HP Volatility	0.047***		0.050***	
	(0.005)		(0.006)	
Industry Expertise × LTI		0.058***		0.058***
		(0.006)		(0.006)
Observations	188,511	257,382	188,511	257,382
Controls	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.775	0.773	0.796	0.804

TABLE 7

Bank Size and Real Estate Loan Share and the Industry Expertise Channel

This table presents the effects of bank asset size and real estate loan share on banks' use of the industry expertise channel in mortgage lending. The dependent variables are the natural logarithm of the number of mortgages a bank approves (columns 1 – 2) and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves (columns 3 – 4). The key independent variable is the interaction term between *Industry Expertise* and the partition variables. *Industry Expertise* is a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Size is the standardized bank total assets. RE Loans is the standardized bank real estate loan share. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)* (columns 2 and 4), *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets* (columns 1 and 3), *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Approved Mortgages)		Log(Volume of Approved Mortgages)	
Industry Expertise	0.068***	0.024***	0.069***	0.025***
	(0.006)	(0.006)	(0.006)	(0.006)
Industry Expertise x Size	0.067***		0.056***	
	(0.006)		(0.006)	
Industry Expertise x RE Loans		0.134***		0.139***
		(0.006)		(0.006)
Observations	257,382	257,382	257,382	257,382
Controls	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes
Bank x State FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.773	0.773	0.804	0.805

TABLE 8
Dispersion in Mortgage Contractual Terms

This table presents the effects of the industry expertise channel on the dispersion of mortgage contractual terms. The dependent variables are the natural logarithm of the standard deviations of loan amounts, loan-to-income ratios, interest rates and loan-to-value ratios. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Columns 1 and 2 use the HMDA sample. columns 3 and 4 use the matched sample between HMDA and the Fannie Mae, Freddie Mac, and McDash datasets. Common controls include *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. In addition, columns 1 and 2 control for the LTI ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants. Columns 3 and 4 control for the average loan-to-value ratio, the percentage of male, the percentage of minority, the average credit score, the average loan-to-value ratio, and the average interest rate of approved mortgages. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(STD. Mortgage Size)	Log(STD. LTI)	Log(STD. Interest Rates)	Log(STD. LTV)
Industry Expertise	0.006***	0.005**	0.021***	0.022***
	(0.002)	(0.002)	(0.006)	(0.004)
Observations	256,055	257,382	58,772	58,764
Controls	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.450	0.688	0.595	0.568

TABLE 9

The Percentage of Conventional Mortgages

This table presents the effects of the industry expertise channel on banks' originations of conventional versus government-insured mortgages. The dependent variables are the number-based percentage of conventional mortgages a bank approves in a county in columns 1 - 3 and the volume-based percentage of conventional mortgages a bank approves in a county in columns 4 - 6. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6
	% Conventional Mortgages					
	Number			Volume		
Industry Expertise	0.004***	0.003***	0.002**	0.004***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	318,940	267,037	259,510	318,940	267,037	259,510
Controls	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
Bank FE	Yes	Yes	No	Yes	Yes	No
County FE	Yes	Yes	No	Yes	Yes	No
County×Year FE	No	No	Yes	No	No	Yes
Bank×State FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.265	0.308	0.459	0.255	0.295	0.452

TABLE 10

Mortgage Delinquency and Foreclosure

This table presents the effects of the industry expertise channel on banks' mortgage delinquency and foreclosure rates. The dependent variables are *Delinquency 60 Days*, *Delinquency 90 Days*, and *Foreclosure*. *Delinquency 60 Days* is the percentage of mortgages that are more than 60 days past due on monthly payments. *Delinquency 90 Days* is the percentage of mortgages that are more than 90 days past due on monthly payments. *Foreclosure* is the percentage of mortgages that have gone through a foreclosure. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Controls include *Credit Score*, *LTV*, *DTI*, *Interest Rate*, *LTI*, *Male Applicants*, *Minority Applicants*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3
	Delinquency 60 Days	Delinquency 90 Days	Foreclosure
Industry Expertise	-0.005***	-0.004***	-0.003**
	(0.001)	(0.001)	(0.001)
Observations	58,779	58,779	58,779
Controls	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes
Adjusted R^2	0.649	0.634	0.578

TABLE 11
Industry Distress and the Industry Expertise Channel

This table presents the effects of industry distress on banks' use of the industry expertise channel in mortgage lending. The dependent variables are the logarithm of the number of mortgages a bank approves in a county in columns 1 - 3 and the logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 4 - 6. The key independent variable is the interaction term between *Industry Expertise* and *Distress*. *Industry Expertise* is a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county, measured at t-2. *Distress* is a dummy that equals one for a bank-county pair if distress happens in any of the industries that a bank specializes in and provides at least 5% of jobs in a county, measured at t-1. A three-digit NAICS industry is classified as distressed in a year if, from the beginning of that year, the industry-level two-year sales growth is negative and the industry-level two-year stock return is less than –10% (columns 1 & 4), -20% (columns 2 & 5), or -30% (columns 3 & 6). Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6
	Log(Number of Approved Mortgages)			Log(Volume of Approved Mortgages)		
	Return<-10%	Return<-20%	Return<-30%	Return<-10%	Return<-20%	Return<-30%
Industry Expertise	0.020**	0.020**	0.020**	0.025***	0.025***	0.025***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Industry Expertise × Distress	0.044*	0.052**	0.056**	0.041	0.046*	0.049*
	(0.025)	(0.026)	(0.028)	(0.026)	(0.027)	(0.028)
Observations	165,306	165,306	165,306	165,306	165,306	165,306
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.820	0.820	0.820	0.840	0.840	0.840

TABLE 12

The 2008 Financial Crisis and the Industry Expertise Channel

This table presents the effects of the 2008 financial crisis on banks' use of the industry expertise channel in mortgage lending. The dependent variables are the logarithm of the number of mortgages a bank approves in a county in columns 1 - 2 and the logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 3 - 4. The key independent variable is the interaction term between *Industry Expertise* and *Crisis* in columns 1 & 3, the interaction terms between *Industry Expertise* and year dummies in columns 2 & 4. *Industry Expertise* is a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county, measured at the year 2003. *Crisis* is a dummy that equals one for the period 2008 - 2010 and zero for the period 2004 - 2007. *Year 2004*, *Year 2005*, *Year 2006*, *Year 2008*, *Year 2009* and *Year 2010* are year dummies. Year 2007 is the base year and thus omitted. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 2004 to 2010. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Approved Mortgages)		Log(Volume of Approved Mortgages)	
Industry Expertise	0.038**	0.026	0.047***	0.045**
	(0.018)	(0.022)	(0.018)	(0.022)
Industry Expertise × Crisis	0.085***		0.073***	
	(0.023)		(0.024)	
Industry Expertise × Year 2004		-0.011		-0.021
		(0.023)		(0.024)
Industry Expertise × Year 2005		0.035		0.026
		(0.022)		(0.023)
Industry Expertise × Year 2006		0.023		0.006
		(0.019)		(0.020)
Industry Expertise × Year 2008		0.023		0.022
		(0.030)		(0.033)
Industry Expertise × Year 2009		0.142***		0.126***
		(0.030)		(0.030)
Industry Expertise × Year 2010		0.129***		0.081**
		(0.033)		(0.034)
Observations	87,166	87,166	87,166	87,166
Controls	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.829	0.829	0.853	0.853

TABLE 13

Negative Lending Practices

This table presents the effects of industry distress on banks' use of the industry expertise channel in setting mortgage contractual terms. The dependent variables are the loan-to-value (LTV) ratio in column 1, the interest rate in column 2, the number-based percentage of conventional mortgages a bank approves in a county in column 3, and the volume-based percentage of conventional mortgages in column 4. The key independent variable is the interaction term between *Industry Expertise* and *Distress*. *Industry Expertise is* a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. *Distress* is a dummy that equals one for a bank-county pair if distress happens in any of the industries that a bank specializes in and provides at least 5% of jobs in a county. A three-digit NAICS industry is classified as distressed in a year if, from the beginning of that year, the industry-level two-year sales growth is negative and the industry-level two-year stock return is less than -30%. Controls include *LTI*, *Male*, *Minority*, *Branch*, *Distance*, *SBL*, *Mortgage Exposure*, *Log(Assets)*, *Total Loans/Assets*, *Deposits/Assets*, *C&I Loans/Assets*, *RE Loans/Assets*, *ROA*, *Liquidity/Assets*. See Appendix A for variable definitions. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	LTV	Interest Rate	% Conventional Mortgages	
			Number	Volume
Industry Expertise	0.453***	-0.013*	0.003***	0.003***
	(0.142)	(0.007)	(0.001)	(0.001)
Industry Expertise x Distress	-1.541**	0.061*	-0.007**	-0.006**
	(0.707)	(0.034)	(0.003)	(0.003)
Observations	59,025	59,025	257,378	257,378
Controls	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes
Bank x State FE	Yes	Yes	Yes	Yes
Bank x Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.538	0.950	0.474	0.459

Internet Appendix to

"The Industry Expertise Channel of Mortgage Lending"

Yongqiang Chu Zhanbing Xiao Yuxiang Zheng

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IA.I. The Distribution of Counties Connected with Banks through the Industry Expertise Channel

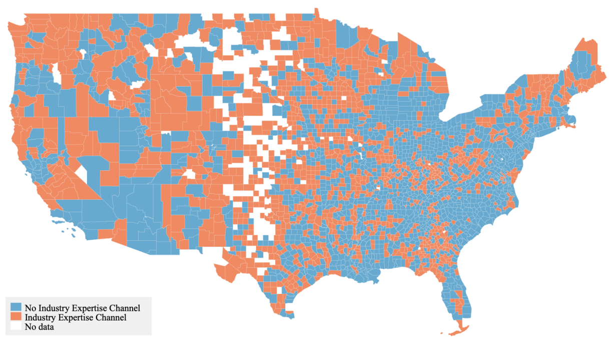
Figure IA.1 presents the distribution of counties in the contiguous US that are connected to at least one bank in our sample through the industry expertise channel in 1999, 2004, 2009, and 2014. The maps suggest that connected counties are evenly distributed throughout the US during the sample period.

FIGURE IA.1

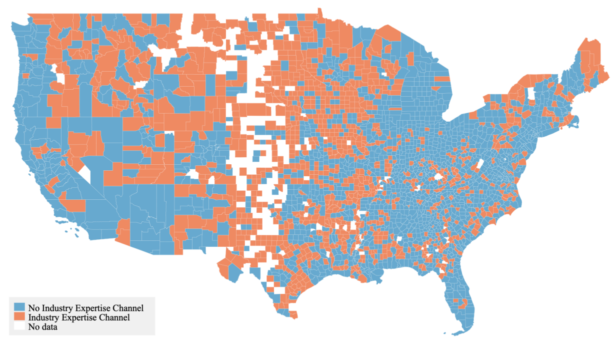
The Distribution of Counties Connected with Banks through the Industry Expertise Channel

The figures present the geographic distribution of counties in the contiguous U.S. that are connected with at least one bank in our sample through the industry expertise channel in the years 1999, 2004, 2009, and 2014 (in orange). Counties in blue denote those without such connections. Counties in white denote those where banks in our sample do not have mortgage businesses. A bank and a county are connected if there exists at least one industry which a bank specializes in and provides at least 5% of jobs in a county.

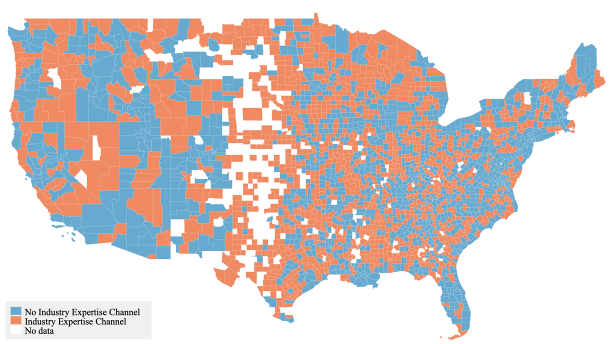
(A) Year 1999



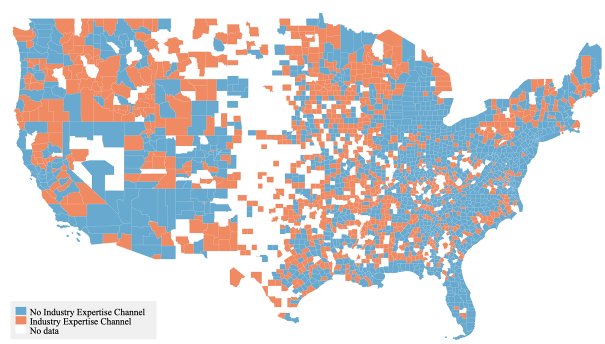
(B) Year 2004



(C) Year 2009



(D) Year 2014



IA.II. Robustness Checks of Baseline Results in Table 2

In this section, we conduct several additional tests to show the robustness of our baseline results in Table 2 by using alternative measures, more fixed effects, and alternative model specifications, and estimating loan shares.

A Alternative Measures of the Industry Expertise Channel

In general, industry leaders have more advanced technologies and are more closely linked to the latest industry dynamics relative to followers. Thus, lending to industry leaders allows banks to accumulate industry expertise faster and more effectively, relative to lending to followers. To capture the knowledge gap between industry leaders and followers, we construct a new measure of banks' lending specialization. Specifically, we use a firm's size to proxy for its position in an industry. We first classify all firms in an industry into ten groups based on total assets, with group 10 including firms with the largest assets.[1] We then use the rank as the weight to calculate a bank's total lending to a given industry in the following way:

$$L^{b}_{i,t} = \frac{\sum_{j=1}^{K} Loan^{b}_{i,j,t} * Rank_{i,j,t}}{\sum_{i=1}^{I}\sum_{j=1}^{K} Loan^{b}_{i,j,t} * Rank_{i,j,t}} \tag{IA.1}$$

where b denotes bank, i denotes industry, j denotes firm, and t denotes year. $Rank_{i,j,t}$ is the rank of a firm's assets in its industry i. We then reconstruct the dummy *Industry Expertise* using the same method as in equation (1). Columns 1 and 5 of Table IA.1 present the results.

[1] Using a rank variable rather than the assets avoids high skewness in the distribution of firm assets in an industry and the uneven distribution of firm assets across industries.

In addition, we construct two continuous measures that capture the intensity of the connections between banks and counties through the industry expertise channel. The first measure, *Industry Expertise (Fraction, 5%)*, is the fraction of a county's residents working in any industries that a bank specializes in and that provide at least 5% of jobs in the county. The second measure, *Industry Expertise (Fraction, All)*, is the fraction of a county's residents working in any industry in which a bank specializes, regardless of the number of jobs provided in the county. The results using the two measures are reported in columns 2, 3, 6, and 7 of Table IA.1 and are consistent with Table 2.

Lastly, we construct a measure that reflects the level of a bank's industry expertise. This measure is calculated as the difference between a bank's loan share in an industry minus the threshold used to identify an outlier loan share in equation (1). The results using this measure are consistent and are reported in columns 4 and 8 of Table IA.1.

B More Fixed Effects

Even though we add bank and bank-by-state fixed effects and bank-level variables to control for heterogeneities across banks in Table 2 and Table 3, the concern over omitted time-varying bank-level characteristics remains. To better address the concern, we add bank-by-year fixed effects in columns 1 and 3 of Table IA.2. Additionally, we use bank-by-county fixed effects to replace bank-by-state fixed effects to control for time-invariant links between banks and counties in columns 2 and 4 of Table IA.2. Our results hold.

C Alternative Empirical Specifications

Another concern is that using the logarithm of the dependent variables may produce biased estimates. To address this issue, we repeat the tests in Table 2 using alternative empirical specifications. Specifically, in columns 1 and 4 of Table IA.3, we use a linear regression model to estimate the effect of industry expertise on the raw number and the raw dollar volume of a bank's mortgage originations in a county. The coefficient estimates are statistically significant, and the economic effects are important; industry expertise increases banks' mortgage lending by 7.2% in numbers and 9.2% in dollar volumes. We also use the population-scaled raw number and dollar volume of approved mortgages as the dependent variables and get consistent results in columns 2 and 5. In columns 3 and 6, we follow Cohn, Liu, and Wardlaw (2022) and use the fixed effects Poisson model to redo the estimation. Our results still hold. The economic effects are even greater: industry expertise increases banks' mortgage lending by 10.6% in numbers and 12.3% in dollar volumes.

D Predicted Loan Shares

The loan share information contains many missing values in DealScan. When constructing our measure of bank lending specialization, we assume that lead lenders commit all capital in a loan because they bear the primary monitoring responsibilities and acquire industry knowledge by overseeing the entire loan amount rather than just their own capital commitments, which is consistent with previous studies (e.g., Bharath, Dahiya, Saunders, and Srinivasan (2007), Sufi (2007), Giannetti and Saidi (2019), Gustafson et al. (2021), Saidi and Streitz (2021)). Additionally, lead lenders have stronger incentives and better opportunities than participating lenders to acquire information about borrowers and develop industry expertise.

Nevertheless, this assumption has its limitations. To further demonstrate the robustness of our results, we estimate banks' missing loan shares by following the methodology proposed by Blickle et al. (2022) and reconstruct our measure of the industry expertise channel. We report the results in Table IA.4, and our findings remain robust.

TABLE IA.1

Robustness Checks - Alternative Measures of the Industry Expertise Channel

This table presents robustness checks of baseline results in Table 2 using alternative measures of the industry expertise channel. The dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 4 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 5 - 8. The independent variable in columns 1 and 5, *Industry Expertise (Weighted)*, is adjusted by each corporate borrower's market position (see equation (IA.1)). The independent variable in columns 2 and 6, *Industry Expertise (Fraction, 5%)*, is the fraction of a county's residents working in industries that a bank specializes in and provide at least 5% of jobs in the county. The independent variable in columns 3 and 6, *Industry Expertise (Fraction, All)*, is the fraction of a county's residents that work in any industry in which a bank specializes, regardless of the number of jobs provided in the county. The independent variable in columns 4 and 8, *Industry Expertise (Level)*, is the level of a bank's industry expertise, measured as the difference between the bank's loan share in an industry minus the threshold used to identify an outlier loan share. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is from 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Number of Approved Mortgages)				Log(Volume of Approved Mortgages)			
Industry Expertise (Weighted)	0.063***				0.066***			
	(0.006)				(0.006)			
Industry Expertise (Fraction, 5%)		0.537***				0.569***		
		(0.047)				(0.048)		
Industry Expertise (Fraction, All)			0.357***				0.381***	
			(0.046)				(0.046)	
Industry Expertise (Level)				0.138***				0.143***
				(0.022)				(0.022)
Observations	265,664	257,382	257,382	257,382	265,664	257,382	257,382	257,382
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County$\times$Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank$\times$State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.774	0.773	0.773	0.773	0.807	0.804	0.804	0.804

TABLE IA.2

Robustness Checks - Expanded Fixed Effects

This table presents robustness checks of baseline results in Table 2 with additional fixed effects. The dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 2 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 3 - 4. Columns 1 and 3 present the results with bank-by-year fixed effects. Columns 2 and 4 present the results using bank-by-county fixed effects to replace bank-by-state fixed effects. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry which a bank specializes in and provides at least 5% of jobs in a county. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is from 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Approved Mortgages)		Log(Volume of Approved Mortgages)	
Industry Expertise	0.028***	0.051***	0.029***	0.052***
	(0.007)	(0.005)	(0.008)	(0.005)
Observations	257,378	248,844	257,378	248,844
Controls	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Bank×State FE	Yes	No	Yes	No
Bank×Year FE	Yes	No	Yes	No
Bank×County FE	No	Yes	No	Yes
Adjusted R^2	0.807	0.852	0.832	0.868

TABLE IA.3

Robustness Checks - Alternative Empirical Specifications

This table presents robustness checks of baseline results in Table 2 using alternative empirical specifications. We use the linear regression model to estimate equation (2) in columns 1, 2, 4, and 5, and the fixed effects Poisson model in columns 3 and 6. In columns 1 and 3, the dependent variable is the number of mortgages a bank approves in a county. In columns 2, the dependent variable is the number of mortgages a bank approves in a county scaled by the county's population and multiplied by 1000. In columns 4 and 6, the dependent variable is the dollar volume (in millions) of mortgages a bank approves in a county. In column 5, the dependent variable is the dollar volume (in thousands) of mortgages a bank approves in a county scaled by the county's population. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry which a bank specializes in and provides at least 5% of jobs in a county. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is from 1999 to 2017. Numbers in parentheses are standard errors. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6
	Number of Approved Mortgages			Volume of Approved Mortgages		
	Linear	Linear Scaled by Population	Poisson	Linear	Linear Scaled by Population	Poisson
Industry Expertise	6.377***	0.074***	0.106***	1.330***	0.013***	0.123***
	(1.076)	(0.007)	(0.007)	(0.185)	(0.001)	(0.007)
Observations	257,382	251,718	257,382	257,382	251,718	257,382
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County$\times$Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank$\times$State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.631	0.525	0.864	0.645	0.514	0.836

TABLE IA.4

Robustness Checks - Predicted Loan Shares

This table presents robustness checks of baseline results in Table 2 using the methodology in Blickle et al. (2022) to estimate loan shares. The dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 2 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 3 - 4. The key independent variable is Industry Expertise, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Approved Mortgages)		Log(Volume of Approved Mortgages)	
Industry Expertise	0.024**	0.018***	0.031***	0.023***
	(0.009)	(0.007)	(0.009)	(0.007)
Observations	316,524	257,382	316,524	257,382
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
County FE	Yes	No	Yes	No
County x Year FE	No	Yes	No	Yes
Bank x State FE	No	Yes	No	Yes
Adjusted R^2	0.472	0.773	0.580	0.804

IA.III. Excluding Alternative Information Channels

Our documented industry expertise channel is distinct from the bank's private information about local economies through its local corporate borrowers, geographic specializations, or local depository branches. In other words, this channel adds an additional layer of information beyond other information channels discussed in previous studies. In this section, we conduct further tests to exclude these alternative channels and confirm the robustness of our results.

An alternative lending channel is through the bank's interactions with its local corporate borrowers. Specifically, a bank may have superior information about a mortgage market by collecting private information about its corporate borrowers located in the market, especially when they are dominant local employers. These corporate borrowers may also send their employees' salaries as deposits to the bank's local branches, which directly reveals local households' financial health. In this case, the bank could simply extend mortgage credits based on information collected through its networks of corporate borrowers, rather than the industry expertise channel. Furthermore, the bank may prioritize lending mortgages to employees of its local corporate borrowers due to information advantages or special lending programs.[1] Therefore, this alternative lending channel coincides with the industry expertise channel when a bank has corporate borrowers in its specialized industries and the corporate borrower provides significant jobs in the county. We show that our baseline results in Table 2 remain robust after excluding the alternative channel. To this end, we obtain

[1] Some firms may have joint programs with their relationship banks to help employees get mortgages with favorable terms.

firms' headquarters states from the Compustat and then drop bank-state pairs from the regression sample if the bank has a syndicated loan borrower located in the state. We present the results in columns 1 and 4 of Table IA.5 Panel A. Our results hold. In addition, we obtain the geographic distribution of a firm's business operations at the state level from Garcia and Norli (2012), which is extracted from firms' 10-K filings. Then, each year, we drop bank-state pairs if the bank has a syndicated loan borrower located in the state or the borrower has a reported establishment/subsidiary in the state. The results are reported in columns 2 and 5 of Table IA.5 Panel A.[2] Last, we use the distribution of a firm's employees across counties from the YTS establishment-level data and drop bank-county pairs if the bank has a syndicated loan borrower located in the county or the borrower has an establishment in the county. We present the results in columns 3 and 6 of Table IA.5 Panel A. The results continue to hold.

The above discussions focus on the bank's public corporate borrowers, and thus ignore its private and small borrowers. We address this issue by examining banks' small business lending across counties. Specifically, in columns 1 and 4 of Table IA.5 Panel B, we show that our baseline results in Table 2 hold after removing counties where the bank has significant shares of small business loans.

Another information channel is through banks' geographic specialization in mortgage lending. In specialized areas, banks extend substantial volumes of mortgages and, hence, accumulate rich experience and knowledge of local business and mortgage markets. Consequently, geographic specialization also allows banks to better assess the

[2]The data covering most firms is only available until 2007. To better use the information, we assume that a firm's geographic dispersion in 2008 - 2017 is the same as 2007. For unmatched syndicated borrowers, we drop their headquarters states.

risk and affordability of local mortgage applicants. For example, Dursun-de Neef (2023) shows that in specialized areas banks increase lending relatively less during the boom (2004 - 2006) and cut lending relatively less through the following bust (2007 - 2009). We shut down this channel by focusing on counties where banks have limited lending experience in the past and present the results in columns 2 and 5 of Table IA.5 Panel B. The results show that the industry expertise channel is distinct from banks' geographic specialization in mortgage lending.

Furthermore, previous studies highlight the importance of depository branches in banks' information collection and mortgage lending (e.g., Gilje et al. (2016)). In columns 3 and 6 of Table IA.5 Panel B, we show that our results hold after excluding counties where banks have depository branches. Interestingly, we find that the economic magnitude is smaller than the results of the full sample in Table 2, such as 4.6% in column 6 compared to 6.5% in column 10 of Table 2. This may suggest that the information collected through the industry expertise channel complements the information banks acquire through their onsite presence at the depository branches. At least three explanations could account for this. First, branch managers may have deeper knowledge of local industry conditions and key employers — such as details on plant expansions or closures — allowing for more informed decision-making through the industry expertise channel. Second, there could be a self-selection issue if the bank does not open branches in counties where it lacks a comparative advantage in information collection through the industry expertise channel. Third, having a depository branch may provide banks with better insight into the performance of various industries in a county because corporations are likely to deposit profits and households to deposit income at these branches. This cash flow information from different industries offers additional insight for banks' mortgage lending decisions through the industry expertise channel.

TABLE IA.5

Excluding Alternative Information Channels

This table presents robustness checks of the baseline results in Table 2 after excluding alternative information channels. Panel A focuses on the bank's private information of a mortgage market through interactions with its local public corporate borrowers. The sample in Panel A columns 1 and 4 drops a bank's mortgage lending in a state if it has a syndicated loan borrower located in the state. The sample in Panel A columns 2 and 5 drops a bank's mortgage lending in a state if the bank has a syndicated loan borrower located in the state or the borrower has a reported establishment/subsidiary in the state. The establishment/subsidiary information is from firms' 10K filings, compiled by Garcia and Norli (2012). The sample in Panel A columns 3 and 6 drops a bank's mortgage lending in a county if the bank has a syndicated loan borrower located in the county or the borrower has an establishment in the county. The establishment information is obtained from the Your Economy Time Series (YTS). Panel B focuses on the bank's private information of a mortgage market through its local private corporate borrowers, geographic specializations, and local depository branches. The sample in Panel B columns 1 and 4 drops counties where the bank has significant shares of small business loans ($\geq$ 0.01%). The sample in Panel B columns 2 and 5 drops counties where the bank has significant shares of mortgage lending in the past three years ($\geq$ 0.01%). The sample in Panel B columns 3 and 6 drops counties where the bank has depository branches. In both panels, the dependent variables are the natural logarithm of the number of mortgages a bank approves in a county in columns 1 - 3 and the natural logarithm of the dollar volume (in millions) of mortgages a bank approves in a county in columns 4 - 6. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry which a bank specializes in and provides at least 5% of jobs in a county. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is from 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A

	1	2	3	4	5	6
	Log(Number of Approved Mortgages)			Log(Volume of Approved Mortgages)		
	HQ States	Reported States	YTS Counties	HQ States	Reported States	YTS Counties
Industry Expertise	0.066***	0.087***	0.052***	0.067***	0.090***	0.056***
	(0.007)	(0.013)	(0.007)	(0.007)	(0.013)	(0.007)
Observations	211,293	79,871	205,074	211,293	79,871	205,074
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.764	0.753	0.745	0.796	0.782	0.779

Panel B

	1	2	3	4	5	6
	Log(Number of Approved Mortgages)			Log(Volume of Approved Mortgages)		
	SBL	Geographic Specialization	Branches	SBL	Geographic Specialization	Branches
Industry Expertise	0.053***	0.067***	0.045***	0.055***	0.063***	0.046***
	(0.008)	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)
Observations	127,263	93,569	175,407	127,263	93,569	175,407
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank×State FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.630	0.576	0.688	0.687	0.610	0.733

IA.IV. Soft Rejection

One potential concern regarding our results is that banks with industry expertise might "soft reject" applicants before they submit application documentation. To address this concern, we test the total mortgage applications received by banks across counties in Table IA.6. Our analysis shows that banks receive more mortgage applications in counties connected through the industry expertise channel, both in terms of the number and volume of applications. Furthermore, our analysis in Table 3 of the paper shows that, conditional on the received applications, the industry expertise channel significantly increases both number- and volume-based approval rates. Together, these findings suggest that banks are not more likely to "soft reject" mortgage applicants through the industry expertise channel. This evidence further supports our conjecture that the channel reduces information asymmetry and alleviates credit rationing, leading to fewer rejections and increased mortgage lending.

TABLE IA.6
Total Mortgage Applications

This table presents the effects of the industry expertise channel on the total mortgage applications received by banks across counties. The dependent variables are the natural logarithm of the number of mortgage applications a bank receives in a county in columns 1 - 2 and the natural logarithm of the dollar volume (in millions) of mortgages applications a bank receives in a county in columns 3 - 4. The key independent variable is *Industry Expertise*, a dummy that equals one for a bank-county pair if there exists at least one industry in which a bank specializes and provides at least 5% of jobs in a county. Controls include the average loan-to-income ratio of all mortgage applicants, the percentage of male applicants, the percentage of minority applicants, the natural logarithm of one plus the number of branches a bank has in the county, the natural logarithm of the geographic distance between the headquarters county of a bank and the borrower's home county, the natural logarithm of one plus the number of small business loans a bank originates in the borrower's home county, the average percentage of mortgages retained on balance sheets in the borrower's home county in the past three years, the natural logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, commercial and industrial (C&I) loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquidity scaled by assets. The sample period is 1999 to 2017. Standard errors clustered by county are reported in parentheses below the coefficient estimates. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Number of Applications)		Log(Volume of Applications)	
Industry Expertise	0.029***	0.055***	0.031***	0.056***
	(0.008)	(0.006)	(0.008)	(0.006)
Observations	316,524	257,382	316,524	257,382
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Bank FE	Yes	No	Yes	No
County FE	Yes	No	Yes	No
County x Year FE	No	Yes	No	Yes
Bank x State FE	No	Yes	No	Yes
Adjusted R^2	0.468	0.778	0.585	0.812

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