The Industry Expertise Channel of Mortgage Lending *

Zhanbing Xiao† Yuxiang Zheng‡

Dec 2021

Abstract

This paper documents an *industry expertise channel* that reduces the information asymmetry between banks and mortgage borrowers. This channel is a result of information spillover from a bank's specialization in corporate lending to its mortgage lending. We find that banks allocate more mortgage credits to counties with shared industry specialization, especially when the information asymmetry or borrower risk is high. Further tests show that mortgages originated through the channel contain more soft information and have better performance. The findings suggest that information from the channel improves banks' screening and monitoring efficiency in the mortgage market.

Keywords: Information Asymmetry, Industry Expertise, Syndicated Loans, Mortgages.

JEL Codes: G21, G30, D82.

---

*We thank David Martinez-Miera, Mikhail Mamonov, Klaas Mulier, José Luis Peydro, and seminar participants at the SWFA Annual Meeting 2021, 28*th* AEFIN PhD Mentoring Day, 28*th* AEFIN Finance Forum, AAA Annual Meeting 2021, and FMA Annual Meeting 2021 for helpful comments. A previous version was circulated under the title "Spillover Effects of Banks' Specialization in Corporate Lending on Mortgage Lending: The Industry Expertise Channel". All errors are our own.

†Zhanbing Xiao, Sauder School of Business, University of British Columbia. Email: zhanbing.xiao@sauder.ubc.ca.

‡Yuxiang Zheng, Sauder School of Business, University of British Columbia. Email: yuxiang.zheng@sauder.ubc.ca

1 Introduction

The 2008 great crisis caused significant losses to both the U.S. and the rest of the world. Numerous studies have shown that banks' loosing screening and over securitization of mortgage are key triggers of the crisis (e.g., Keys et al. (2010), Mian and Sufi (2009)). Meanwhile, there was also widespread mortgage fraud (e.g., Garmaise (2015), Griffin and Maturana (2016), Mian and Sufi (2017)). However, as of today, some important questions are still understudied and remain to be answered. For example, are the loosing screening and mortgage fraud because of banks' risk taking or banks' lack of credible information of borrowers? In addition to the hard information from household credit reports and tax records, what other information do banks use in mortgage lending? Do banks rely on any channels beyond physical branches to acquire soft information of mortgage borrowers? Answering these questions not only can deepen our understanding of banks' mortgage lending decisions but also can inform regulators to better monitor banks' risk taking.

Our paper aims to contribute to answer these questions. Specifically, in this paper, we argue and show a new channel that reduces the information asymmetry between banks and borrowers in the mortgage market, which we call the *industry expertise channel*. This channel relies on the industry expertise a bank gains in the corporate loan market through lending specialization. As such, this channel is a consequence of information spillover from the corporate loan market to the mortgage market. Our empirical results show that the industry expertise channel does exist and has important influences in banks' allocation of mortgage credits across counties. In particular, we find that banks lend more mortgages to counties that are connected to them through the industry expertise channel.

Our propose of the industry expertise channel is motivated by existing studies showing that banks often concentrate their lending in certain industries (e.g., Giometti and Pietrosanti (2020), Blickle, Parlatore, and Saunders (2021)). This lending specialization enables banks to develop relevant industry expertise, which allows them to collect and process information of the industry more efficiently. Therefore, the industry expertise increases banks' screening and monitoring abilities in the corporate loan market (e.g., Carey, Post, and Sharpe (1998), Acharya, Hasan, and Saunders (2006), Loutskina and Strahan (2011), Di and Pattison (2020)). For example, Berger, Minnis, and Sutherland (2017) find that banks are less likely to collect audited financial statements from firms in industries and regions where they have more exposure. Giometti and Pietrosanti (2020) show that a typical loan contract between a bank specialized in an industry and a firm in the same industry has less restrictive covenants and lower spreads.

Building on the literature, we argue that the industry expertise enables a bank to better predict a county's household income growth if the bank's specialized industry is a major sector in the county. This is because a county's household income is impacted by the county's economic growth to a large extent, which is eventually determined by the development of major industries in the county. It is worth to emphasize that the expertise enables the bank to predict income growth of any mortgage borrowers living in the county, not just those working in its specialized industries. Considering the importance of regular monthly income for U.S. households to make mortgage payments[1], predictions of household income through the industry expertise channel thus reduce the information asymmetry between banks and mortgage borrowers.[2] Therefore, information from the industry expertise channel is vital for banks to screen eligible borrowers and allocate credits in the mortgage market.

To conduct the empirical analysis, we first construct a measure of industry specialization for each bank using the DealScan syndicated loan data. We then construct a measure of industry specialization for each county in the U.S. using the most comprehensive data on employment at the county-industry level from the Quarterly Census of Employment and Wages (QCEW).

[1] Statistics from the website of Federal Reserve Bank of St. Louis show that the average saving rate in the U.S. from 1990 to 2019 was about 6.5%. Moreover, various surveys show that more than half of the U.S. adults do not even have $500 for emergency use, while data from the Census Bureau shows that the median U.S. household monthly mortgage payment is about $1,200.

[2] For example, when an industry recession is about to happen, it's important for banks to foresee it and understand its potential impacts on household financial health, as mortgage borrowers working in the industry or other related industries very likely will experience stagnant or even negative income growth, resulting in higher probabilities of mortgage defaults.

Based on the two measures, we construct a dummy indicating there exists at least one industry that both a bank and a county specialize in. Therefore, a given bank and a given county are connected through the industry expertise channel if they share same industry specialization.[3]

We start our empirical investigations by showing positive correlations between sales growth of the top-three industries in a county and the county's economic development, measured using both GDP growth and household income growth. The finding implies that the top-three industries are key engines of local economic development. Meanwhile, we also find a strong negative relation between sales growth of the top-three industries in a county and the county's mortgage delinquency rate. Combined together, the evidence indicates that banks' industry expertise indeed can help them evaluate borrowers' mortgage affordability.

Next, we investigate the existence of the industry expertise channel and its impacts on banks' mortgage lending decisions. Our baseline results show that banks allocate more mortgage credits to counties sharing their industry specialization. The results are robust to the inclusion of loan, borrower, and bank characteristics, and the inclusion of bank and county by year fixed effects. The economic magnitude is also significant. Relative to non-connected counties, a bank lends about 2.8% more mortgages to connected counties.

To further address the concern that our results could be driven by demand-side factors, we use a bank's mortgage approval rate as the dependent variable. The approval rate reflects a bank's lending decisions conditional on received mortgage applications, which helps isolate any demand-side factors. The results show that, compared to non-connected counties, mortgage approval rates are about 40 basis points higher in connected counties. Taken together, the two findings suggest that the industry expertise channel does exist and allows banks to lend out more mortgages to connected counties.

The fundamental logic behind the industry expertise channel is that it reduces the information asymmetry between banks and mortgage borrowers, leading to increased screening and monitoring efficiencies. We identify the information mechanism in the channel from the follow-

[3]For simplicity, we call the county a connected county hereafter.

ing three angles. First, if the information mechanism holds and information from the channel is a substitute for information from other sources, we should expect the channel to become more important when banks face higher information barriers in evaluating mortgage borrowers. We follow the literature and use both depository branches and social networks as proxies for alternative sources of information available to banks. Our results show that banks rely more on the channel when they have little branch presence in a county or have few connections with borrowers through social networks.

Second, banks' need for information should be larger when local risk is high, as borrowers are more likely to miss their mortgage payments and default. We use three measures as proxies for local risk - a county's economic growth (the sales growth of the top-three industries in a county), a county's housing price growth, and the average loan-to-income ratio of all mortgage applicants in a county. Empirical tests using the three measures support our prediction. A one standard deviation increase in housing price growth leads to a 74% reduction in the importance of the channel, which is quite significant. Moreover, for counties with low loan-to-income ratios, banks do not even rely on the channel for information acquisition.

Third, we directly examine banks' use of soft information in mortgage lending by investigating the dispersion in mortgage sizes. The screening model in Cornell and Welch (1996) shows that lower information frictions lead to larger loan size dispersion, as better information allows banks to better discriminate between "good" and "bad" borrowers. As such, banks can grant mortgages with favorable terms to "good" borrowers and mortgages with strict terms to "bad" borrowers. We find that mortgages originated through the channel have less standardized contractual terms. The standard deviation and interquartile range of mortgage sizes are 0.5% and 1.5% higher for mortgages originated through the industry expertise channel. Taken together, the three findings provide strong supports to the information mechanism of the industry expertise channel.

Having established that the industry expertise channel facilitates the transmission of information from the corporate loan market to the mortgage market, we turn to study how the channel works under exogenous shocks to alleviate endogeneity concerns. In particular, we utilize defaults in banks' corporate loan portfolios and study their use of the industry expertise channel in mortgage lending. This bank-specific shock updates a bank's perception of its own screening ability and thus make the bank less confident in its industry expertise (e.g., Murfin (2012), Giometti and Pietrosanti (2020)). We hypothesize that the defaulting shock leads to banks' decreased reliance on the industry expertise channel. Consistent with this prediction, the results show that banks' reliance on the channel drops by 11.6% after a defaulting shock.

In the last part of this paper, we test the performance implication of the industry expertise channel. If the channel indeed improves banks' screening and monitoring efficiencies, we expect to see better performances of mortgages originated through this channel. Due to the lack of loan-level performance information in the Home Mortgage Loan Disclosure Act (HMDA) data, we test the implication at the bank level. Our empirical results show that the more a bank relies on the channel in mortgage lending, the higher return the bank achieves in real estate loans. An one unit increase in the rank of a bank's reliance on the channel leads to about 1% increase in a bank's return on residential real estate loans. The finding lends further support to the information mechanism of the industry expertise channel.

This paper makes several contributions to the literature. First, there is a large literature on banks' lending concentration or specialization in certain dimensions, such as borrowers from certain geographic areas or industries, or borrower using certain types of collateral (e.g., Gopal (2019), Di and Pattison (2020), Liberti, Sturgess, and Sutherland (2020), Paravisini, Rappoport, and Schnabl (2020), Blickle, Parlatore, and Saunders (2021)). This lending specialization can improve efficiencies in banks' information collection and screening and monitoring of borrowers (e.g., Berger, Minnis, and Sutherland (2017), Giometti and Pietrosanti (2020), De Franco, Edwards, and Liao (2021)). Consequently, lending specialization not only increases bank values and decreases banks risk, but also has important implications for firm financing (e.g.,Acharya, Hasan, and Saunders (2006), Giometti and Pietrosanti (2020), Loutskina and Strahan (2011), Giannetti and Saidi (2019), Beck, De Jonghe, and Mulier (2021)). We follow the literature and examine the industry expertise banks accumulate in their corporate loans. Yet, different from existing studies, we investigate implications of the industry expertise for banks' mortgage lending. In this regard, we show that banks exploit the industry expertise in screening and monitoring mortgage borrowers. As such, our paper reveals a positive spillover of banks' specialization in corporate lending in their mortgage lending.

Second, this paper contributes to the literature on information asymmetry and credit access. Prior studies document various information barriers in the market and examine what information channels banks rely on to overcome the barriers (e.g., Degryse and Ongena (2005), Agarwal and Hauswald (2010), Giannetti and Yafeh (2012), Hollander and Verriest (2016), Levine, Lin, Peng, and Xie (2020), Nguyen (2019)). However, most of the studies focus on the syndicated loan or the small business loan market. The are limited studies on the mortgage market, though some of the information channels in the syndicated loan or the small business loan market may apply to the mortgage market as well. Some recent studies show that banks also acquire information of mortgage borrowers through online technologies, social networks and CEOs' hometown advantages (e.g., Fuster et al. (2019), Rehbein and Rother (2020), Lim and Nguyen (2020)). Our paper complements this literature by uncovering a new information channel, the industry expertise channel, that exclusively applies to the mortgage market. This channel reduces the information friction in mortgage lending.

Third, this paper contributes to the fast-growing literature on banks' allocation of mortgage credits across different areas (e.g., Cortés and Strahan (2017), Chavaz and Rose (2019), Chu and Zhang (2020), Lim and Nguyen (2020)). Our paper adds new evidence that the proximity of banks' and counties' industry specialization matters for credit allocation.

The remainder of this paper is organized as follows. Section 2 describes data and measures used in empirical analyses. Section 3 presents the baseline empirical results. Section 4 present evidence supporting the information mechanism of the channel. Section 5 addresses endogeneity concerns. Section 6 presets implications for mortgage performance. Section 7 discusses the interpretation of our results. Section 8 concludes.

2 Data and Measures

2.1 Sample Construction

Our sample starts from the LPC DealScan Loan database, which provides the most comprehensive coverage of the U.S syndicated loan market from 1987. The data provides detailed information on each loan, including the lender, the borrower, loan amount, starting date, ending date, interest rate, covenants, etc. Loans with missing information on loan amounts, lenders, borrowers, starting dates, or ending dates are dropped. To merge borrowers with their accounting and industry information in Compustat, we use the link table provided by Chava and Roberts (2008).[4] As most of the loans in Dealscan are syndicated, there can be multiple lenders associated with a particular loan. In cases of syndicated loans with multiple lenders, we follow prior work and only consider those serving as lead lenders. We define lead lenders in each syndicated loan based on the procedure outlined in Chakraborty, Goldstein, and MacKinlay (2018).[5] Considering that the allocation of loan shares is missing in most loans, we follow the literature and split the loan amount equally among lead lenders if there are multiple lead lenders in a loan.[6] As lead lenders take most responsibilities for monitoring borrowers, they are more likely than participants to acquire information about borrowers and accumulate industry expertise in the lending process. In addition, relative to participants, lead lenders are

[4]We thank Sudheer Chava and Michael Roberts for making the link table available.

[5]Specifically, Chakraborty, Goldstein, and MacKinlay (2018) developed the following ranking hierarchy: 1) lender is denoted as "Admin Agent", 2) lender is denoted as "Lead bank", 3) lender is denoted as "Lead arranger", 4) lender is denoted as "Mandated lead arranger", 5) lender is denoted as "Mandated arranger", 6) lender is denoted as either "Arranger" or "Agent" and has a "yes" for the lead arranger credit, 7) lender is denoted as either "Arranger" or "Agent" and has a "no" for the lead arranger credit, 8) lender has a "yes" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), 9) lender has a "no" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), and 10) lender is denoted as a "Participant" or "Secondary investor". For a given loan package, the lender with the highest title (following the ten-part hierarchy) is considered as the lead agent.

[6]We get similar results if we set loan shares provided by lead arrangers equal to the median of the sample with non-missing information on the syndicate allocation (Giannetti and Saidi (2019)), or if we estimate the average loan share given a lender's position in a syndicate and the syndicate size using the sample with non-missing information on the syndicate allocation (Chakraborty, Goldstein, and MacKinlay (2018)).

less likely to sell their loan shares in the secondary market (Irani et al. (2021)).

To obtain additional information on lenders, we use the link table provided by Gomez et al. (2020) to merge lenders in Dealscan with banks.[7] Characteristics of these banks are from Call Reports. We also get data on bank's depository branches from the Summary of Deposits (SOD), which covers the universe of banks' depository branches at an annual frequency from 1994. Information on branch characteristics, such as branch name, geographic coordinates, address, the BHC and deposits, is available from the SOD. The link table is an updated version of the one constructed by Schwert (2018). Building on Schwert (2018), Gomez et al. (2020) manually assign another 199 DealScan lenders to 69 BHCs, which increases the total number of lenders from 490 to 587, and the total number of BHCs from 79 to 148. The sample period for this link table is from 1986 to 2013.[8]

We get data on banks' mortgage lending from the Home Mortgage Loan Disclosure Act (HMDA) database, which covers over 90% of mortgages originated in the U.S. It reports detailed information on the lender, the borrower, the loan, and the property, among others. We follow prior literature and exclude non-conventional loans and loans for manufactured housing and multi-family dwelling.[9] This helps filter out factors such as government subsidies in influencing banks' lending decisions. Non-standard mortgages, such as mortgages used for home improvement and non-owner-occupied dwellings, are also excluded. We follow Dagher and Kazimov (2015) to merge the HMDA data with banks in the syndicated loan data by matching agency-specific IDs in HMDA (Federal Reserve RSSD-ID, FDIC Certificate Number, and OCC Charter Number) to RSSD IDs in the lender link table. Counties where a bank has fewer than 5 mortgage applications are excluded to ensure the accuracy of estimation.[10]

Data on county-level household employment and industry patterns is from the Bureau of

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

[8] We thank Michael Schwert and Matthieu Gomez for sharing the link tables. For more details regarding the link table, please refer to Schwert (2018) and Gomez et al. (2020).

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

[10] Our results are robust if we require at least 10 or 20 mortgage applications or remove the requirement.

Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW) database. The QCEW program publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs, available at the county, MSA, state, and national levels by industry. QCEW provides full data set access via their website. For the purpose of this study, we use the data QCEW provides at the annual frequency and covers every six-digit NAICS industry for more than 3,000 counties in the United States. The sample period is from 1990 to 2018.

In addition, we also get data on U.S. county to county distances and data on county-level characteristics (e.g., GDP, household income, housing price index, population, race, and age, etc.) from the Bureau of Economic Analysis (BEA), the Federal Housing Finance Agency (FHFA), and the NBER database. Data on county-level mortgage delinquency rate is from the Consumer Financial Protection Bureau (CFPPB). Data on county-to-county social connections, the *Social Connectedness Index (SCI)*, is from Bailey et al. (2018). The measure is based on Facebook friendship links in the year 2016.[11]

2.2 Measuring Bank and County Industry Specialization

To test the existence of the industry expertise channel and its influence, we need to measure industry specialization for each bank and each county. For banks, we follow prior studies and use a bank's lending activities in the syndicated loan market to measure its industry specialization (Giannetti and Saidi (2019), Giometti and Pietrosanti (2020)).[12]. Given that DealScan only provides information on loans at origination, we create a panel that dynamically tracks

[11] $Social\ Connectedness\ Index_{i,j} = \frac{FB\_Connections_{i,j}}{FB\_Users_i * FB\_Users_j}$, where $FB\_Connections_{i,j}$ is the total number of Facebook friendship connections between individuals in the two counties i and j, and FB_Users_i and FB_Users_j are the number of Facebook users in the two counties separately. See Bailey et al. (2018) and Bailey et al. (2019) for details of the measure. We thank the authors for sharing this data.

[12] We do not use data from Call Reports or data on banks' small business lending, as these data do not provide banks' lending activities at the industry level. DealScan represents a sizable portion of the corporate loan market in the U.S, which makes using the syndicated loan data a good alternative to evaluate bank lending policies and influences (e.g., Chakraborty, Goldstein, and MacKinlay (2018), Saidi and Streitz (2021))

each bank's lending portfolios at any given point of time.[13] With this panel, we aggregate a bank's lending at the three-digit NAICS code level in each year. Our choice of the three-digit NAICS code level not only ensures a sufficient precision of industry breakdowns but also ensures a reasonable number of firms and loans in each industry. Firms in the financial industry are excluded. We classify a bank as being specialized in an industry if the bank's loan share in that industry is an outlier compared to other banks' loan shares in the industry (Paravisini, Rappoport, and Schnabl (2020)). In doing so, the measure accounts for not only heterogeneities in sizes of different banks but also heterogeneities in sizes of different industries.[14] Specifically,

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

where $L^{b}_{i,t} = \frac{Loan^{b}_{i,t}}{\sum_{i=1}^{I} Loan^{b}_{i,t}}$ represents a bank b's portfolio share of syndicated loans towards the industry i in the list of industries from 1 to I, at time t.[15] $L^{*}_{i,t}$ is a threshold to identify the outlier in the distribution of $L^{b}_{i,t}$ among all banks. For each industry, the threshold is the 75^{th} percentile of the distribution of all banks' portfolio shares in the industry plus the 1.5 inter-quartile range of the distribution. Thus, $L^{b}_{i,t} \geqq L^{*}_{i,t}$ captures banks whose loan portfolio extremely concentrates

[13] Some loans are refinancing loans that replace prior deals. Our results hold if we take this into consideration by setting the refinancing date of the new deal as the ending date of the prior deal it replaces.

[14] Scaling a bank's loans to each industry using its 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.

[15] However, a bank may accumulate the industry expertise faster by lending to leading firms in an industry. To capture this effect, we follow Paravisini, Rappoport, and Schnabl (2020) and construct a weighted measure of a bank's lending specialization. Specifically, we first classify all firms in an industry into 10 groups based on total assets, with group 10 indicating firms with largest assets. We then use the rank as the weight to calculate a bank's total lending to a given industry. This avoids the issue of high skewness in the distribution of firm assets in an industry and the uneven distribution of firm assets across industries. The measure is constructed in the following way:

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

where b represents a bank, i represents an industry, j represents a firm in industry i. Results based on this weighted measure are consistent and are presented in Appendix A. Results hold using this measure.

in the industry i relative to other banks.

Next, to identify a county's industry specialization, we first drop jobs created by government-owned entities or by the financial industry. Then, we rank the relative importance of each industry in a county based on the number of residents working in each industry. For consistency, we still use the three-digit NAICS code for industry classification. After that, we classify a county as being specialized in an industry if the industry is ranked among the top-three industries in that county. Put differently, the top-three industries that provide most jobs in a county represent industries that the county specializes in. In our sample, a county on average has about 39 industries providing jobs to local residents. The top-three industries in total create about 46% of all jobs in a county, which is a sizeable portion. Specifically, the top-three industries separately provide about 23%, 13%, and 10% of jobs in a county.[16] Therefore, the top-three industries represent major industries in a county. Banks' expertise in these industries should matter for their prediction of the whole county's economy.

After defining industry specialization for each bank and each county, we construct a dummy variable, *Same Industry*, to capture the information link between banks and counties through the industry expertise channel. The dummy variable equals one if there is at least one industry that a bank and a county both specialize in and zero otherwise.[17]

2.3 Summary Statistics

Our final sample includes 103 banks for the period 1995 to 2013. Table 1 reports summary statistics of variables used in empirical analyses. Panel A provides summary statistics of county characteristics. The average sales growth of public U.S. firms in the top-three industries in a county has a mean of 4.201% and a standard deviation of 4.485%. The mean of a county's in-

[16]The fourth, the fifth, and the sixth industry separately provides about 7%, 6%, and 5% jobs in a county.

[17]In Appendix B, we measure the intensive connection between a bank and a county based on the proportion of local residents working in industries in which both the bank and the county specialize in. In Appendix C, we measure the intensive connection between a bank and a county based on the proportion of local residents working in any industry in which a bank specializes, not matter whether the industry belongs to the top-three industries in the county. That is, we consider all industries in a county that a bank may specialize in. Results hold using either measure.

come growth is 3.678%, the mean of a county's GDP growth is -0.911%, and the mean of the change in a county's mortgage delinquency rate is -0.222%. Panel B reports summary statistics of bank characteristics. The average bank size is 10.403. About 26% of banks' loans are commercial loans, and about 50% are real estate loans. Panel C reports summary statistics of variables at the bank-county level. The logarithm of the number of mortgages a bank approves to a county has a mean value of 3.260 and a median value of 2.996. The standard deviation is 1.524, suggesting large variations across bank-county pairs. The mean mortgage approval rate is 0.748 and the median is 0.778. In addition, for the 321,067 bank-county pairs, about 10.3% of bank-county pairs specialize in the same industries.

[Insert Table 1 about here.]

Figure 1(A), 1(B), 1(C), and 1(D) present the geographic distribution of counties in the contiguous U.S. that share same industry specialization with at least one bank in our sample versus those do not in the year 1995, 2001, 2007, and 2013 separately. The figures suggest that connected counties have a relative even distribution across the contiguous U.S. over the sample period.

[Insert Figure 1 about here.]

3 Empirical Results

3.1 Growth of Top-three Industries and County Economic Development

The key argument in this paper is that the industry expertise channel does exist and reduces the information asymmetry between banks and mortgage borrowers. With reduced information friction, banks are more likely to lend mortgages to counties sharing their industry specialization. For the argument to hold, a prerequisite is that the growth of the top-three industries in a county is highly correlated with the county's household income growth and mortgage performance, as household income is key to mortgage payments. We start our empirical analyses by testing the prerequisite. However, data on sales of all firms in the top-three industries in a county is not available. Instead, we use sales of U.S. public firms. For each county, we calculate the weighted average of sales growth of all public firms in the top-three industries in the county, with the number of people working in an industry as the weight. We then regress county-level economic indicators or mortgage performance on the top-three industry sales growth. The empirical specification is as follows.

$$Y_{jt} = \theta_j + \tau_t + \beta * \mathit{Sales\ Growth}_{jt} + \delta \boldsymbol{X}_{jt} + \varepsilon_{jt} \tag{2}$$

where j represents county, t represents year, Y_{jt} is the GDP growth, household income growth or annual change in mortgage delinquency rate, $\mathit{Sales\ Growth}_{jt}$ is the weighted average of sales growth of all public firms in the U.S. in the top-three industries in county j, $\boldsymbol{X}_{jt}$ is a vector of county-level controls including the logarithm of population, the proportion of the population that are above 65, the proportion of the population that are male, and the proportion of the population that are minorities. θ_j represents county fixed effects, and τ_t represents year fixed effects.

[Insert Table 2 about here.]

Table 2 column (1) - (3) report the results on GDP growth. The coefficient estimate of sales growth is positive and statistically significant in all columns, suggesting that the higher the sales growth of the top-three industries is, the higher a county's GDP growth is. Column (4) - (6) report the results on household income growth. It shows a positive relationship between industry sales growth and income growth, implying that household income grows faster when the top-three industries grow faster. A one standard deviation increase in sales growth is associated with an 8.8% increase in income growth. In column 7) - (9), we examine the mortgage delinquency rate - an indicator of mortgage performance.[18] The coefficient estimate of sales

[18]Data on mortgage delinquency rate from the CFPB only covers 470 counties per year. CFPB constructs the

growth is negative and statistically significant, suggesting that higher growth of the top-three industries in a county leads to lower mortgage delinquency rate.

Taken together, the findings indicate that the top-three industries are critical to a county' economic growth. More importantly, the fact that the growth of top-three industries positively correlates with household income growth and negatively correlates with mortgage delinquency rate provides strong support to the industry expertise channel. That is, banks can use this channel to evaluate household income prospects and their mortgage affordability during the lifetime of a mortgage.

3.2 The Industry Expertise Channel and Mortgage Lending

We then turn to test the existence of the industry expertise channel and it importance in banks' mortgage lending. The empirical specification is as follows.

$$Y_{ijt} = \mu_i + \pi_{jt} + \beta * \mathit{Same\ Industry}_{ijt} + \delta \mathbf{X}_{ijt} + \varepsilon_{ijt} \tag{3}$$

where i represents bank, j represents borrower home county, t represents mortgage origination year, Y_{ijt} is the logarithm of the number of mortgages a bank i approves to county j in year t, $\mathit{Same\ Industry}_{ijt}$ is a dummy variable indicating that there exists at least one common industry in which the bank i and the county j both specialize in year t, X_{ijt} is a vector of controls at the bank-county or the bank level including the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, a bank's exposure to a county through mortgage retaining, the logarithm of one plus the number of small business loans a bank originate in a county, the logarithm of bank assets, total loans scaled by assets,

data in the following way: (1) the raw data is based on a nationally representative 5 percent sample of closed-end, first-lien, 1–4 family residential mortgages; (2) counties with fewer than 1,000 mortgages are excluded. To best use the information and allow enough within-county variations in mortgage performance, we use the data from 2008 to 2018 in our test, which is five years beyond the ending year of our main sample.

deposits scaled by assets, C&I loans scaled by total loans, real estate loans scaled by total loans, return on assets, and total liquid assets scaled by assets. μ_i represents bank fixed effects and π_{jt} represents county by year fixed effects. In more complete specifications, we use bank by borrower home state fixed effects to replace bank fixed effects.

[Insert Table **3** about here.]

The results are reported in Table 3. Column (1) reports the regression estimates without any controls or fixed effects. As can be seen, the coefficient estimate of *Same Industry* is positive and statistically significant, indicating that banks approve more mortgages towards counties connected with them through same industry specialization, which is consistent with our conjecture. In column (2), we include borrower home county by year fixed effects so that we only compare different banks' mortgage originations in the same county. This helps control for any unobserved county characteristics including local mortgage demand from contaminating our estimations. We also add bank fixed effects to control for time-invariant bank characteristics. In addition, we control for characteristics of mortgage applicants, banks and bank-county pairs in column (4). The results hold. To further address the concern regarding any special links between certain banks and states that are omitted from our model specifications, we add bank by borrower home state fixed effects in column (5). The coefficient estimate remains statistically significant, though the magnitude is smaller. Depending on model specification, relative to non-connected counties, connected counties receive about 2.8% - 20.3% more mortgage credits, which is economically significant. [19]

[19]In Appendix D, we repeat the same analyses but using the logarithm of dollar volumes of approved mortgages. In Appendix E, we construct another continuous variable reflecting the level of a bank's industry expertise, which is defined as the difference between a bank's loan share in an industry minus the threshold used to identify an outlier loan share. The conjecture is that, the higher industry expertise a bank has, the better information the bank can get from the channel, and therefore the more the bank relies on the channel in mortgage lending. Results hold using either measure.

3.3 The Industry Expertise Channel and Mortgage Approval Rate

A potential concern for our baseline findings is that the results can still be driven by demand-side factors, even though we include county by year fixed effects in the analysis. For instance, households living in a county may prefer to borrow from banks with shared industry specialization out of private reasons, i.e., brand preferences, or the availability and usability of mobile phone apps. These factors are either not observable or not directly measurable and therefore are not controlled in our baseline model specification. To address this concern, we examine banks' mortgage approval decision conditional on received applications. In particular, we use a bank's mortgage approval rate as the dependent variable, which is defined as the number of mortgage a bank approves scaled by the number of mortgage applications the bank receives in a county.

[Insert Table 4 about here.]

The results are reported in Table 4. Consistent with previous results, we find a positive and statistically significant relation between the *Same Industry* and mortgage approval rate in all five columns. Compared to non-connected counties, the approval rate is about 40 - 370 basis points higher in connected counties. The finding further corroborates that banks do rely on their industry expertise when deciding whether to approve or reject a mortgage application. Put another way, the baseline results in section 3.2 hold after controlling for household preferences for certain banks and are purely driven by banks' supply decisions.[20]

Overall, results in section 3.2 and 3.3 show that the industry expertise a bank obtains in the corporate loan market plays an important role in the bank's mortgage lending decisions. In this regard, banks allocate more mortgage credits towards counties sharing their industry specialization, indicating that this information source is indeed important for banks' evaluation of mortgage applicants.

[20]In untabulated results, we repeat the same analyses but using the dollar volumes to calculate the approval rate. Results hold.

4 The Information Mechanism

Results so far have confirmed the existence of the industry expertise channel and its importance in banks' mortgage lending decisions. In this section, we provide evidence that supports the information mechanism of the channel.

4.1 Information Asymmetry

We first test whether banks rely more on the channel when information from alternative sources is limited. The information banks collect through the industry expertise channel regarding local economies and borrowers' mortgage affordability could be a substitute to the information that banks collect through other channels. As such, when the information asymmetry between banks and mortgage borrowers is high and banks have few other ways to collect information about borrowers, the industry expertise channel should play a bigger role in supplying information to banks. In contrast, when the information asymmetry is low or when banks have alternative information channels, they may not need the industry expertise channel as much. Following the above arguments, in this section, we investigate how the information asymmetry between banks and mortgage borrowers affects banks' reliance on the industry expertise channel.

Prior studies have shown that long geographic distance erodes bank's ability to collect proprietary information of borrowers, creating information barriers for banks to reach distant borrowers. In consequence, access to credits is limited for borrowers in areas with few banks. This distance-induced information asymmetry not only exists in the mortgage market and small business loan market but also exists in the syndicated loan market for large public firms (e.g., Degryse and Ongena (2005), Agarwal and Hauswald (2010), Hollander and Verriest (2016)). Such information asymmetry, however, can be mitigated through banks' branch expansions (e.g., Alessandrini, Presbitero, and Zazzaro (2009), Ergungor (2010), Nguyen (2019)). Therefore, we expect banks to rely less on the industry expertise channel when they have branch presence in a county.

[Insert Table **5** about here.]

The results are reported in Table 5 column (1) - (2). The coefficient estimate of the same industry specialization variable is still positive and statistically significant. Meanwhile, the coefficient estimate for *VAR*, the logarithm of one plus the number of depository branches a bank has in a county, is also positive and statistically significant, showing that banks approve more mortgages in counties where they have branch presence. More importantly, the coefficient estimate for the interaction term between *Same Industry* and *VAR* is negative and statistically significant in column (1) and (2), suggesting that banks rely less on the industry expertise channel when they have high depository branch presence in a county.

Next, we test the influence of social networks in banks' use of the industry expertise channel. Existing studies have shown the importance of social networks in reducing information asymmetries and connecting multiple parties together in the financial market (e.g., Bailey et al. (2018), Bailey et al. (2019), Kuchler et al. (2021), Rehbein and Rother (2020)). For example, Rehbein and Rother (2020) show that banks allocate more small business loans and mortgages to socially connected counties, as social connections reduce information friction. Building on the literature, we expect the effects of the industry expertise channel to be weaker when there are many social connections between banks' headquarter counties and borrowers' home counties. The results are reported in Table 5 column (3) - (4). Consistent with the literature, the coefficient estimates of the *VAR* variable, the logarithm of the county-to-county *SCI*, is positive and statistically significant, implying that banks allocate more mortgage credits to socially connected counties. In addition, the coefficient of the interaction term *Same Industry*VAR* is negative and significant, indicating that banks rely less on the industry expertise channel when there are many social connections, which is consistent with our conjecture.

4.2 Local Risk

Banks' reliance on the industry expertise channel in mortgage lending may also depend on local risk. Borrowers from high-risk areas are more likely to miss mortgage payments and default, resulting in significant losses to banks. As a result, banks should demand more information in mortgage decisions in high-risk counties. This predicts banks' higher reliance on the industry expertise channel in high-risk counties.

Our first measure of local risk is a county's economic growth. An economic slowdown or recession often results in massive layoffs and spikes in unemployment rates, generating negative shocks to household income. Households that manage to keep jobs may still experience wage cuts. These disturbing factors increase the probabilities of household mortgage defaults and thus requiring banks to better screen and monitor the borrowers (DeFusco and Mondragon (2020)). Therefore, banks may demand more information on local economic prospects and household income prospects in counties with stagnant economic conditions. Information from the industry expertise channel can help meet the demand, with which banks can forecast local economy and household income growth more accurately. Therefore, we predict that banks rely more on the industry expertise channel in counties with slow economic growth.

[Insert Table **6** about here.]

We test this prediction in Table 6 columns (1) and (2). We use the standardized sales growth of all U.S. public firms in the top-three industries in a county to proxy for the county's economic conditions.[21] Consistent with our findings before, the coefficient estimate of *Same Industry* is positive and significant, suggesting that industry expertise channel matters in counties with relatively slow economic growth. More importantly, the interaction term between *Same Industry* and *VAR*, the standardized sales growth of the top-three leading industries in a county, is negative and significant. In counties with sales growth one standard deviation above the mean, banks do not even rely on the channel. This indicates that banks rely less on the industry ex-

[21] Results in Table 2 confirm the validity of this proxy.

pertise channel when the local economy grows rapidly, which is consistent with our conjecture.

In addition, we construct another proxy for local risk - the housing price growth rate, which is quite relevant to the mortgage market. Declining housing prices reduces the collateral value of a house, increasing household financial constraints and probabilities of mortgage defaults. Large plunge in house prices may even result in negative home equities and induce strategic defaults (e.g., DeFusco and Mondragon (2020), Gerardi et al. (2018)). Therefore, we expect banks to rely more on the industry expertise channel when the local housing market is in downturn. The results are reported in Table 6 column (3) and (4). The interaction term between *Same Industry* and *VAR*, the standardized housing price growth rate in a county, is negative and statistically significant. Compared to counties with slow housing price growth, the importance of the channel is about 74% smaller in counties with a one standard deviation increase in the housing price growth rate. Post-estimation tests show that the statistical significance of the *Same industry* variable is gone for counties with high housing price growth. In other words, banks do not even rely on the industry lending channel when the local housing price growth rate is high, which is consistent with our conjecture.

Last, we measure local risk using the average of loan-to-income ratios of all mortgage applicants in a county. A high loan-to-income ratio means high delinquency risk *ex ante*. Consequently, banks should collect more information to make sure the risk is correctly assessed and reasonably priced. Results are reported in Table 6 column (5) and (6). The results show banks rely more on the industry expertise channel in mortgage origination when the loan-to-income ratio is high. The coefficient estimate of *Same Industry* is even gone in column (6). Only the interaction term is positive and statistically significant, implying that out baseline results mainly hold in counties with high loan-to-income ratios.

4.3 Soft Information in Mortgages

To provide more evidence on the information mechanism, we test the soft information contained in mortgage contracts directly. To this end, we examine whether mortgages originated through the industry expertise channel are less standardized, i.e., larger dispersion in mortgage sizes. The key idea is that better information allows banks to better discriminate between "good" and "bad" borrowers (e.g., Cornell and Welch (1996), Rajan, Seru, and Vig (2015), Skrastins and Vig (2019)). As a result, banks can grant mortgages with favorable terms to "good" borrowers and mortgages with strict terms to "bad" borrowers. In contrast, if banks do not have much information in evaluating borrowers, they can only design mortgage terms based on the average quality of all mortgage borrowers and thus originate loans with similar terms.

[Insert Table **7** about here.]

We follow the literature and construct two variables reflecting the dispersion in mortgage sizes (Fisman, Paravisini, and Vig (2017), Lim and Nguyen (2020)). The two variables are the logarithm of the standard deviation and the logarithm of the interquartile range of the amount of mortgages a bank approves in a county. Empirical results using the two variables are presented in Table 7. Consistent with our conjecture, we find that mortgages originated through the channel have less standardized contractual terms. In particular, the standard deviation and interquartile range of mortgage sizes are 0.5% and 1.5% higher separately for mortgages originated through the industry expertise channel.

To sum up, analyses in this section show that banks rely more on the industry expertise channel when they have limited other channels to acquire information of mortgage borrowers or when local risk is high. In addition, mortgages originated through the channel contain more soft information. Combined together, the findings provide strong support to the information mechanism of the industry expertise channel. This explains why banks lends out more mortgages to counties sharing their industry specialization.

5 Addressing Endogeneity Issues

Our analyses so far have provided consistent and robust evidence that the industry expertise channel facilities banks' mortgage lending towards connected counties. The results are not likely driven by bank-level or county-level characteristics, or by household preference for borrowing from certain banks. However, our results can still be driven by either unobserved or observed but omitted variables. In addition, our results can also be biased due to reverse causalities. That is, banks may intentionally choose which industries to lend to in the corporate loan market according to their geographic expansions of mortgage lending. In this section, we try to address the endogeneity concerns.

We follow Murfin (2012) and use defaults in banks' corporate loan portfolios as exogenous shocks.[22] This bank-specific shock informs banks' perceptions of their own screening abilities in the corporate loan market, resulting in lower confidence in their expertise.[23] In response, banks write tighter loan contracts to new borrowers (Murfin (2012), Christensen et al. (2021), Gao, Kleiner, and Pacelli (2020), Giometti and Pietrosanti (2020)). Therefore, our test focuses on how a bank responds in using the industry expertise channel in mortgage lending when corporate borrowers in its specialized industries default. We expect that banks rely less on the industry expertise channel after experiencing the shock that hurts their confidence.

The following hypothetical case illustrates the design in detail. Suppose a bank i sees one of its corporate borrowers from industry k defaults, and the industry k is one of the industries that the bank specializes in. Compared to other banks having no such experience, this bank i is shocked. This shock can also spillover to other industries that the bank has expertise with confidence (Murfin (2012)). Put differently, the bank i has lower confidence in its expertise in

[22] We focus on payment defaults rather technical defaults because the literature has shown payment defaults have larger and more significant effects on lenders.

[23] Specifically, Murfin (2012) show that defaults on new loans have much larger impacts than defaults on legacy loans. They also show that deterioration in lenders' balance sheets and damage in lenders' reputation are not the mechanisms at work. Meanwhile, our results in Appendix E show that a bank relies more on the industry expertise channel when the level of its industry expertise is high.

any industry that it specializes in after the shock. Importantly, not all counties where the bank i has mortgage lending are impacted. Rather, only counties that share industry specialization with the bank i are impacted. As such, the impacts of reduced confidence should only exist in counties where the bank uses its industry expertise in mortgage lending. The empirical model is as follows.

$$Y_{ijt} = \mu_i + \pi_{jt} + \beta_1 * \textit{Corporate Default}_{\ ijt} + \delta X_{ijt} + \varepsilon_{ijt} \tag{4}$$

where i represents bank, j represents county, and t represents year, *Corporate Default* $_{ijkt}$ is a dummy that equals to one if there exists a default in any of the bank i's specialized industries and the bank i and the county j are connected through same industry specialization in year t.[24] All the controls and the fixed effects are defined in the same way as in equation (3).

[Insert Table 8 about here.]

To conduct the test, we extract firms' crediting status from the rating database in Compustat. Defaulting status is identified when a firm reports a credit rating of "D" (default) or "SD" (selective default). The regression results are reported in Table 8. It shows a negative and statistically significant effect of corporate defaults on banks' mortgage lending, implying that banks experiencing defaulting shocks in their specialized industries significantly cuts their mortgage lending. The economic magnitude is also significant. After experiencing defaulting shocks, banks' reliance on the channel reduces by 11.6%. Overall, results using borrower defaults in the syndicated loan market as exogenous shocks to banks' confidence in their industry expertise further corroborate our previous findings.

[24] Again, the default does not have to happen in the industry that the bank i and the county j both specialize in. So, we allow for the spillover effects. Nevertheless, our results are much stronger if we do not allow for the spillover effects and only consider defaults in the industry that the bank i and the county j both specialize in. In addition, we only use bank-county pairs that share same industry specialization but do not experience the shocks as the control group, as they are better counterparts to the treated group.

6 Implications for Mortgage Performance

We also study implications of the industry expertise channel for banks' mortgage performance. Results in Section 4 show that this channel does provide useful information for banks to screen eligible mortgage borrowers. Consequently, with reduced information asymmetries, we expect this channel to have a positive effect on banks' mortgage performance. In this regard, a given mortgage should be less likely to default if the industry expertise channel can improve banks' screening efficiencies.

However, the HMDA data does not contain loan-level information on mortgage performance after originations. Due to the data limitation, we test the implication for mortgage performance at the bank level. To this end, we first calculate the proportion of mortgages a bank originates in counties sharing their industry specialization as a proxy for the bank's reliance on the industry expertise channel. We calculate the proportion based on numbers of mortgages banks originate.[25] Then, we rank banks' use of the channel into five groups. Banks with higher ranks have more mortgages originated through the channel. Last, we regress a bank's return on real estate loans, measured as income on real estate loans scaled by total assets, on the rank. Our prediction is that, the more mortgages a bank originates through the channel, the higher return on real estate loans the bank gets.

[Insert Table **9** about here.]

We empirically test the above prediction in Table 9. To avoid biases due to a bank's concurrent decision in its use of the industry expertise channel and decision in affecting its mortgage performance, we examine effects of a bank's reliance on the channel this year on the bank's return on real estate loans next year. The results show that the channel has a positive effect and banks' real estate loan performance. A one unit increase in the rank leads to about 1% increase in a bank's return on real estate loans. The results hold when using changes in a bank's return

[25]Our results hold if we use dollar volumes of mortgages banks originate to calculate the proportion.

on real estate loans.

7 Discussions

In this section, we discuss some issues that are not mentioned before but are important for interpreting our results.

7.1 Excluding An Alternative Channel - Employees of Banks' Corporate Borrowers

An alternative story to the industry expertise channel is that a bank may prioritize lending mortgages to employees of its corporate borrowers. No doubt a bank knows the income streams of a mortgage borrower better if she is an employee of the bank's corporate borrower, as the bank has access to private information of the firm through corporate lending. Some firms may even have joint programs with their main banks to help employees get mortgages with better terms. Importantly, this channel does not work through a bank's industry expertise, though the expertise can help the bank better process the private information. Considering that banks may have corporate borrowers or borrowers' subsidiaries and establishments in connected counties, this alternative channel could be a reasonable explanation for our results.

The control of a bank's small business lending in a county in our regression analyses help exclude this alternative channel partially, assuming that small business loan amounts are positively correlated with small businesses' employment and thus the importance of this alternative channel. However, this does not capture employees of banks' borrowers in the syndicated loan market. To better address this concern, we conduct more tests in Table 10.

We first obtain historical headquarter states of each bank's syndicated loan borrowers from Compustat. Then, in each year, for each bank, we drop a state if the bank has a syndicated loan borrower located in the state, regardless of whether the borrower is in the bank's and the county's jointly specialized industry or not. The underlying assumption is that most of a firm's workers are employed in its headquarter state. The results are reported in the first three columns in Table 10. As can be seen, after applying the exclusion, the sample size is smaller. However, the significance of the channel remains. The magnitude is also comparable to that in Table 3.

Nevertheless, a cautious reader may worry that the assumption that most of a firm's workers are employed in its headquarter state may not be true, even though this is a commonly used assumption in the literature (e.g., Klasa et al. (2018)). To further address the concern, we obtain the geographic dispersion of a firm's business operations at the state level from Garcia and Norli (2012).[26] Then, in each year, for each bank, we drop a state if the bank has a syndicated loan borrower located in the state or the borrower has an establishment/subsidiary in the state. The results are reported in column (4) - (6) in Table 10. We still see a statistically significant and positive relation between a bank's reliance on the channel and its mortgage lending. Taken together, evidence in Table 10 help exclude the alternative story that banks allocate more mortgage credits to a county simply because they have corporate borrowers located in the county directly or indirectly.

[Insert Table **10** about here.]

7.2 Mortgage Securitization

One of the potential concerns in interpreting our results is that banks often securitize their mortgages to third parties, especially to GSEs (i.e., Fannie Mae and Freddie Mac)[27], which are the dominant players in the securitization market. The rules regulating GSEs' purchase of mortgages are well-written in official documents and well-known to banks. Therefore, if a bank simply originates mortgages following GSEs' purchasing policies with a purpose to sell

[26] Garcia and Norli (2012) construct the data using firms' 10K filings. Please refer to their paper for more details. The raw data is from 1994 to 2008. To keep our sample the same as before, we use firm's geographic dispersion in 2008 for the period 2009 - 2013. We thank the authors for making the data available.

[27] Note that non-conventional mortgages (FHA-insured mortgages, VA-guaranteed mortgages, FSA mortgages and RHS mortgages) are not included in our sample.

the mortgages to GSEs soon, there is no point in spending large efforts in acquiring information of borrowers. As such, the information channel we proposed should not matter much, as the default risk in sold mortgages is all born by GSEs, not by banks.[28]

However, banks are not naive players that purely rely on the originate-to-distribute (OTD) model in the mortgage market like shadow banks. Rather, banks hold a significant fraction of mortgages on balance sheets.[29] They choose what mortgages to originate and what mortgages to sell strategically (e.g., Jiang, Nelson, and Vytlacil (2014), Agarwal, Chang, and Yavas (2012), Xiao (2021)). As such, information from the industry expertise channel and other channels is still crucial to banks and matters for their mortgage lending.

The concern, however, does hold for certain mortgages that banks know for sure they are going to sell later, or for certain banks that are very active in selling mortgages. This predicts that our results should be stronger in mortgages that are retained on banks' balance sheets, or in banks that are not active in selling mortgages. We test the prediction at the bank level, as it's extremely hard to know which mortgages banks plan to sell. To this end, we follow Drechsler, Savov, and Schnabl (2021) and construct a deposit beta for each bank and then calculate a weighted average at the BHC level, using each bank's asset as the weight.[30] According to Drechsler, Savov, and Schnabl (2021), this beta reflects the sensitivity of banks' interest expenses to changes in market interest rates. The lower beta a bank has, the longer maturity the bank's liability has. Xiao (2021) further show that high-beta banks are much more aggressive in selling mortgages to third parties, due to their inability to take much interest rate risk. Therefore, we

[28]There exists a buyback risk if banks originate loans that do not meet GSEs' eligibility and underwriting guidelines or banks do not perform enough due diligence in the originating process.

[29]The average securitization ratio at the bank level from 1994 to 2017 is about 30% (Xiao (2021)).

[30]Specifically, the deposit beta is estimated in the following way:

$$\Delta Int\ Exp_{i,t} = \alpha_{i,t} + \Sigma_{\tau=0}^{3}\beta_{i,t,\tau}^{Exp}\Delta Fed\ Funds\ Rate_{t-\tau} + \varepsilon_{i,t}$$

where i represents bank, t represents quarter, $\Delta Int\ Exp_{i,t}$ is the change in bank $i's$ interest expense rate from t to $t+1$, and $\Delta Fed\ Funds\ Rate_t$ is the change in Fed funds rate from t to $t+1$. The interest expense rate is calculated as the total quarterly interest expenses divided by quarterly assets and then annualized. Three lags of the Fed funds rate are allowed to account for the response of interest expenses to current and past changes in Fed funds rate. The measure of the interest expense beta is the sum of the four coefficients of changes in Fed funds rate, i.e., $\beta_{i,t} = \sum_{\tau=0}^{3}\beta_{i,t,\tau}^{Exp}$. The beta is further averaged at the year level, as the mortgage data is at the year level.

expect low-beta banks to rely more on the channel.

We test the conjecture in Table 11. The coefficient estimate of *Same Industry* remains to be positive and statistically significant in all the five columns. However, the interaction term between *Same Industry* and a bank's deposit beta is negative and statistically significant. This suggests that the industry expertise channel is less important for banks with high deposit betas. In column (5), a one standard deviation increase in the beta leads to about a 54% drop in the importance of the channel. Overall, the findings are consistent with the conjecture that banks that are active in mortgage securitization rely less on the channel.

[Insert Table **11** about here.]

8 Conclusion

In this paper, we uncover a new channel that reduces the information asymmetry between banks and borrowers in the mortgage market - the *industry expertise channel*. Unlike other channels documented in the literature that rely on banks' branch expansions or social networks, this channel relies on the industry expertise banks develop in the corporate loan market. As such, this channel reveals a positive spillover from the corporate loan market to the mortgage market. We show that this channel improves banks' mortgage performance through enhanced screening and monitoring of borrowers.

Our empirical results provide strong supports for the industry expertise channel. We find that banks allocate more mortgage credits to counties sharing their industry specialization. Moreover, we show evidence supporting the information mechanism of the channel. Specifically, we find that banks rely more on the channel when they have higher information needs and mortgages originated through the channel contain more soft information. We also find that using the channel helps banks get higher income from residential real estate loans. Overall, our work demonstrates that the industry expertise banks gain in the corporate loan market have important implications for their credit allocation in the mortgage market.

References

Acharya, V. V., I. Hasan, and A. Saunders (2006). Should banks be diversified? evidence from individual bank loan portfolios. *Journal of Business 79*(3), 1355–1412.

Agarwal, S., Y. Chang, and A. Yavas (2012). Adverse selection in mortgage securitization. *Journal of Financial Economics 105*(3), 640–660.

Agarwal, S. and R. Hauswald (2010). Distance and private information in lending. *Review of Financial Studies 23*(7), 2757–2788.

Alessandrini, P., A. F. Presbitero, and A. Zazzaro (2009). Banks, distances and firms' financing constraints. *Review of Finance 13*(2), 261–307.

Bailey, M., R. Cao, T. Kuchler, J. Stroebel, and A. Wong (2018). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives 32*(3), 259–80.

Bailey, M., E. Dávila, T. Kuchler, and J. Stroebel (2019). House price beliefs and mortgage leverage choice. *Review of Economic Studies 86*(6), 2403–2452.

Beck, T., O. De Jonghe, and K. Mulier (2021). Bank sectoral concentration and risk: Evidence from a worldwide sample of banks. *Journal of Money Credit and Banking*.

Berger, P. G., M. Minnis, and A. Sutherland (2017). Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Journal of Accounting and Economics 64*(2-3), 253–277.

Blickle, K., C. Parlatore, and A. Saunders (2021). Specialization in banking. *FRB of New York Staff Report* (967).

Carey, M., M. Post, and S. A. Sharpe (1998). Does corporate lending by banks and finance companies differ? evidence on specialization in private debt contracting. *Journal of Finance 53*(3), 845–878.

Chakraborty, I., I. Goldstein, and A. MacKinlay (2018). Housing price booms and crowding-out effects in bank lending. *Review of Financial Studies 31*(7), 2806–2853.

Chava, S. and M. R. Roberts (2008). How does financing impact investment? the role of debt covenants. *Journal of Finance 63*(5), 2085–2121.

Chavaz, M. and A. K. Rose (2019). Political borders and bank lending in post-crisis america. *Review of Finance 23*(5), 935–959.

Christensen, H. B., D. Macciocchi, A. Morris, and V. V. Nikolaev (2021). Financial shocks to lenders and the composition of financial covenants. *Journal of Accounting and Economics*, 101426.

Chu, Y. and T. Zhang (2020). The political economy of mortgage lending. *Available at SSRN 3286398*.

Cornell, B. and I. Welch (1996). Culture, information, and screening discrimination. *Journal of Political Economy 104*(3), 542–571.

Cortés, K. R. and P. E. Strahan (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics 125*(1), 182–199.

Dagher, J. and K. Kazimov (2015). Banks liability structure and mortgage lending during the financial crisis. *Journal of Financial Economics 116*(3), 565–582.

De Franco, G., A. Edwards, and S. Liao (2021). Product market peers in lending. *Management Science 67*(3), 1876–1894.

DeFusco, A. A. and J. Mondragon (2020). No job, no money, no refi: Frictions to refinancing in a recession. *Journal of Finance*.

Degryse, H. and S. Ongena (2005). Distance, lending relationships, and competition. *Journal of Finance 60*(1), 231–266.

Di, W. and N. Pattison (2020). Distant lending, specialization, and access to credit. *Federal Reserve Bank of Dallas Working Paper*.

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on deposits: Maturity transformation without interest rate risk. *Journal of Finance 76*(3), 1091–1143.

Ergungor, O. E. (2010). Bank branch presence and access to credit in low-to moderate-income neighborhoods. *Journal of Money, Credit and Banking 42*(7), 1321–1349.

Fisman, R., D. Paravisini, and V. Vig (2017). Cultural proximity and loan outcomes. *American Economic Review 107*(2), 457–92.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery (2019). The role of technology in mortgage lending. *Review of Financial Studies 32*(5), 1854–1899.

Gao, J., K. Kleiner, and J. Pacelli (2020). Credit and punishment: Are corporate bankers disciplined for risk-taking? *Review of Financial Studies 33*(12), 5706–5749.

Garcia, D. and Ø. Norli (2012). Geographic dispersion and stock returns. *Journal of Financial Economics 106*(3), 547–565.

Garmaise, M. J. (2015). Borrower misreporting and loan performance. *Journal of Finance 70*(1), 449–484.

Gerardi, K., K. F. Herkenhoff, L. E. Ohanian, and P. S. Willen (2018). Can't pay or won't pay? unemployment, negative equity, and strategic default. *Review of Financial Studies 31*(3), 1098–1131.

Giannetti, M. and F. Saidi (2019). Shock propagation and banking structure. *Review of Financial Studies 32*(7), 2499–2540.

Giannetti, M. and Y. Yafeh (2012). Do cultural differences between contracting parties matter? evidence from syndicated bank loans. *Management Science 58*(2), 365–383.

Giometti, M. and S. Pietrosanti (2020). Bank specialization and the design of loan contracts. *Unpublished working paper*.

Gomez, M., A. Landier, D. Sraer, and D. Thesmar (2020). Banks' exposure to interest rate risk and the transmission of monetary policy. *Journal of Monetary Economics*.

Gopal, M. (2019). How collateral affects small business lending: The role of lender specialization. *Unpublished working paper*.

Griffin, J. M. and G. Maturana (2016). Who facilitated misreporting in securitized loans? *Review of Financial Studies 29*(2), 384–419.

Hollander, S. and A. Verriest (2016). Bridging the gap: the design of bank loan contracts and distance. *Journal of Financial Economics 119*(2), 399–419.

Irani, R. M., R. Iyer, R. R. Meisenzahl, and J.-L. Peydro (2021). The rise of shadow banking: Evidence from capital regulation. *Review of Financial Studies 34*(5), 2181–2235.

Jiang, W., A. A. Nelson, and E. Vytlacil (2014). Securitization and loan performance: Ex ante and ex post relations in the mortgage market. *Review of Financial Studies 27*(2), 454–483.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig (2010). Did securitization lead to lax screening? evidence from subprime loans. *Quarterly Journal of Economics 125*(1), 307–362.

Klasa, S., H. Ortiz-Molina, M. Serfling, and S. Srinivasan (2018). Protection of trade secrets and capital structure decisions. *Journal of Financial Economics 128*(2), 266–286.

Kuchler, T., Y. Li, L. Peng, J. Stroebel, and D. Zhou (2021). Social proximity to capital: Implications for investors and firms. *Review of Financial Studies, forthcoming*.

Levine, R., C. Lin, Q. Peng, and W. Xie (2020). Communication within banking organizations and small business lending. *Review of Financial Studies 33*(12), 5750–5783.

Liberti, J., J. Sturgess, and A. Sutherland (2020). Information sharing and lender specialization: Evidence from the us commercial lending market. *Available at SSRN 3579149*.

Lim, I. and D. D. Nguyen (2020). Hometown lending. *Journal of Financial and Quantitative Analysis*, 1–65.

Loutskina, E. and P. E. Strahan (2011). Informed and uninformed investment in housing: The downside of diversification. *Review of Financial Studies 24*(5), 1447–1480.

Mian, A. and A. Sufi (2009). The consequences of mortgage credit expansion: Evidence from the us mortgage default crisis. *Quarterly Journal of Economics 124*(4), 1449–1496.

Mian, A. and A. Sufi (2017). Fraudulent income overstatement on mortgage applications during the credit expansion of 2002 to 2005. *Review of Financial Studies 30*(6), 1832–1864.

Murfin, J. (2012). The supply-side determinants of loan contract strictness. *Journal of Finance 67*(5), 1565–1601.

Nguyen, H.-L. Q. (2019). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics 11*(1), 1–32.

Paravisini, D., V. Rappoport, and P. Schnabl (2020). Specialization in bank lending: Evidence from exporting firms. *National Bureau of Economic Research Working Paper No. 21800*.

Rajan, U., A. Seru, and V. Vig (2015). The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics 115*(2), 237–260.

Rehbein, O. and S. Rother (2020). Distance in bank lending: The role of social networks. *Unpublished working paper.*.

Saidi, F. and D. Streitz (2021). Bank concentration and product market competition. *Review of Financial Studies*.

Schwert, M. (2018). Bank capital and lending relationships. *Journal of Finance 73*(2), 787–830.

Skrastins, J. and V. Vig (2019). How organizational hierarchy affects information production. *Review of Financial Studies 32*(2), 564–604.

Xiao, Z. (2021). Interest rate risk, prepayment risk and banks' securitization of mortgages. *Available at SSRN 3761540*.

Variable Definitions

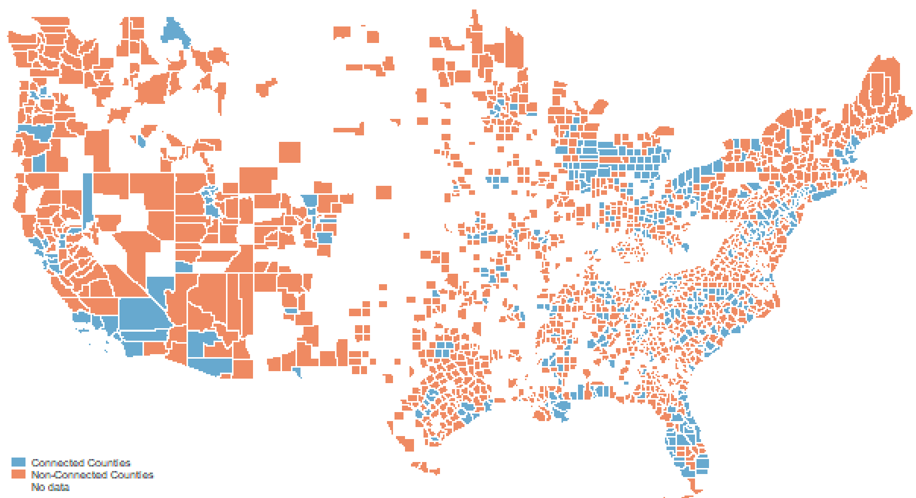
Variables	Description
Dependent Variables	
GDP Growth	A county's GDP growth rate (%).
Income Growth	A county's household income growth rate (%).
Change in Delinquency Rate	Annual change in a county's 1-4 family residential mortgage delinquency rate.
Log(No. Approved Mortgages)	The logarithm of the number of mortgages a bank approves in a county.
Mortgage Approval Rate	The number of mortgages a bank approves in a county scaled by the number of mortgage applications a bank receives in a county.
Log(STD. Mortgage Size)	The logarithm of the standard deviation of the amount of mortgages a bank approves in a county.
Log(IQ. Mortgage Size)	The logarithm of the interquartile range of the amount of mortgages a bank approves in a county.
ROA- RE Loans	A banks' real estate loan income scaled by assets.
Key Independent Variables	
Sales Growth	The weighted average of sales growth of all U.S. public firms in the top-three industries in a county, with the number of people working in each industry as the weight.
Same Industry	A dummy indicating there exists at least one industry that a bank and a county both specialize in.
Rank of Specialized Lending	The rank of the proportion of mortgages a bank originates in counties sharing its industry specialization.
Corporate Default	A dummy indicating there exists a default in any of a bank's specialized industries and the bank and the county are connected through same industry specialization.
Control Variables	
Loan-to-Income Ratio	The average of mortgage applicants' loan to income ratio in a county.
Prop. Male	The proportion of the population that are male in a county (Table 2 only). The proportion of mortgage applicants that are male in a county.
Prop. Minority	The proportion of the population that are minorities in a county (Table 2 only). The proportion of mortgage applicants that are minorities in a county.
Depository Branches	The log of one plus the number of branches a bank has in a county.
Distance	The logarithm of one plus the geographic distance between a mortgage borrower's home county and a bank's headquarter county.
Log(No. SBL)	The logarithm of one plus the number of small business loans a bank lends out in a county.
Mortgage Exposure	The average proportion of mortgages a bank retains in a county in the past three year.
Log(Population)	The logarithm of the total population in a county.
Prop. Age>60	The proportion of the population with age above 65 in a county.
Log(Assets)	The logarithm of bank assets.
Total Loans/Assets	Total loans scaled by assets.
C&I Loans/Total Loans	Commercial & industrial loans scaled by total loans.
RE Loans/Total Loans	Real estate loans scaled by total loans.
ROA	Total income scaled by assets.
Total 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.
Deposit Beta	The standardized sensitivity of changes in a banks' interest expense rate to changes in Fed funds rate.

Figures

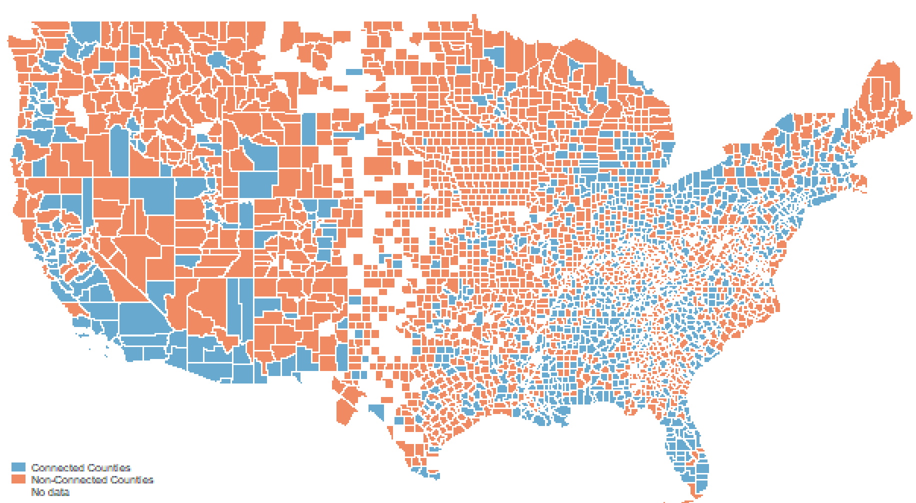
Figure 1. Distributions of Counties Connected with Banks through Same Industry Specialization

This figure presents the distribution of counties that have connections with at least one bank through same industry specialization in our sample in the year 1995, 2001, 2007 and 2013 separately.

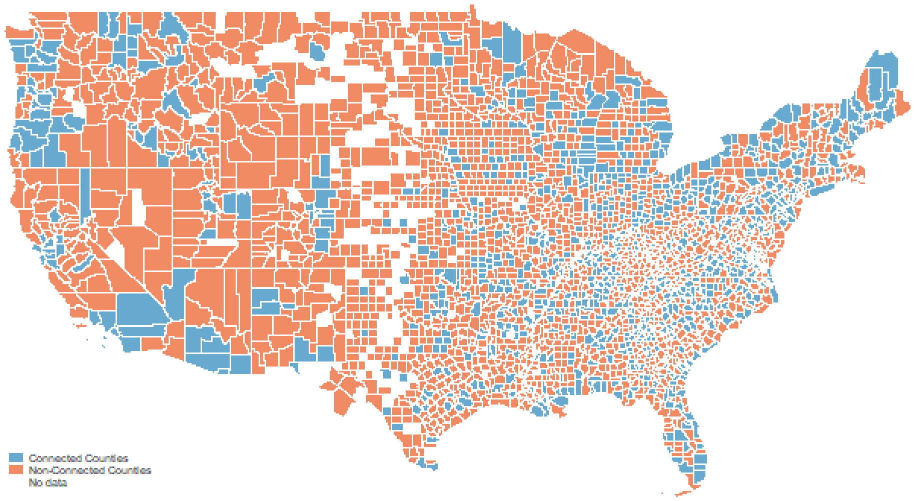
(A) Year 1995



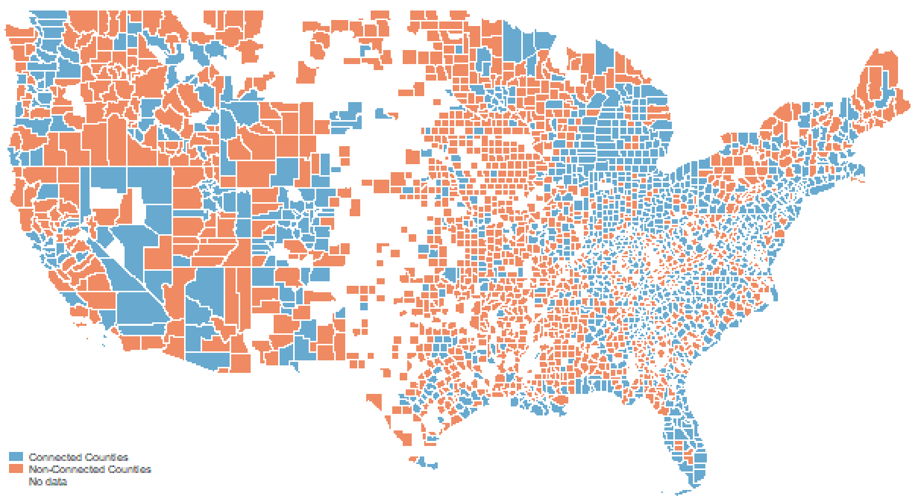
(B) Year 2001



(C) Year 2007



(D) Year 2013



Tables

Table 1. Summary Statistics

This table presents summary statistics of variables used in empirical analyses. Panel A presents the statistics at the county level, Panel B presents the statistics at the bank level, and Panel C presents the statistics at the bank-county level. The sample period is from 1995 to 2013.

	N	Mean	SD	P25	P50	P75
Panel A: County Level						
Sales Growth	57,513	4.201	4.485	1.781	3.382	5.707
Income Growth	57,512	3.678	4.395	1.656	3.700	5.645
GDP Growth	39,774	-0.911	41.796	-2.477	1.507	5.374
Housing Price Growth	46,650	2.611	5.207	-0.390	2.640	5.350
Change in Delinquency Rate	4,700	-0.222	1.010	-0.767	-0.358	0.067
Population	57,513	10.289	1.369	9.360	10.157	11.085
Prop. Age > 65	57,513	0.108	0.032	0.087	0.105	0.126
Prop. Male	57,513	0.497	0.018	0.487	0.494	0.502
Prop. Minority	57,417	0.123	0.156	0.019	0.053	0.165
Panel B: Bank Level						
Log(Assets)	705	10.403	1.473	9.270	10.256	11.358
Total Loans/Assets	705	0.621	0.137	0.565	0.657	0.713
Deposits/Assets	705	0.720	0.091	0.658	0.718	0.789
C&I Loans/Total Loans	705	0.264	0.118	0.186	0.240	0.328
RE Loans/Total Loans	705	0.502	0.166	0.407	0.502	0.625
Total Liquidity/Assets	705	0.236	0.110	0.159	0.212	0.287
Rank of Specialized Lending	705	2.809	1.636	1.000	3.000	4.000
Deposit Beta	700	0.000	1.000	-0.595	0.019	0.657
ROA	705	0.010	0.008	0.009	0.011	0.014
ROA_RE Loans	705	0.021	0.010	0.015	0.021	0.027
Panel C: Bank-county Level						
Same Industry	321,067	0.103	0.304	0	0	0
Log(No. Approved Mortgages)	321,067	3.260	1.524	2.079	2.996	4.277
Mortgage Approval Rate	321,067	0.748	0.172	0.636	0.778	0.875
Loan-to-Income Ratio	320,794	1.939	0.539	1.567	1.899	2.264
Distance	321,067	6.256	0.962	5.634	6.337	6.969
Log(No. SBL)	321,067	2.024	2.086	0.000	1.609	3.664
Mortgage Exposure	253,572	0.398	0.265	0.193	0.357	0.566
Depository Branches	321,067	0.352	0.712	0.000	0.000	0.000
Social Network	320,823	8.142	1.321	7.211	7.922	8.758
Prop. Residents	321,067	0	1.000	-0.330	-0.330	-0.330
Log(STD. Mortgage Size)	320,418	4.156	0.656	3.735	4.146	4.560
Log(IQ. Mortgage Size)	320,380	4.227	0.652	3.829	4.248	4.644

Table 2. Growth of the Top-three Industries and County Economic Development

This table presents the relation between sales growth of the top-three industries in a county and the county's economic development. The dependent variable is a county's GDP growth in column (1)-(3), a county's household income growth in column (4) -(6), and annual change in a county's mortgage delinquency rate in column (7) - (9). The key dependent variable is sales growth, which is the weighted average of sales growth of all U.S. public firms in a country's top-three industries, with the number of people working in each industry as the weight. Controls include the the logarithm of the population, the proportion of the population that are above 65, the proportion of the population that are male, and the proportion of the population that are minorities. The sample that examines GDP growth covers the period from 2001 to 2013, the sample that examines income growth covers the period from 1995 to 2013, and the sample that examines mortgage delinquency rate covers the period from 2008 to 2020. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GDP Growth			Income Growth			Change in Mortgage Delinquency		
Sales Growth	0.809***	1.230***	1.056***	0.203***	0.068***	0.072***	-0.463***	-0.024**	-0.027**
	(0.061)	(0.090)	(0.088)	(0.006)	(0.008)	(0.008)	(0.013)	(0.011)	(0.011)
Population			-107.071***			-5.768***			1.809***
			(12.404)			(0.307)			(0.368)
Prop. Old			288.820***			-6.168**			-8.205**
			(72.044)			(2.755)			(3.648)
Prop. Male			736.911***			1.483			62.461***
			(107.084)			(3.601)			(10.210)
Prop. Minority			-612.964***			-2.641*			0.473
			(94.733)			(1.577)			(1.705)
Observations	39,774	39,769	39,769	57,512	57,507	57,411	4,700	4,700	4,700
R-squared	0.004	0.114	0.134	0.046	0.235	0.244	0.327	0.727	0.734
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Table 3. The Industry Expertise Channel and Mortgage Lending

This table presents impacts of the industry expertise channel on banks' allocation of mortgage credits across counties. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originates in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(No. Approved Mortgages)				
Same Industry	0.185***	0.102***	0.087***	0.053***	0.028***
	(0.012)	(0.010)	(0.008)	(0.008)	(0.007)
Loan-to-Income Ratio			-0.027***	-0.035***	0.011
			(0.009)	(0.009)	(0.008)
Prop. Male			0.037*	0.061***	0.068***
			(0.022)	(0.022)	(0.019)
Prop. Minority			0.545***	0.503***	0.385***
			(0.049)	(0.048)	(0.038)
Depository Branches			0.627***	0.616***	0.521***
			(0.011)	(0.011)	(0.011)
Distance			-0.215***	-0.222***	-0.189***
			(0.007)	(0.008)	(0.016)
Log(No. SBL)			0.181***	0.190***	0.126***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.018	0.028*	0.057***
			(0.017)	(0.016)	(0.015)
Log(Assets)				0.182***	0.366***
				(0.015)	(0.016)
Total Loans/Assets				0.171**	0.224***
				(0.083)	(0.082)
Deposits/Assets				-0.960***	-0.801***
				(0.056)	(0.055)
C&I Loans/Total Loans				2.041***	2.136***
				(0.092)	(0.088)
RE Loans/Total Loans				2.125***	2.331***
				(0.068)	(0.065)
ROA				-4.013***	-3.602***
				(0.402)	(0.373)
Total Liquidity/Assets				-2.315***	-2.327***
				(0.085)	(0.085)
Observations	321,067	314,508	245,786	245,250	245,117
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.001	0.433	0.688	0.696	0.770

Table 4. The Industry Expertise Channel and Mortgage Approval Rate

This table presents impacts of the industry expertise channel on banks' mortgage approval rates across counties. The dependent variable is the mortgage approval rate based on the number of mortgage applications and the number of approved mortgages. The key independent variable is *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Mortgage Approval Rate				
Same Industry	0.037***	0.004***	0.006***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Loan-to-Income Ratio			0.013***	0.011***	0.005***
			(0.001)	(0.001)	(0.001)
Prop. Male			0.129***	0.125***	0.105***
			(0.003)	(0.003)	(0.003)
Prop. Minority			-0.207***	-0.205***	-0.182***
			(0.006)	(0.006)	(0.006)
Depository Branches			0.009***	0.010***	0.009***
			(0.001)	(0.001)	(0.001)
Distance			-0.008***	-0.008***	-0.013***
			(0.001)	(0.001)	(0.001)
Log(No. SBL)			0.005***	0.003***	0.000
			(0.000)	(0.000)	(0.000)
Mortgage Exposure			-0.118***	-0.112***	-0.097***
			(0.002)	(0.002)	(0.002)
Log(Assets)				-0.001	0.005***
				(0.002)	(0.002)
Total Loans/Assets				-0.122***	-0.148***
				(0.012)	(0.012)
Deposits/Assets				-0.115***	-0.111***
				(0.008)	(0.008)
C&I Loans/Total Loans				-0.219***	-0.259***
				(0.014)	(0.014)
RE Loans/Total Loans				0.156***	0.190***
				(0.010)	(0.010)
ROA				0.072	0.023
				(0.068)	(0.063)
Total Liquidity/Assets				0.034***	0.012
				(0.012)	(0.011)
Observations	321,067	314,508	245,786	245,250	245,117
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.004	0.322	0.387	0.393	0.452

Table 5. Information Asymmetry and Banks' Reliance on the Industry Expertise Channel

This table presents impacts of information asymmetries between banks and mortgage borrowers on banks' reliance on the industry expertise channel. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is the interaction between *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in, and *VAR*. *VAR* is the logarithm of one plus the number of branches a bank has in a county in column (1) and (2), and is the logarithm of county-to-county Social Connectedness Index between a bank's headquarter county and a borrower's home county in column (3) and (4). Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	Log(No. Approved Mortgages)			
	Depository Branch		Social Network	
Same Industry	0.067***	0.044***	0.318***	0.278***
	(0.009)	(0.008)	(0.052)	(0.046)
VAR	0.620***	0.526***	0.293***	0.237***
	(0.011)	(0.011)	(0.009)	(0.013)
Same Industry*VAR	-0.028***	-0.032***	-0.033***	-0.030***
	(0.009)	(0.008)	(0.006)	(0.005)
Loan-to-Income Ratio	-0.035***	0.011	-0.022***	0.015**
	(0.009)	(0.008)	(0.009)	(0.008)
Prop. Male	0.061***	0.068***	0.057***	0.061***
	(0.022)	(0.019)	(0.021)	(0.019)
Prop. Minority	0.502***	0.385***	0.486***	0.379***
	(0.048)	(0.038)	(0.047)	(0.038)
Depository Branches	-	-	0.629***	0.529***
	-	-	(0.010)	(0.010)
Distance	-0.222***	-0.189***	0.100***	0.072***
	(0.008)	(0.016)	(0.012)	(0.021)
Log(No. SBL)	0.190***	0.126***	0.168***	0.123***
	(0.003)	(0.003)	(0.003)	(0.003)
Mortgage Exposure	0.027*	0.056***	0.021	0.059***
	(0.016)	(0.015)	(0.016)	(0.015)
Log(Assets)	0.183***	0.367***	0.188***	0.338***
	(0.015)	(0.016)	(0.016)	(0.016)
Total Loans/Assets	0.178**	0.231***	0.166**	0.191**
	(0.083)	(0.082)	(0.083)	(0.081)
Deposits/Assets	-0.959***	-0.798***	-1.005***	-0.816***
	(0.056)	(0.055)	(0.056)	(0.055)
C&I Loans/Total Loans	2.041***	2.138***	2.052***	2.105***
	(0.092)	(0.088)	(0.091)	(0.088)
RE Loans/Total Loans	2.124***	2.330***	2.203***	2.372***
	(0.068)	(0.065)	(0.068)	(0.065)
ROA	-4.002***	-3.588***	-3.856***	-3.775***
	(0.402)	(0.373)	(0.396)	(0.373)
Total Liquidity/Assets	-2.308***	-2.322***	-2.230***	-2.242***
	(0.085)	(0.085)	(0.085)	(0.085)
Observations	245,250	245,117	245,118	244,986
County*Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No
Bank*State FE	No	Yes	No	Yes
Adjusted R-squared	0.696	0.770	0.706	0.772

Table 6. Local Risk and Banks' Reliance on the Industry Expertise Channel

This table presents impacts of local risk on banks' reliance on the industry expertise channel. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is the interaction between *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in, and *VAR*. *VAR* is the standardized sales growth of all U.S. public firms in the top-three leading industries in a county in column (1) and (2), the standardized housing price growth rate in column (3) and (4), and the standardized loan-to-income ratio in column (5) and (6). Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(No. Approved Mortgages)					
	Industry Growth		Housing Price Growth		Loan to Income Ratio	
Same Industry	0.049***	0.025***	0.044***	0.023***	0.026***	0.008
	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)	(0.008)
Same Industry*VAR	-0.028***	-0.020***	-0.035***	-0.017***	0.081***	0.059***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.009)	(0.007)
Loan-to-Income Ratio	-0.039***	0.008	-0.032***	0.014*	-0.033***	0.013*
	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
Prop. Male	0.060***	0.066***	0.064***	0.068***	0.061***	0.068***
	(0.022)	(0.019)	(0.022)	(0.019)	(0.022)	(0.019)
Prop. Minority	0.504***	0.385***	0.504***	0.391***	0.502***	0.385***
	(0.049)	(0.039)	(0.049)	(0.039)	(0.048)	(0.038)
Depository Branches	0.620***	0.527***	0.615***	0.520***	0.615***	0.520***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Distance	-0.220***	-0.183***	-0.224***	-0.189***	-0.222***	-0.189***
	(0.008)	(0.017)	(0.008)	(0.017)	(0.008)	(0.016)
Log(No. SBL)	0.188***	0.125***	0.190***	0.126***	0.191***	0.127***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mortgage Exposure	0.024	0.053***	0.018	0.046***	0.026	0.057***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.016)	(0.015)
Log(Assets)	0.174***	0.357***	0.182***	0.368***	0.178***	0.362***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
Total Loans/Assets	0.122	0.172**	0.210**	0.251***	0.177**	0.229***
	(0.084)	(0.084)	(0.083)	(0.083)	(0.083)	(0.082)
Deposits/Assets	-0.997***	-0.835***	-0.977***	-0.812***	-0.964***	-0.805***
	(0.057)	(0.056)	(0.057)	(0.055)	(0.056)	(0.055)
C&I Loans/Total Loans	2.030***	2.124***	2.020***	2.144***	2.010***	2.115***
	(0.093)	(0.089)	(0.093)	(0.089)	(0.092)	(0.088)
RE Loans/Total Loans	2.181***	2.382***	2.168***	2.375***	2.143***	2.342***
	(0.069)	(0.067)	(0.068)	(0.066)	(0.068)	(0.065)
ROA	-3.839***	-3.476***	-4.125***	-3.666***	-4.122***	-3.684***
	(0.404)	(0.374)	(0.404)	(0.375)	(0.402)	(0.373)
Total Liquidity/Assets	-2.359***	-2.377***	-2.284***	-2.308***	-2.275***	-2.300***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.085)	(0.086)
Observations	239,425	239,297	240,778	240,647	245,250	245,117
County*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	No	Yes	No
Bank*State FE	No	Yes	No	Yes	No	Yes
Adjusted R-squared	0.697	0.771	0.694	0.769	0.696	0.770

Table 7. Dispersion in Mortgage Size

This table presets evidence on soft information contained in mortgages originated through the industry expertise channel. The dependent variables measure the dispersion in mortgage sizes, which are the logarithm of the standard deviation and the logarithm of the interquartile range of the amounts of mortgages a bank approves in a county and a year. The key independent variable is *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	Log(STD. Mortgage Size)		Log(IQ. Mortgage Size)	
Same Industry	0.144***	0.005*	0.146***	0.015***
	(0.005)	(0.003)	(0.004)	(0.003)
Loan-to-Income Ratio		0.140***		0.115***
		(0.004)		(0.004)
Prop. Male		0.257***		0.309***
		(0.009)		(0.011)
Prop. Minority		-0.258***		-0.335***
		(0.015)		(0.019)
Depository Branches		0.013***		-0.019***
		(0.002)		(0.002)
Distance		-0.029***		-0.024***
		(0.004)		(0.004)
Log(No. SBL)		0.026***		0.019***
		(0.001)		(0.001)
Mortgage Exposure		-0.090***		-0.103***
		(0.006)		(0.006)
Log(Assets)		0.006		0.005
		(0.005)		(0.005)
Total Loans/Assets		0.260***		0.083**
		(0.033)		(0.036)
Deposits/Assets		-0.168***		-0.186***
		(0.024)		(0.025)
C&I Loans/Total Loans		0.110***		0.181***
		(0.038)		(0.041)
RE Loans/Total Loans		0.385***		0.313***
		(0.028)		(0.030)
ROA		-0.862***		-0.398**
		(0.178)		(0.193)
Total Liquidity/Assets		0.169***		0.273***
		(0.036)		(0.040)
Observations	320,418	244,859	320,380	244,841
County*Year FE	No	Yes	No	Yes
Bank FE	No	No	No	No
Bank*State FE	No	Yes	No	Yes
Adjusted R-squared	0.00447	0.659	0.00466	0.595

Table 8. Defaulting Shocks and Banks' Reliance on the Industry Expertise Channel

This table presents impacts of banks' defaulting experience in corporate loans on their reliance on the industry expertise channel. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is *Corporate Default*, a dummy indicating that a bank has one of its syndicated loan borrowers defaulting in any of its specialized industries, and the bank and the county share same industry specializations. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
	Log(No. Approved Mortgages)		
Corporate Default	-0.201***	-0.400***	-0.123*
	(0.070)	(0.079)	(0.069)
Loan-to-Income Ratio	-0.149***	-0.120***	-0.028
	(0.036)	(0.036)	(0.031)
Prop. Male	0.063	0.049	0.107
	(0.103)	(0.100)	(0.088)
Prop. Minority	0.250	0.279	0.352**
	(0.176)	(0.177)	(0.149)
Depository Branches	0.514***	0.477***	0.437***
	(0.024)	(0.025)	(0.023)
Distance	-0.163***	-0.150***	-0.373***
	(0.025)	(0.025)	(0.052)
Log(No. SBL)	0.177***	0.212***	0.117***
	(0.009)	(0.010)	(0.010)
Mortgage Exposure	-0.076	-0.089	0.003
	(0.079)	(0.081)	(0.081)
Log(Assets)		0.491***	0.706***
		(0.109)	(0.112)
Total Loans/Assets		-0.059	0.528
		(0.744)	(0.793)
Deposits/Assets		2.886***	3.197***
		(0.458)	(0.422)
C&I Loans/Total Loans		-1.626**	1.537*
		(0.779)	(0.921)
RE Loans/Total Loans		3.581***	4.326***
		(0.624)	(0.615)
ROA		-3.911	-2.280
		(2.621)	(2.204)
Total Liquidity/Assets		-1.712**	-3.047***
		(0.752)	(0.739)
Observations	14,086	14,037	13,837
County*Year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	No
Bank*State FE	No	No	Yes
Adjusted R-squared	0.721	0.730	0.828

Table 9. Mortgage Performance

This table presents impacts of the industry expertise channel on banks' mortgage performance. The dependent variable is a bank's return on residential real estate loans in column (1) - (2) and is the annual change in a bank's return on residential real estate loans in column (3) - (4). The independent variable is the rank of the proportion of mortgages a bank originates in counties sharing their industry specialization. This proportion is calculated based on numbers of mortgages. We rank banks into five groups. Banks with higher ranks have more mortgages originated through the channel. Controls include the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, C&I loans scaled by total loans, real estate loans scaled by total loans, total liquidity scaled by assets. The sample period is from 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at the bank level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	ROA - RE Loans		ΔROA - RE Loans	
Rank of Specialized Lending	0.0006***	0.0002**	0.0003**	0.0002*
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Log(Assets)	-0.0047***	0.0007	-0.0002	0.0012**
	(0.0007)	(0.0007)	(0.0002)	(0.0005)
Total Loans/Assets	0.0239***	0.0187***	-0.0036	-0.0064*
	(0.0064)	(0.0056)	(0.0041)	(0.0037)
Deposits/Assets	-0.0190***	-0.0000	-0.0003	-0.0039
	(0.0040)	(0.0034)	(0.0027)	(0.0035)
RE Loans/Total Loans	0.0305***	0.0401***	-0.0002	0.0022
	(0.0046)	(0.0033)	(0.0026)	(0.0031)
C&I Loans/Total Loans	-0.0009	-0.0003	-0.0015	0.0033
	(0.0053)	(0.0038)	(0.0029)	(0.0033)
Total Liquidity/Assets	-0.0065	0.0023	0.0029	-0.0028
	(0.0063)	(0.0053)	(0.0037)	(0.0034)
Observations	651	651	651	651
Bank FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Adjusted R-squared	0.850	0.935	0.034	0.389

Table 10. Excluding An Alternative Channel - Employees of Banks' Corporate Borrowers

This table presents results excluding an alternative channel. The sample in column (1)-(3) drops a bank's mortgages in a state if the bank has a syndicated loan borrower located in the state. The sample in column (4)-(6) drops a bank's mortgages in a state if the bank has a syndicated loan borrower located in the state or the borrower has an establishment/subsidiary in the state. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originates in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(No. Approved Mortgages)					
	Exclude Headquarter State			Exclude Operating States from 10K		
Same Industry	0.081***	0.042***	0.038***	0.111***	0.089***	0.080***
	(0.009)	(0.009)	(0.008)	(0.013)	(0.013)	(0.012)
Loan-to-Income Ratio	-0.000	-0.010	0.030***	-0.011	-0.008	0.003
	(0.009)	(0.009)	(0.008)	(0.010)	(0.010)	(0.009)
Prop. Male	0.047**	0.076***	0.073***	0.095***	0.124***	0.141***
	(0.023)	(0.023)	(0.020)	(0.031)	(0.030)	(0.026)
Prop. Minority	0.570***	0.530***	0.426***	0.355***	0.318***	0.206***
	(0.051)	(0.050)	(0.040)	(0.054)	(0.054)	(0.047)
Depository Branches	0.635***	0.626***	0.528***	0.598***	0.590***	0.486***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Distance	-0.231***	-0.239***	-0.160***	-0.202***	-0.200***	-0.215***
	(0.007)	(0.008)	(0.020)	(0.008)	(0.009)	(0.022)
Log(No. SBL)	0.178***	0.186***	0.126***	0.248***	0.258***	0.185***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mortgage Exposure	0.039**	0.034*	0.046***	0.061***	0.042*	0.154***
	(0.019)	(0.018)	(0.017)	(0.023)	(0.023)	(0.023)
Log(Assets)		0.217***	0.390***		0.136***	0.424***
		(0.019)	(0.019)		(0.022)	(0.023)
Total Loans/Assets		0.187**	0.193**		-2.144***	-1.948***
		(0.091)	(0.090)		(0.146)	(0.134)
Deposits/Assets		-1.121***	-0.805***		-1.371***	-1.022***
		(0.065)	(0.064)		(0.100)	(0.101)
C&I Loans/Total Loans		2.371***	2.212***		1.448***	1.021***
		(0.112)	(0.103)		(0.152)	(0.151)
RE Loans/Total Loans		2.304***	2.416***		1.974***	1.924***
		(0.077)	(0.076)		(0.106)	(0.103)
ROA		-4.326***	-4.403***		-5.763***	-5.802***
		(0.452)	(0.419)		(0.468)	(0.445)
Total Liquidity/Assets		-2.404***	-2.455***		-3.547***	-3.617***
		(0.098)	(0.093)		(0.142)	(0.139)
Observations	203,336	202,998	202,865	118,872	118,629	118,496
County*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	Yes	Yes	No
Bank*State FE	No	No	Yes	No	No	Yes
Adjusted R-squared	0.674	0.683	0.763	0.680	0.686	0.770

Table 11. Mortgage Securitization and Banks' Reliance on the Industry Expertise Channel

This table presents impacts of a bank's deposit beta on its reliance on the industry expertise channel. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is the interaction between *Same Industry* and a bank's deposit beta. The beta is standardized. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(No. Approved Mortgages)				
Same Industry	0.186***	0.103***	0.079***	0.052***	0.028***
	(0.012)	(0.010)	(0.008)	(0.008)	(0.007)
Deposit Beta	-0.012***	0.010***	0.062***	-0.002	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Same Industry*Deposit Beta	-0.136***	-0.081***	-0.085***	-0.060***	-0.015**
	(0.011)	(0.009)	(0.008)	(0.008)	(0.007)
Loan-to-Income Ratio			-0.024***	-0.035***	0.011
			(0.009)	(0.009)	(0.008)
Prop. Male			0.050**	0.059***	0.067***
			(0.022)	(0.022)	(0.019)
Prop. Minority			0.538***	0.504***	0.386***
			(0.049)	(0.048)	(0.038)
Depository Branches			0.623***	0.615***	0.521***
			(0.011)	(0.011)	(0.011)
Distance			-0.216***	-0.222***	-0.189***
			(0.007)	(0.008)	(0.016)
Log(No. SBL)			0.185***	0.191***	0.127***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.022	0.024	0.056***
			(0.017)	(0.016)	(0.015)
Log(Assets)				0.170***	0.363***
				(0.016)	(0.016)
Total Loans/Assets				0.127	0.206**
				(0.083)	(0.082)
Deposits/Assets				-1.009***	-0.817***
				(0.058)	(0.056)
C&I Loans/Total Loans				2.016***	2.135***
				(0.092)	(0.089)
RE Loans/Total Loans				2.179***	2.351***
				(0.069)	(0.066)
ROA				-4.087***	-3.618***
				(0.404)	(0.374)
Total Liquidity/Assets				-2.364***	-2.350***
				(0.088)	(0.087)
Observations	319,385	312,819	245,197	245,197	245,066
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.002	0.434	0.689	0.696	0.770

Internet Appendix to

"The Industry Expertise Channel of Mortgage Lending "

Zhanbing Xiao, Yuxiang Zheng

Dec 2021

Appendix A The Industry Expertise Channel and Mortgage Lending - A Weighted Measure of Lending Specialization

This table presents impacts of the industry expertise channel on banks' allocation of mortgage credits across counties. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable is *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in. When calculating a bank's lending specialization, we first classify all firms in an industry into 10 groups based on total assets, with group 10 indicating firms with largest assets. We then use the rank as a weight to calculate a bank's total lending to a given industry. The specific formula for the construction of lending specialization is as follows: $L^b_{i,t} = \frac{\sum_{j=1}^{K} Loan^b_{i,j,t} * Rank_{i,j,t}}{\sum_{i=1}^{I}\sum_{j=1}^{K} Loan^b_{i,j,t} * Rank_{i,j,t}}$, where b represents a bank, i represents an industry, j represents a firm in industry i. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(No. Approved Mortgages)				
Same Industry	0.208***	0.066***	0.087***	0.063***	0.031***
	(0.013)	(0.010)	(0.008)	(0.008)	(0.007)
Loan-to-Income Ratio			-0.039***	-0.037***	0.017**
			(0.009)	(0.009)	(0.008)
Prop. Male			0.036*	0.046**	0.065***
			(0.021)	(0.021)	(0.018)
Prop. Minority			0.488***	0.476***	0.350***
			(0.046)	(0.045)	(0.036)
Depository Branches			0.628***	0.622***	0.526***
			(0.011)	(0.011)	(0.011)
Distance			-0.211***	-0.212***	-0.153***
			(0.007)	(0.007)	(0.016)
Log(No. SBL)			0.166***	0.174***	0.113***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.034**	0.048***	0.053***
			(0.017)	(0.017)	(0.016)
Log(Assets)				0.048***	0.220***
				(0.015)	(0.015)
Total Loans/Assets				-0.076	-0.014
				(0.075)	(0.073)
Deposits/Assets				-0.955***	-0.808***
				(0.055)	(0.054)
C&I Loans/Total Loans				3.379***	3.583***
				(0.088)	(0.084)
RE Loans/Total Loans				3.156***	3.312***
				(0.061)	(0.060)
ROA				-8.320***	-8.161***
				(0.389)	(0.353)
Total Liquidity/Assets				-1.151***	-1.178***
				(0.072)	(0.070)
Observations	345,290	338,965	265,121	264,585	264,452
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.002	0.445	0.685	0.692	0.765

Appendix B The Industry Expertise Channel and Mortgage Lending: Intensive Connection, Top-three Industries in A County

This table presents impacts of the industry expertise channel on banks' allocation of mortgage credits across counties at the intensive margin. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable, *Prop. Residents*, is the proportion of local residents working in industries that both banks and counties specialize in. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(No. Approved Mortgages)				
Prop. Residents	0.038***	0.033***	0.028***	0.016***	0.008***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Loan-to-Income Ratio			-0.027***	-0.035***	0.011
			(0.009)	(0.009)	(0.008)
Prop. Male			0.037*	0.061***	0.068***
			(0.022)	(0.022)	(0.019)
Prop. Minority			0.545***	0.504***	0.385***
			(0.049)	(0.048)	(0.038)
Depository Branches			0.626***	0.616***	0.521***
			(0.011)	(0.011)	(0.011)
Distance			-0.215***	-0.222***	-0.189***
			(0.007)	(0.008)	(0.016)
Log(No. SBL)			0.181***	0.190***	0.126***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.017	0.028*	0.057***
			(0.017)	(0.016)	(0.015)
Log(Assets)				0.180***	0.366***
				(0.015)	(0.016)
Total Loans/Assets				0.170**	0.224***
				(0.083)	(0.082)
Deposits/Assets				-0.961***	-0.802***
				(0.056)	(0.055)
C&I Loans/Total Loans				2.032***	2.132***
				(0.092)	(0.088)
RE Loans/Total Loans				2.123***	2.330***
				(0.068)	(0.065)
ROA				-4.018***	-3.602***
				(0.402)	(0.373)
Total Liquidity/Assets				-2.315***	-2.327***
				(0.085)	(0.085)
Observations	321,067	314,508	245,786	245,250	245,117
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.001	0.433	0.688	0.696	0.770

Appendix C The Industry Expertise Channel and Mortgage Lending - Intensive Connection, All Industries in a County

This table presents impacts of the industry expertise channel on banks' allocation of mortgage credits across counties. The dependent variable is the logarithm of the number of mortgages a bank approves in a county. The key independent variable, $Prop.Residents_{All}$, is the standardized proportion of residents in a county that work in any industry in which a bank specializes, not matter whether the industry belongs to the top-three industries in the county. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(No. Approved Mortgages)				
Prop. $Residents_{All}$	0.072***	0.039***	0.024***	0.013***	0.004*
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)
Loan-to-Income Ratio			-0.028***	-0.036***	0.011
			(0.009)	(0.009)	(0.008)
Prop. Male			0.036*	0.061***	0.068***
			(0.022)	(0.022)	(0.019)
Prop. Minority			0.546***	0.504***	0.385***
			(0.049)	(0.048)	(0.038)
Depository Branches			0.628***	0.617***	0.522***
			(0.011)	(0.011)	(0.011)
Distance			-0.215***	-0.222***	-0.189***
			(0.007)	(0.008)	(0.016)
Log(No. SBL)			0.180***	0.190***	0.126***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.017	0.027*	0.057***
			(0.017)	(0.016)	(0.015)
Log(Assets)				0.186***	0.370***
				(0.015)	(0.016)
Total Loans/Assets				0.187**	0.232***
				(0.083)	(0.082)
Deposits/Assets				-0.965***	-0.806***
				(0.056)	(0.055)
C&I Loans/Total Loans				2.063***	2.151***
				(0.092)	(0.088)
RE Loans/Total Loans				2.125***	2.333***
				(0.068)	(0.065)
ROA				-4.010***	-3.576***
				(0.402)	(0.373)
Total Liquidity/Assets				-2.305***	-2.325***
				(0.085)	(0.085)
Observations	321,067	314,508	245,786	245,250	245,117
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.00224	0.433	0.688	0.696	0.770

Appendix D The Industry Expertise Channel and Mortgage Lending - Dollar Volumes

This table presents the impacts of the industry expertise channel and banks' allocation of mortgage credits across counties. The dependent variable is the logarithm of the dollar volumes of mortgages a bank approves in a county. The key independent variable is *Same Industry*, a dummy indicating that there exists at least one industry that a county and a bank both specialize in. Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log($ Approved Mortgages)				
Same Industry	0.341***	0.105***	0.103***	0.066***	0.042***
	(0.013)	(0.010)	(0.008)	(0.008)	(0.007)
Loan-to-Income Ratio			0.268***	0.258***	0.286***
			(0.010)	(0.009)	(0.009)
Prop. Male			0.377***	0.396***	0.364***
			(0.022)	(0.022)	(0.019)
Prop. Minority			0.252***	0.212***	0.142***
			(0.046)	(0.045)	(0.039)
Depository Branches			0.613***	0.605***	0.509***
			(0.011)	(0.011)	(0.010)
Distance			-0.217***	-0.225***	-0.201***
			(0.008)	(0.008)	(0.017)
Log(No. SBL)			0.188***	0.194***	0.129***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			-0.107***	-0.096***	-0.047***
			(0.017)	(0.016)	(0.016)
Log(Assets)				0.198***	0.381***
				(0.015)	(0.015)
Total Loans/Assets				0.442***	0.471***
				(0.083)	(0.082)
Deposits/Assets				-1.052***	-0.937***
				(0.057)	(0.056)
C&I Loans/Total Loans				1.912***	2.007***
				(0.092)	(0.089)
RE Loans/Total Loans				2.129***	2.393***
				(0.071)	(0.069)
ROA				-4.082***	-3.583***
				(0.422)	(0.393)
Total Liquidity/Assets				-1.868***	-1.896***
				(0.084)	(0.086)
Observations	321,067	314,508	245,786	245,250	245,117
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.004	0.544	0.734	0.741	0.802

Appendix E The Industry Expertise Channel and Mortgage Approval Rates - Level of Industry Expertise

This table presents the impacts of the industry expertise channel and banks' allocation of mortgage credits across counties. The dependent variable is the logarithm of the dollar volumes of mortgages a bank approves in a county. The key independent variable is *Lev. Ind Exp* - the standardized levels of banks' expertise in an industry in which both banks and counties specialize. The level of a bank's industry expertise in an industry is defined as the difference between a bank's loan share in an industry minus the threshold used to identify an outlier loan share (see equation (1) for the calculation of a bank's loan share and the threshold). Controls include the average of loan amount to income ratio of all mortgage applicants, the proportion of male applicants, the proportion of minority applicants, the logarithm of one plus the number of branches a bank has in a county, the geographic distance between a bank's headquarter county and the borrower's county, the logarithm of one plus the number of small business loans a bank originate in a county, a bank's exposure to a county through mortgage retaining, the logarithm of bank assets, total loans scaled by assets, deposits scaled by assets, 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 1995 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(No. Approved Mortgages)				
Lev. Ind Exp	0.026***	0.024***	0.014***	0.013***	0.015***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Loan-to-Income Ratio			-0.029***	-0.037***	0.011
			(0.009)	(0.009)	(0.008)
Prop. Male			0.039*	0.062***	0.068***
			(0.022)	(0.022)	(0.019)
Prop. Minority			0.544***	0.502***	0.385***
			(0.049)	(0.048)	(0.038)
Depository Branches			0.629***	0.618***	0.521***
			(0.011)	(0.011)	(0.011)
Distance			-0.216***	-0.222***	-0.189***
			(0.007)	(0.008)	(0.016)
Log(No. SBL)			0.180***	0.189***	0.126***
			(0.003)	(0.003)	(0.003)
Mortgage Exposure			0.020	0.029*	0.058***
			(0.017)	(0.016)	(0.015)
Log(Assets)				0.193***	0.372***
				(0.015)	(0.015)
Total Loans/Assets				0.176**	0.221***
				(0.083)	(0.082)
Deposits/Assets				-0.961***	-0.793***
				(0.056)	(0.055)
C&I Loans/Total Loans				2.055***	2.132***
				(0.092)	(0.088)
RE Loans/Total Loans				2.115***	2.313***
				(0.067)	(0.065)
ROA				-3.888***	-3.524***
				(0.401)	(0.372)
Total Liquidity/Assets				-2.337***	-2.353***
				(0.085)	(0.085)
Observations	321,067	314,508	245,786	245,250	245,117
County*Year FE	No	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes	No
Bank*State FE	No	No	No	No	Yes
Adjusted R-squared	0.000279	0.433	0.688	0.696	0.770