Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

Bank Lending in the Knowledge Economy

Giovanni Dell'Ariccia, Dalida Kadyrzhanova, Camelia Minoiu, Lev Ratnovski

2020-040

Please cite this paper as:
Giovanni Dell'Ariccia, Dalida Kadyrzhanova, Camelia Minoiu, Lev Ratnovski (2020). "Bank Lending in the Knowledge Economy," Finance and Economics Discussion Series 2020-040. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2020.040.

Bank Lending in the Knowledge Economy*

Giovanni Dell'Ariccia Dalida Kadyrzhanova Camelia Minoiu Lev Ratnovski

April 3, 2020

Abstract

We study the composition of bank loan portfolios during the transition of the real sector to a knowledge economy where firms increasingly use intangible capital. Exploiting heterogeneity in bank exposure to the compositional shift from tangible to intangible capital, we show that exposed banks curtail commercial lending and reallocate lending to other assets, such as mortgages. We estimate that the substantial growth in intangible capital since the mid-1980s explains around 30% of the secular decline in the share of commercial lending in banks' loan portfolios. We provide suggestive evidence that this reallocation increased the riskiness of banks' mortgage lending.

JEL Codes: E22, E44, G21.

Keywords: corporate intangible capital, bank lending, commercial loans, real estate loans.

*Authors' contacts: Giovanni Dell'Ariccia, International Monetary Fund, gdellariccia@imf.org, Dalida Kadyrzhanova (*corresponding author*), Georgia State University, dkadyrzhanova@gsu.edu, Camelia Minoiu, Federal Reserve Board, camelia.minoiu@frb.gov, Lev Ratnovski, European Central Bank, lev.ratnovski@ecb.int. We thank Jean-Edouard Colliard, Sapnoti Eswar, Rohan Ganduri, Linda Goldberg, Jessie Handbury, Ann Harrison, Lixin Huang, Wei Jiang, Tumer Kapan, Divya Kirti, David Lipton, Adrien Matray, Fergal McCann, Tomasz Michalski, Ander Perez-Orive, Dianne Pierret, Adriano Rampini, Chip Ryan, Sascha Steffen, Roberto Steri, Tina Yang, Xiaoyun Yu, Kathy Yuan, Missaka Warusawitharana, Jing Zeng, seminar participants at UNSW, University of Delaware, Fordham, Georgia State University, Villanova, Wharton, ETH Zurich, Florida International University, ECB, FRB, IMF, and conference participants at the Wharton Liquidity and Financial Fragility Conference, AEA meetings, Swiss Winter Conference on Financial Intermediation, Adam Smith Workshops in Corporate Finance, Chicago Financial Institutions Conference, NBER Summer Institute, FIRS and EFA meetings, Financial Stability Implications of New Technology Conference, and the CBI Workshop on Banking, Credit and Macroprudential Policy for helpful comments. We thank Andrew Castro, Jae Chung, Huy Nguyen, and Yangfan Sun for excellent research assistance. Camelia Minoiu is grateful to the Wharton School at the University of Pennsylvania for its hosting during the development of this research project. The views expressed in this paper are those of the authors, and should not be attributed to the IMF, the ECB, the Federal Reserve System, their management or policies.

1 Introduction

U.S. corporate intangible capital has increased dramatically over the past five decades. The stock of assets such as intellectual property, human capital, business strategy, and brand equity has tripled since the 1960s, reaching \$3.6 trillion by the early 2000s (Corrado et al., 2009). A growing literature shows that firms with more intangible assets use less debt.[1] Yet, little is known about how this lower reliance on borrowed funds affects banks' asset allocations. We argue that the rise of corporate intangible capital at the aggregate level reduces the market for commercial debt and thus the market for bank commercial and industrial (C&I) loans. In turn, reduced commercial lending opportunities induce banks to reallocate their lending capacity to non-C&I assets, such as mortgages.

Aggregate trends for the U.S. economy are strikingly consistent with this story. Over the thirty-year period between 1984 and 2016, as corporate intangible capital grew from 30% to over 100% of tangible assets,[2] the composition of bank loan portfolios shifted away from C&I loans and towards real estate loans: the share of C&I loans in total loans fell by a third, while the share of real estate loans more than doubled (Figure 1). Bank C&I lending declined not only relative to the size of the banking sector, but also relative to firms' total stock of capital as it shifted towards greater intangible capital intensity (Figure A1).[3]

Our goal is to show that these trends in the composition of bank portfolios are driven by the rise in corporate intangible capital and do not simply reflect other economic developments over the same time period, such as higher mortgage demand, innovations in securitization, or deeper bond markets. To this end, we exploit heterogeneity in bank exposure to intangible capital growth across metropolitan statistical areas (MSAs) and examine changes in bank loan portfolios when local firms invest more in intangible capital. If a rise in intangible capital implies fewer commercial lending opportunities, then the decline in C&I loan growth should be more pronounced for banks operating in MSAs where the increase in intangible capital is greater.

[1] See, e.g., Hart and Moore (1994); Bates et al. (2009); Rampini and Viswanathan (2013); Döttling and Perotti (2016); Falato et al. (2018), and Sun and Xiaolan (2019).

[2] According to a measure conceptually similar to Corrado et al. (2009) but constructed at the firm level from financial statements of public firms by Falato et al. (2018).

[3] In fact, bank C&I lending declined moderately even relative to GDP (Figure A1).

Using comprehensive data on bank balance sheets from the U.S. Call Reports over 1984–2016, we show robust empirical evidence that banks facing an increase in local intangible capital ("exposed banks") curtail C&I lending, controlling for time-varying bank characteristics and variables that capture MSA-level demand for bank loans. The estimates are not only statistically significant but also economically meaningful. One standard deviation increase in local intangible capital growth is associated with one percentage point decline in bank C&I loan growth (close to 13% of the sample mean).

Next, we examine the impact of fewer commercial lending opportunities on the non-C&I part of bank balance sheets. If banks face limits on raising capital or other funding, they are likely to reallocate their spare lending capacity to assets other than C&I loans that previously were rationed out as less profitable (Chakraborty et al., 2018). Indeed, we find that banks exposed to a rise in intangible capital do not shrink their balance sheets, rather they grow non-C&I assets, including real estate loans. We estimate that the rise of intangible capital since the mid-1980s explains close to 30% of the decline in the share of C&I loans and 12% of the increase in the share of residential real estate loans in bank loan portfolios.

A key ingredient in our baseline empirical analysis is banks' exposure to local intangible capital growth. We construct this measure using two key ingredients: industry-level data on intangible capital growth and MSA-level industry employment shares as a proxy for industrial structure at the MSA-industry level. The MSA refers to the bank's headquarters location. This measure of intangible capital has two important advantages in our empirical setting. First, the industry-level data captures intangible capital investment across all establishments in the U.S. By capturing all firms, the measure is well suited for matching banks and firms on location given that small firms borrow predominantly from local banks. Second, this measure is plausibly exogenous to local bank lending shocks as it is constructed using national industry-level intangible asset growth rates and lagged MSA-level industry composition. Thus, by construction, this measure alleviates potential reverse causality concerns that a reduction in bank C&I loans induces local firms to invest more in intangible capital, generating a spurious negative correlation. We show that the baseline results are robust to alternative measures of bank exposure to intangible capital that (a) capture the entire geographic distribution of a bank's operations, and (b) use deeper lags of industry shares, including as of 1975 (preceding our sample period). Remarkably, the alternative measures deliver results that are virtually identical in economic magnitude to our baseline results.

Taken together, our results provide robust evidence that exposed banks reduce commercial lending and expand into other types of lending, including real estate. These results are consistent with our hypothesized relationship between bank lending and the limited use of debt by firms with intangible capital. That said, a potential alternative interpretation of the evidence is that the effect of intangible capital on the composition of bank loan portfolios is driven by a "real estate crowding-out channel" rather than the lower use of debt in firms with intangible capital. Chakraborty et al. (2018) document this channel by showing that banks exposed to buoyant housing markets reduce commercial lending. In our setting, more R&D-intensive firms may attract a high-skill workforce with higher incomes and greater mortgage demand, which in turn results in a contraction of C&I portfolios. Not controlling for local mortgage demand could then overstate the importance of the intangible capital channel. Therefore, to better isolate our channel we conduct three additional analyses using microdata on loans to businesses and households. The loan-level data allow us to carefully control for the real estate crowding-out channel using borrower-MSA$\times$year fixed effects (in the spirit of Khwaja and Mian (2008)), which absorb time-varying local loan demand, including mortgage demand, in the borrowers' locations.

We test the relationship between corporate intangible capital and bank commercial lending at the loan level using data on syndicated loans to large firms (from DealScan) and loans to small firms (from the U.S. Small Business Administration, SBA). These data have a number of useful features beyond the ability to control for local demand. Chief among these is the fact that they contain information not only on loan volumes, but also on loan spreads and maturity. Examining the effects of intangible capital on the price and nonprice terms of lending allows us to shed some light on the mechanisms behind our results. If the decline in C&I loans stems from collateral-related financial frictions in firms with intangible assets, such firms should experience worse lending terms, for instance, higher spreads and shorter maturities. By contrast, if intangible capital reduces firms' demand for external funds, we would observe improved lending terms for firms with intangible capital. For both large and small firms, more intangible capital is associated with smaller loans—a result that confirms our main conjecture on the negative link between intangible capital and bank commercial lending—as well as worse lending terms. These findings suggest an important role for collateral-related frictions in lending to intangible capital firms.

Next, we use loan-level data collected by U.S. supervisory agencies under the Home Mortgage Disclosure Act (HMDA) and test the link between corporate intangible capital and banks' mortgage lending. Here, too, we leverage the granular data and include borrower-MSA×year fixed effects to absorb local real estate demand. An additional benefit of the HMDA data is that we observe mortgages granted by the same bank to borrowers in multiple MSAs. As a result, we can examine how a bank's exposure to intangible capital in one MSA affects its mortgage lending decisions in other locations. This strategy allows us to separate the MSAs where banks are exposed to intangible capital and real estate demand shocks from the MSAs where they extend mortgages, therefore mitigating concerns that our results are confounded by the real estate crowding-out channel.

We find that banks experiencing higher intangible asset growth in their headquarters MSA increase mortgage loan volumes and acceptance rates in other MSAs. This result reinforces our baseline finding that bank reallocation to non-C&I lending is driven by intangible capital rather than higher real estate demand. If intangible asset growth in the headquarters MSA affected banks through higher mortgage demand in that MSA, then banks would try to meet that demand by directing their spare lending capacity toward their headquarters MSA and away from other MSAs.[4] Instead, the results are consistent with our conjecture that intangible capital in bank headquarters MSA reduces commercial lending opportunities in that MSA, and induces banks from that MSA to reallocate funds elsewhere.

Our results raise questions about the economic efficiency implications of reduced bank lending to firms with intangible capital. A decline in commercial lending that stems from firms' lower demand for external funds is efficient. But a decline in lending that is due to collateral-related frictions can hinder firm investment. Our finding that firms with intangible capital experience worse price and nonprice terms of lending lends support to the financial frictions channel over the credit demand channel. To shed more light on this question,

[4] Cortés and Strahan (2017) show, for instance, that banks respond to positive local credit demand shocks by reallocating capital from other markets to meet the additional credit demand.

we exploit cross-sectional heterogeneity in bank constraints, proxied by bank capital, size, dividend payout ratio, access to internal capital markets, and regulatory restrictions. We find that the negative effect of intangible capital on C&I lending is relatively stronger for more constrained banks, consistent with the financial frictions channel.

Finally, we examine the impact of banks' reallocation to real estate lending on the riskiness of their mortgage portfolios and explore the broader implications for overall bank performance. As the spare lending capacity generated by fewer commercial lending opportunities induces banks to seek new opportunities in the mortgage market, banks start lending to more marginal borrowers. Consistent with the notion that lending standards are lower for marginal borrowers, we show in bank-level data that real estate lending becomes ex-ante and ex-post riskier, with larger loan-to-income (LTI) ratios and non-performing loan (NPL) ratios, and less profitable, in response to higher intangible capital. These adverse impacts on mortgage portfolios extend to overall balance sheet performance through higher NPLs and lower return on assets (ROA). These results provide suggestive evidence that the rise in intangible capital over the past thirty years has reduced lending efficiency from the viewpoint of the commercial bank: the reallocation induced by intangible capital has increased risk-taking in mortgage lending and has made bank balance sheets riskier and less profitable.

While the external finance frictions associated with intangible capital have been studied extensively from the firms' side (Bates et al., 2009; Hart and Moore, 1994; Rampini and Viswanathan, 2013; Falato et al., 2018), to our knowledge, this is the first paper to document the effects of such frictions on the composition of bank lending. In doing so, our paper provides an empirical counterpart to the emerging theoretical literature on the effects of corporate financial capital on financial intermediation and economic efficiency. Döttling and Perotti (2016) develop a general equilibrium model where banks increase household lending in response to lower loan demand from firms with intangible capital. We confirm their prediction that intangible capital induces banks to lend to households, but our results point to external finance frictions rather than loan demand as the dominant channel behind lower commercial lending. Caggese and Perez-Orive (2017) show that intangible capital investment by firms that lack external funds may be constrained by low collateral values of intangible assets. Our results on lending volumes and terms for firms with intangible capital are consistent with frictions in the external financing of intangible capital.

Our findings offer a new perspective on the long-term shift from commercial to real estate lending in the U.S. banking sector. This trend so far has been explained by developments in housing markets and the growth of securitization. Loutskina and Strahan (2009) show that deeper secondary markets for securitized mortgages increase banks' willingness to originate illiquid loans, raising mortgage supply. Chakraborty et al. (2018) show that banks exposed to buoyant housing markets reduce the supply of commercial loans and increase the supply of mortgage loans, with negative effects for the real economy. We add to these studies an additional explanation, that greater use of intangible capital in the real sector induces a decline in bank commercial lending and a subsequent reallocation of lending capacity towards other assets, notably mortgages. In this way, the rise in intangible capital contributes to the expansion of real estate lending through a portfolio reallocation mechanism. Our paper is the first to empirically document the impact of the knowledge economy on mortgage markets.

2 Literature Review and Hypothesis Development

There is growing evidence that firms' investment in intangible assets has grown significantly over the past five decades. In a seminal paper, Corrado et al. (2009) undertake the most comprehensive approach to date to measuring aggregate intangible capital in the U.S. economy—based on capitalized past investments in intangible assets—and show that the share of aggregate intangible capital stock increased three-fold relative to tangible capital during 1973–2003, reaching an estimated $3.6 trillion, or 50% of the tangible capital stock by 2003. Corporate finance studies use financial statements of public firms in the U.S. to build firm-level measures of intangible capital (Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017) and document a steep upward trend in aggregate intangible capital (Falato et al., 2018).

Firms with more intangible assets have been shown to use less debt and to finance themselves with equity and retained earnings instead (Carpenter and Petersen, 2002; Brown et al., 2009; Bates et al., 2009; Brown et al., 2013; Falato et al., 2018). The literature offers two explanations for this behavior. One explanation is that intangible assets have relatively low collateral values, exacerbating frictions in debt financing (Bates et al., 2009; Hart and Moore, 1994; Rampini and Viswanathan, 2013; Falato et al., 2018). Indeed, intangible assets are often firm-specific and more difficult to value and liquidate than tangible assets. For example, the value of a partially-developed technology is likely to be intrinsically linked with the human capital of the researchers who work on it. Should a bank take over this asset and try to sell it on the market, it would likely recoup only a very small fraction of its original value.[5] While some intangible assets, notably patents, can be used as collateral, as discussed, for example, in Mann (2018) and Loumioti (2012), this practice is not yet widespread, suggesting that the collateral value of intangible assets is significantly lower than that of similarly productive tangible assets.[6] Another explanation is that firms with intangible assets may have lower demand for external funds. This may be the case when the production of intangible assets uses human capital that is remunerated with delayed compensation, reducing the need for upfront cash outlays (Döttling and Perotti, 2016; Sun and Xiaolan, 2019).

Our paper focuses on the how the lower use of debt by firms with more intangible assets affects the composition of bank' portfolios. In our baseline analysis, we do not take a stand on the exact mechanism behind the relationship between intangible capital and debt. Put differently, we test whether a technological trend that increases the use of corporate intangible assets dampens bank lending to firms. Later, in Sections 5 and 6.1, we present suggestive evidence on the relative importance of the two channels discussed above in explaining our baseline results. This leads us to our first baseline empirical hypothesis:

Hypothesis 1: An increase in the share of intangible assets in firms' capital reduces the equilibrium volume of bank C&I lending.

[5] Collateral facilitates financial intermediation by limiting the agency problems associated with asymmetric information and the inalienability of human capital (Bester, 1985; Chan and Thakor, 1987; Hart and Moore, 1994) and facilitating the enforcement of repayment (Rampini and Viswanathan, 2013). Consequently, credit is cheaper and more abundant when collateral is readily available. This phenomenon is evident in real estate finance markets, where standardized mortgage loan terms (both volumes and interest rates) are available for a wide variety of households. Overall, the literature suggests that collateral reduces agency costs in lending in a way that cannot be replicated by other means, such as enhanced borrower screening or monitoring (see, e.g., Berger and Udell (1990), Rajan and Winton (1995), and Rampini and Viswanathan (2013)).

[6] For bank lending, frictions are amplified by limited regulatory recognition of intangible collateral, which is related to difficulties in its valuation and verification. See "Banks eye intangible assets as collateral" in Financial Times (June 11, 2012).

A contraction in commercial lending opportunities may in turn affect other components of bank balance sheets. Banks are usually constrained in raising capital and other funding, and hence in their lending capacity. This premise is standard in the literature, and underpins, for example, the bank lending channel of monetary policy (Kashyap and Stein, 2000; Kishan and Opiela, 2000). When banks are constrained, a reduction in their commercial lending generates spare lending capacity, which banks can reallocate to other assets. The argument that capital- and lending-constrained banks are more likely to adjust their asset allocation than their size was developed in Chakraborty et al. (2018). They document that banks with profitable real estate lending opportunities reduce commercial lending. Our paper highlights a mirroring channel. Banks facing fewer commercial lending opportunities due to a rise in the share of intangible assets in firm's capital, increase their non-C&I assets. This idea generates our second empirical hypothesis:

Hypothesis 2: An increase in the share of intangible assets in firms' capital increases the equilibrium volume of bank non-C&I assets.

Empirically testing Hypotheses 1 and 2 forms the core of our analysis. These hypotheses are consistent with the aggregate trends depicted in Figures 1–2, which show that the secular rise in intangible capital has been accompanied by a bank balance sheet reallocation from commercial lending towards real estate lending. To establish a causal link between the rise of intangible capital and the composition of bank loan portfolios, our empirical strategy exploits cross-sectional variation in bank exposure to intangible capital. We examine how bank lending portfolios change in response to intangible capital growth in the MSAs where banks operate, while controlling for aggregate trends with year fixed effects. Furthermore, we conduct the analysis in multiple data sets to empirically test the hypotheses at different granularity levels.

3 Measuring Corporate Intangible Capital

A key ingredient in our empirical analysis, and the main explanatory variable in most empirical specifications, is the growth rate of MSA-level intangible capital. We construct this measure using two ingredients: industry-level intangible capital estimates from the Bureau of Economic Analysis' (BEA) Fixed Assets data and MSA-level industry employment shares from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages.

The BEA calculates industry-level intangible capital based on capitalized private expenditure on scientific R&D, software, and artistic originals. The BEA measure does not account for organizational capital and product innovation, two fast-growing types of intangible assets, and hence is narrower than the aggregate measure in Corrado et al. (2009). Consequently, relative to the estimates from Corrado et al. (2009), the BEA measure has lower but still sizable levels and growth rates of intangible capital. According to this measure, the stock of intangible capital doubled from 10% of tangible assets in the late 1970s to 20% in 2016, as shown in Figure 2.[7] The fact that the BEA measure underestimates the level of intangible capital compared to more comprehensive measures suggests that our estimates are conservative and provide a lower bound for the impact of intangible capital on bank lending. While the BEA measure is narrower than other measures, it has the advantage that it captures intangible capital investment across all establishments in the U.S. Therefore, this measure is well suited for the geographic matching of banks and firms in our analysis given that small firms borrow predominantly from banks located within 5 miles of their headquarters (Amel and Brevoort, 2005; Agarwal and Hauswald, 2010; Brevort et al., 2010).

To measure geographic variation in intangible capital growth, we weigh BEA industry-level intangible capital growth by MSA-level industry employment shares. Our baseline measure of MSA-level intangible capital growth therefore is:

$$IK_{lt} = \sum_{j \in J_l} \left[s_{jlt-k} IK_{jt}^{BEA} \right] \tag{1}$$

[7] Corrado et al. (2009) identify categories of aggregate expenditures, such as R&D expense, that are likely to be investments in intangible capital, and use a variety of data sources to measure and capitalize such investments to produce estimates of aggregate intangible capital. Of the total intangible capital stock in the 2000s, 49% is knowledge capital (accumulated R&D), 37% is organizational capital (accumulated economic competencies), and 14% is IT capital (software and computerized information). Knowledge capital can further be decomposed into scientific R&D and product innovation. During 1973–2003, the fastest growing categories of intangible assets were product innovation, computerized information, and organizational capital. According to the breakdown provided in Table 2 of Corrado et al. (2009), the BEA measure we use is closest to "scientific innovative property," which accounts for about 25% of total intangible capital, or equivalently, about 12.5% of tangible capital in 2003 (the last year for which estimates are provided).

where l indexes areas (MSAs), j indexes industries, and t indexes years. The first term in brackets is the employment share of industry j in area l in year $t-k$ from the BLS. The second term is the industry-level growth of the ratio of intangible capital to tangible capital (equipment and structures) from the BEA. Industries are based on the three-digit NAICS classification. In the baseline analysis, we use time-varying employment shares that are lagged three years, i.e., $k=3$. We settle on a three-year lag to balance endogeneity and measurement concerns. On the one hand, lagged employment shares make the MSA-level intangible capital measure plausibly exogenous to local economic conditions. On the other hand, a lag of only three years ensures that our measure of local intangible capital is still sufficiently well correlated with current local intangible capital.[8]

The level and growth of intangible capital show substantial geographic variation. Figure 3 depicts the distribution of intangible capital, showing end-sample levels (top panel) and average growth rates across MSAs (bottom panel). The end-sample (2016) intangible-to-tangible capital ratio has a median of 15% with a standard deviation of 5.6%. The top 10% of MSAs have an intangible-to-tangible capital ratio of over 23%. Locations in this category include traditional innovation centers in California (such as San Francisco and San Jose-Santa Clara), the Pacific Northwest (Seattle WA), and the Northeast (Boston MA). This category also includes some former agriculture and transportation-based communities that transitioned to being manufacturing hubs (Montgomery AL), innovation and corporate centers (Denver CO), and education and healthcare centers (Nashville TN).[9]

The average growth rates of intangible capital in the cross-section of MSAs, depicted in panel (b), have a median of 1.6% with a standard deviation of 1.1%. The top 10% of MSAs have intangible capital growth rates of over 2.9% over the sample period. The figure shows

[8] In Section 4.5 we show that our results are robust to using MSA-level measures of intangible capital that employ deeper lags of local industry shares.

[9] The ranking of MSAs by level of intangible capital closely corresponds to the ranking of MSAs by concentration of STEM jobs and education attainment of the workforce in two recent Bloomberg articles (Cannon et al., 2015; Del Guidice and Lu, 2019). In the sample of MSAs for which we have data from Bloomberg indexes, more than half of the top 25% MSAs ranked by the Bloomberg articles are also in the top 25% highest intangible capital MSAs. Additionally, using the list of high-tech industries from Loughran and Ritter (2004), we find that the average share of employment in these industries in the top quartile of MSAs by our measure of intangible capital (which is close to 20%) is more than double that in the bottom quartile of MSAs. This pronounced overlap of our intangible capital measure with measures of innovation and technology suggests that our measure truly captures differences across MSAs in the use and intensity of intangible capital.

that many areas that grew at a sustained rate over the past thirty years are in fact among the highest MSAs by intangible capital intensity today. The rankings of MSAs by intangible capital growth and level have a rank correlation of 0.53 (or 0.7 in a more homogenous sample of MSAs with population over 500,000 people). The correlation is not perfect since several high-growth MSAs, including former agricultural MSAs, started at low levels of intangible capital and are still to reach the intangible capital frontier. For example, Fargo ND, Olympia WA, and Vallejo CA are all in the top 10% of MSAs based on average intangible capital growth, but are closer to the median of the end-sample level distribution. We exploit the significant geographic variation in intangible growth rates to pin down the link between intangible capital and bank lending in our empirical analysis.

We also employ a firm-level measure of intangible capital from Falato et al. (2018) that is constructed from the financial statement data for public firms in Compustat. This firm-level measure computes intangible capital, for each firm-year, as the sum of capital accumulated through three types of intangible investments identified in Corrado et al. (2009): knowledge capital, organizational capital, and informational capital.[10] In the cross-section of firms, the intangible capital measure of Falato et al. (2018) is on average 36%. This is greater than the average of 14.2% for our baseline BEA measure as it includes estimates of organizational capital and is based on the data from large public firms. Both measures exhibit significant growth over 1984–2016 (the time-series correlation between the two variables in growth rates is close to 0.4), but the Compustat measure has a steeper trend than the BEA measure, suggesting that intangible capital grew even more in publicly-listed firms (Figure 2). We use the firm-level intangible capital measure in Section 5.1.1.

4 Intangible Capital and Bank Lending

This section presents our baseline analysis of the impact of intangible capital on bank lending. We study (i) how a bank's commercial lending responds to changes in intangible capital in the areas where the bank operates and (ii) how this response affects the rest of the bank's

[10]This approach is necessary because firms typically report investments in intangible assets as current expense, therefore capital that is created by such investments is not captured on firms' balance sheets (except patents and post-merger goodwill).

balance sheet, specifically, total assets and non-C&I assets. We describe the data, the econometric specification, and our baseline findings. Then, we subject the baseline analysis to two refinements: (i) we examine alternative measures of bank exposure to intangible capital that define a bank's area of operations from the spatial distribution of its activities (rather than the MSA of its headquarters); and (ii) we use alternative measures of intangible capital based on deeper lags of employment shares.

4.1 Bank Balance Sheets and Macro Data

For the main analysis, we use bank-level data on C&I loans and other balance sheet components from the U.S. Call Reports. We use data that reflect banks' domestic operations and restrict the sample to commercial banks. C&I loans are defined as loans for commercial and industrial purposes to sole proprietorships, partnerships, corporations, and other business enterprises. This category excludes loans secured by real estate (classified as "real estate loans"), agricultural loans, and personal consumer loans. We capture a bank's area of operations with its headquarters location. The bank-level panel starts in 1984 to ensure continuity in the definitions of key variables such as C&I loans and total equity. The baseline sample includes about 7,800 commercial banks with headquarters in 271 MSAs during 1984–2016.[11]

Table 1 reports key descriptive statistics. The average bank in the sample has about \$70 million in assets and the distribution of bank size is highly skewed with a few large banks. Commercial loans stand at about 12% of bank assets on average and real estate loans represent over one-third of total bank assets. Over the sample period, commercial loans grew at an average annual rate of about 6.5%, whereas real estate loans grew on average substantially faster at 9.4% per year.

We also employ a broad set of MSA variables to capture local macroeconomic conditions that can affect banks' lending decisions. These variables are household income and population from the U.S. Census; house prices, based on the all-transactions seasonally-adjusted house price index from the Federal Housing Finance Agency, and average sales growth and market-to-book ratio of firms in Compustat by MSA as measures of local business conditions.

[11] See Data Appendix A-II for details.

4.2 Empirical Strategy

We estimate the baseline specification for three dependent variables: banks' commercial loan growth, total asset growth, and non-C&I asset growth. Our hypotheses from Section 2 predict that higher growth of intangible capital leads to a decline in banks' commercial lending and an expansion of their non-C&I assets. We take these predictions to the data by estimating the following empirical model:

$$Y_{it} = \alpha_t + \beta_1 IK_{it} + \beta_2 X_{it} + \beta_3 Z_{it} + \epsilon_{it}, \tag{2}$$

where banks are indexed by i and years by t. Y_{it} is each of the three dependent variables considered. IK_{it} is the growth rate of intangible capital to which the bank is exposed, as defined in Section 3. X_{it} is a matrix of macro controls for economic conditions in the bank's area of operations that may directly impact the demand for bank credit: house prices, per capita income, population, and firm sales growth and market-to-book ratio. Z_{it} is a matrix of bank controls: bank size (log-total assets) and capital ratio (total equity divided by total capital), both lagged by one year. All specifications include year fixed effects α_t to control for shocks that are common to all banks in each year. All variables except bank size, bank capital, and firm market-to-book ratio are expressed as yearly growth rates. By estimating a specification in changes, we exploit within-bank variation and hence control for time-invariant bank heterogeneity. Finally, the specifications for banks' C&I loans and non-C&I assets control for bank asset growth. Therefore, the estimates can be interpreted as the growth of the shares of these balance sheet components in total assets. Standard errors are clustered at the bank level.[12]

The coefficient of interest, β_1, captures the effect of corporate intangible capital growth on the three outcomes of interest: bank commercial loan growth, total asset growth, and non-C&I asset growth. Our hypotheses predict that $\beta_1 < 0$ for commercial loan growth and $\beta_1 > 0$ for non-C&I asset growth. The baseline analysis covers the 1984–2016 period and we drop the years between 2008 and 2010 to exclude shocks to bank lending associated with

[12] In Tables A2 and A5, we examine the sensitivity of our results to alternative specifications that drop total balance sheet growth as a control variable and to alternative clustering approaches.

the global financial crisis.[13]

4.3 Baseline Results

Table 2 presents the baseline results. In Columns 1–4, the dependent variable is C&I loan growth. We first show the bivariate specification that only includes local intangible capital growth as an explanatory variable (Column 1), then add MSA- and bank-level controls (Column 2), and then add year fixed effects (Column 3). Columns 4–6 present the main specifications for the three dependent variables: C&I loan growth, total bank asset growth, and non-C&I asset growth. These specifications include the full set of macro controls, year fixed effects, as well as bank total asset growth in Columns 4 and 6.

The first set of results shows that banks experiencing higher growth in corporate intangible capital have lower commercial loan growth, and the coefficient estimate is statistically significant at conventional levels (Columns 1–4). The magnitude of the coefficient in consistent across specifications and suggests high economic significance. Using estimated coefficients from the full specification in Column 4, a one standard deviation increase in intangible capital growth is associated with a decline in the growth rate of bank commercial loans of 0.8 percentage points, or close to 13% of the sample average annual growth in C&I loans. A back-of-the-envelope calculation suggests that close to 30% of the decline in C&I lending over the sample period (1984–2016) can be explained by changes in intangible capital.[14] Given that our measure of intangible capital does not capture product innovation and organizational capital—which likely rose faster than other components of intangible capital (Corrado et al., 2009)—the 30% estimate can be interpreted as a lower bound for the true impact of intangible assets on commercial lending.

Next, we examine the effects of a rise in intangible capital on other bank balance sheet components. The results in Columns 5 and 6 of Table 2 indicate that exposed banks do

[13] In Table A3, we show that the baseline results are robust to including the crisis years.

[14] We obtain this estimate as follows. Our measure of intangible capital increased at an annual rate of 1.8% in the time series over 1984–2016. Using the coefficient estimate of -0.2107 from Column 4 of Table 2, we infer that $-0.2107 \times 1.8\% = -0.4\%$ is the predicted growth in C&I lending due to changes in intangible capital. Given that C&I lending shrank at an annual average growth rate of –1.3% over the period, we have that the portion of C&I lending decline explained by intangible capital growth is $-0.4\%/-1.3\% = 0.2897$ or close to 30%.

not reduce the size of their balance sheets, but instead grow their non-C&I assets. These findings are consistent with Hypothesis 2 of Section 2, according to which banks that face capital and lending constraints respond to a reduction in commercial lending opportunities by reallocating their lending capacity to other assets rather than shrinking.

The estimated coefficients on the macroeconomic controls have expected signs. Banks' total assets grow faster in response to better local economic conditions, as measured by faster house price, per capita income, population, firm sales growth, and firm market-to-book ratio. Controlling for bank total asset growth, C&I loans respond more to house price and income growth, whereas non-C&I assets respond more to population growth and firm market-to-book ratio. In addition, C&I loans grow slower in larger banks, which might be less well suited for information-sensitive lending (Berger et al., 2005b), but faster in better-capitalized banks, with greater lending capacity.

We conduct a range of tests to verify that the baseline results in Columns 4–6 of Table 2 are robust to alternative specifications and refinements. In Table A5 we show that the results are unchanged if we include the global financial crisis years (2008–2010). In Table A4 we show that our findings are robust to including bank and MSA fixed effects—a very demanding test as our baseline specification from Equation 2 is estimated in growth rates and thus removes time-invariant bank and MSA heterogeneity. In Table A7 we show that our results are also robust to clustering on bank and year (Columns 1–3), MSA (Columns 4–6), and MSA and year (Columns 7–9). Under all alternative clustering approaches, the coefficient on intangible capital growth maintains levels of statistical significance that are similar to the baseline results.

4.4 Results using Banks' Geographic Footprint

In the baseline analysis, we define a bank's area of operations as its headquarters MSA and use intangible capital growth in that MSA as the key explanatory variable. This approach assumes that banks are significantly exposed to loan demand from firms in their headquarters MSA. However, after the removal of geographic restrictions on inter- and intra-state banking activities in 1994 and the subsequent acceleration in bank consolidation (Jayaratne and Strahan, 1996; Berger et al., 1999), banks may have become more exposed to shocks originating outside their headquarters MSA. To allow for this possibility, we construct a measure of exposure to intangible capital that is based on each bank's entire geographic footprint.

We capture the bank's area of operations from the distribution of its deposit-taking or mortgage lending activities across MSAs. Data on deposit balances at the branch level for all banks in our sample come from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits. Loan-level data on bank mortgage lending with information on borrower location are collected by the Federal Financial Institutions Examinations Council (FFIEC) under the provisions of the HMDA. These data cover the near-universe of mortgage loan applications and originations for U.S. mortgage lenders (except for institutions with assets below $30 million). We add up deposit volumes, mortgage origination volumes, and the number of mortgage applications at the MSA level to obtain a measure of each bank's geographic footprint across the MSAs where it has deposit-taking and mortgage lending activities. The resulting alternative measures of bank exposure to intangible capital growth are given by:

$$IK_{it} = \sum_{l \in L} [\omega_{ilt} IK_{lt}] \tag{3}$$

where i indexes banks, l indexes MSAs in which bank i operates, and t indexes years. The first term in brackets is MSA l's share in a bank's total deposit-taking (by volume) or mortgage lending (by the number or by the volume of applications) in year t. The second term is the MSA-level intangible capital growth computed as in Section 3. These alternative measures reflect the spatial distributions of bank activities and therefore vary across banks, including across banks with headquarters in the same MSA.

Table 4 reports the results. Across all three alternative measures of intangible capital, the results are similar to the baseline analysis in Table 2 in terms of statistical and economic significance. These findings suggest that the headquarters-based baseline measure of a bank's area of operations captures well that bank's exposure to changes in intangible capital.

4.5 Ruling out Reverse Causality

A potential concern about the baseline results is reverse causality: intangible capital investment by firms may depend on local banks' supply of commercial loans. The intuition is as follows. Consider banks that reduce their commercial lending for some exogenous reason. Lower credit supply would induce firms to invest more in intangible assets if such assets were less external-finance dependent. Such reverse causality would generate a negative relation between commercial lending and intangible capital, but for reasons that are different from our hypothesized mechanism. Alternatively, if banks primarily curtail unsecured commercial lending, firms may disproportionately reduce their investment in intangible assets, as they lack collateral value. In this case, there would be a positive association between commercial lending and intangible capital, which would work against us finding significant results.

Our baseline analysis is largely immune to this concern given that local intangible capital growth is computed using local industry composition with a lag of three years, and industry-level intangible capital growth rates at the national level. To rule out any residual reverse causality concerns, we examine whether our results hold for measures of intangible capital that use alternative lags of industry employment shares. Specifically, we construct measures of intangible capital as in Equation 1, but using shorter (one year) or deeper (five and ten years) lags of employment shares. We also construct a measure of intangible capital using employment shares from 1975, the first year for which employment data are available from the BLS. As the latter measure is based on employment shares fixed at their values ten years prior to the start of our sample period, we view the results using 1975 shares as best suited to rule out reverse causality concerns.

Table 3 reports the results. For all lags, the effects of intangible capital growth on bank lending are very close to the baseline results in Table 2 in terms of both statistical and economic significance. If anything, the point estimates for the shorter (one-year) lag are somewhat smaller than in the baseline specifications, suggesting that the reverse causality from banks' commercial lending to intangible capital growth, which should be more pronounced for shorter lags, works against our results by attenuating the coefficient on intangible capital growth. For all the deeper lags considered, even for the employment shares fixed at their 1975 value, the point estimates are very close to those in the baseline. These results are consistent with the geography of industry composition being highly persistent, as documented in Autor and Dorn (2013). We conclude that the baseline three-year industry employment share lag is well suited to address reverse causality concerns and continue to use the corresponding intangible capital measure in subsequent analysis.

5 Evidence from Loan-Level Data

Our baseline analysis documents a statistically significant and economically sizable negative relation between local intangible capital and commercial lending. Furthermore, banks offset the reduction in commercial lending by increasing their investment in other assets. These results are consistent with our hypotheses in Section 2 on how bank lending adjusts to the limited use of debt by intangible capital firms. In this section, we examine these hypotheses in more granular loan-level data on syndicated lending to large firms, small business lending, and mortgage lending to households. Analysis of loan-level data allows us to enhance our empirical approach along several key dimensions.

First, we can match banks and firms directly on the basis of individual lending relationships, as opposed to bank and firm locations as in the baseline analysis. This approach is particularly relevant for large firms that are more likely to borrow from banks located outside their headquarters MSA.

Second, loan-level data allow us to exploit variation in intangible capital across borrowers within the same MSA. By doing so, we control for the possibility that our results reflect the crowding-out of bank commercial lending by rising local real estate demand—a real estate crowding-out channel. Chakraborty et al. (2018) show that buoyant housing markets induce banks to increase mortgage lending and reduce commercial lending, with negative effects for firm investment. In our setting, growth in the local share of firms with more intangible capital may attract a different, better paid workforce, leading to stronger mortgage demand, in turn generating a bank balance sheet reallocation that we would spuriously attribute to intangible capital. In the baseline analysis we control for plausible drivers of MSA-level real estate demand such as growth in household income, employment, and house prices. Loan-level data allow us to more carefully control for the real estate crowding-out channel by estimating lending specifications with borrower-MSA×year fixed effects, similar to Khwaja and Mian (2008), Schnabl (2012), and Jiménez et al. (2017).

Third, loan-level data contain information not only on loan volumes, but also on loan spreads and maturity. Examining the effects of intangible capital on the price and nonprice terms of lending allows us to shed some light on the mechanisms behind our results. If the decline in commercial lending stems from collateral-related frictions, firms with more intangible capital should experience worse lending terms. Indeed, low-collateral loans are riskier (Berger and Udell, 1990; Strahan, 1999), which should lead to higher loan spreads. Also, banks prefer to extend risky loans at shorter maturities, as more frequent refinancing events gives them more control over firms' decisions, helping ensure loan repayment (Rajan and Winton, 1995). By contrast, if the decline in commercial lending stems from lower loan demand from intangible capital firms, we expect banks to incentivize firms to borrow by offering lower loan rates and longer maturities.[15]

We start by showing that firms with more intangible assets receive loans that are smaller and have worse price and nonprice terms compared to loans granted in the same year to other firms in the same MSA. We show this result in data on syndicated loans to large firms (Section 5.1.1) and in data on small business loans (Section 5.1.2). Then we present loan-level evidence on bank reallocation to non-C&I assets—banks exposed to higher corporate intangible asset growth in one MSA increase their mortgage lending to borrowers in other MSAs (Section 5.2).

5.1 Intangible Capital and Bank Commercial Lending

Hypothesis 1 in Section 2 states that the lower use of debt in firms with more intangible capital reduces the volume of bank loans to these firms. While in the baseline analysis we examine the equilibrium effect of this mechanism on overall bank balance sheets, in loan-level

[15] Firms prefer loans with longer maturities as they reduce refinancing risks (Graham and Harvey, 2001). Note that while the predictions for loan maturity are directionally unambiguous, loan maturity is influenced by many additional factors. For instance, it may be chosen to reflect future cash flow streams (Morris, 1976; Myers, 1977), credit market conditions at loan origination Mian and Santos (2018), and other agency frictions and security design considerations (see, among others, Flannery (1986), Diamond (1991), and Diamond and He (2014)). Therefore, our predictions for the size of the effect of intangible capital on loan maturity are less clear-cut than for volumes and spreads.

data we are able to test directly the relationship between firms' intangible capital and the amount and terms of the bank loans they receive. We use the following specification:

$$Y_{iblt} = \alpha_{it} + \beta_1 IK_{bt} + \beta_2 X_{bt} + \delta_{lt} + \epsilon_{iblt}, \tag{4}$$

where banks are indexed by i, borrowing firms by b, borrower MSAs by l, and years by t. The key explanatory variable is firm b's intangible capital in year t, IK_{bt}. The regressions include controls for standard determinants of firm borrowing, X_{bt} (described in each subsection below). All specifications control for time-varying bank characteristics using bank×year fixed effects, α_{it}, which absorb bank-specific shocks to commercial lending. Crucially, we also include borrower-MSA×year fixed effects δ_{lt}, which absorb time-varying MSA-level economic conditions, including mortgage demand variation that may stem from shocks to intangible capital. Thus, MSA×year fixed effects allow us to exploit variation in intangible capital across borrowing firms and compare the volume and terms of loans extended to firms in the same MSA and year.[16] In some tests we enrich this specification with additional, even more granular, fixed effects.

The coefficient of interest, β_1, represents the effect of intangible capital on the volume and terms of loans the firm receives from a given bank relative to all other firms in the same MSA receiving loans from the same bank and in the same year. Our hypothesis is that intangible capital reduces firms' borrowing. Therefore, we expect a negative association between a firm's intangible capital and the volume of loans it receives ($\beta_1 < 0$). Further, if the decline in commercial lending stems from collateral scarcity in intangible capital firms, such firms should also experience worse lending terms, such as higher loan spreads and shorter maturities.

5.1.1 Evidence from Syndicated Loans

Loan-level data on large corporate loans, most of which are syndicated (that is, comprising at least two lenders), come from Refinitiv's DealScan Loan Pricing Corporation (LPC). The

[16] Our reported specifications are robust to including triple interacted terms bank×borrower-MSA×year, which allow us to exploit variation in intangible capital across firms and compare the terms of commercial loans granted by the same bank to firms in the same MSA and in the same year (see Tables A8 and A9).

syndicated loan market is a sizeable segment of the credit market, with syndicated loans accounting for about one-quarter of aggregate banking system C&I loans and about one-third of C&I loans on the balance sheets of large U.S. banks (Ivashina and Scharfstein, 2010). DealScan offers detailed information on new loan originations at the bank-firm level, including volume, spreads, and maturities. We limit the sample to loans granted to nonfinancial firms between 1990 and 2016. The average syndicated loan in the regression data amounts to USD 6.3 million, with a spread of 135 bps over the London Interbank Offer Rate or the bank prime rate, and a maturity of 4.2 years (Table 1).

We aggregate the loan-level data at the bank-borrower-year level by computing total loan volumes as well as average loan spreads and maturities (both weighted by loan volumes) for each bank-borrower pair in a given year. Then we estimate Equation 4 to link syndicated loan terms—log-volume, spread, and maturity—to intangible capital. Given that syndicated loans are mainly granted to large public firms, we directly measure intangible capital for each borrower at the firm level using data on firm financials from Compustat. In particular, we use the firm-level measure from Falato et al. (2018) which is constructed for the panel of public firms by analogy with the aggregate measure of intangible capital from Corrado et al. (2009). All specifications include bank×year fixed effects, borrower-MSA×year, and industry fixed effects.

Table 5 reports the results. For each dependent variable, the first specification shows the bivariate specification that only includes firm-specific intangible capital as an explanatory variable. The second specification adds controls for firm-level determinants of borrowing, including firm size, growth opportunities (market-to-book ratio), profitability (return on assets, ROA) and cash ratio. In the third specification we include additional interacted fixed effects to control for unobservable time-varying firm characteristics, including corporate loan demand, at even more granular levels. Specifically, we include industry×credit-rating-category×year fixed effects to capture loan demand shocks that are common to all borrowing firms in a given industry, Standard & Poor's (S&P) risk rating category, and year.[17]

[17] We control for loan demand with fixed effects for relatively homogenous clusters of firms as opposed to individual firms, similar to previous studies of syndicated loan data (e.g., De Haas and Van Horen (2012); Acharya et al. (2018); Hale et al. (2019)). This approach is necessary in our context because our key explanatory variable—intangible capital—varies at the firm-year level. Therefore, estimation of its impact would be infeasible with firm×year fixed effects. There are 23 S&P credit rating categories (including a

Across all specifications, we find that firms with more intangible assets receive smaller, more expensive, and shorter-maturity bank loans. The coefficients have consistent signs across specifications, and are statistically and economically significant. The coefficient estimates indicate that one standard deviation increase in firm-level intangible capital (44.6%) is associated with loan volumes that are smaller by between 6 and 11% (Columns 1–3) and loan spreads that are higher by 5 to 9 basis points (Column 4–6). A one standard deviation increase in firm-level intangible capital is also associated with loan maturities that are shorter by 0.03 years (Columns 7–9), an economically small effect given a loan maturity of 4.2 years on average. The finding that firms with more intangible assets receive smaller loans confirms our baseline results in a different data environment, with a new measure of intangible capital at the firm level, and with granular controls for local real estate demand. Furthermore, the finding that firms with more intangible assets receive worse price and nonprice terms point to external finance frictions in firms with intangible assets as the dominant mechanism behind our results.

To further explore the financial frictions interpretation of our results, we conduct an additional test using firm-level data on patents—a common type of intangible assets. Mann (2018) shows that the pledgeability of patents boosts firms' debt capacity and R&D spending; and that more than one-third of U.S. patenting firms in 2013 pledged patents as collateral. Given the higher collateral value of patents compared to other types of intangible assets, the financial frictions channel implies that, among firms with a similar level of intangible assets, those firms with more patents should have access to larger loans and better loan terms than other firms. In Table A7 we report the results of specifications that interact intangible capital with two measures of firm-level patents (nonweighted and citation-weighted, in % of assets). Consistent with the lower collateral value of patents compared with tangible assets, the coefficient estimates indicate that firms with more patents receive smaller, more expensive, and shorter-maturity loans. Consistent with the financial frictions channel, the estimates also show that—for the same level of intangible capital—firms with more patents experience relatively more favorable lending terms—greater loan volumes, smaller spreads, and longer maturities. Yet, despite patents improving borrowing conditions for intangible capital firms, borrowing terms remain weaker than for other firms.

category for unrated firms) and 503 four-digit SIC industry categories in the regression sample.

5.1.2 Evidence from Small Business Loans

Next, we examine the link between intangible capital and commercial lending using data on individual loans from the SBA database on bank lending to small firms. A key benefit of this data set is that we can confirm our main results in loan-level data on smaller and younger business loan recipients (Brown and Earle (2017) report an average size of 14 employees and median age of 6 years). We use data from the SBA program 7(a) on loans under \$5 million. SBA loans are government supported, with the government repaying up to 75% of a loan loss (85% for the smallest loans) and the bank absorbing the rest (Craig et al., 2004; Brown and Earle, 2017). The data are available for the period between 1990 and 2016. For each loan we observe lender and borrower identities, the industry and location of the borrower, and loan characteristics such as loan volume and maturity.[18] The average small business loan in the regression sample is close to half a million USD and has a maturity of 9.5 years (Table 1).

While the SBA data are at the loan level, they do not provide financial information for individual borrowers. Therefore, we conduct the analysis at the bank-industry-MSA-year level (with industries at the three-digit NAICS level). We compute total loan volumes and average loan maturities (weighted by loan volumes) for each bank that lends to borrowers in a given industry, MSA, and year. We estimate a specification that links bank loan terms—log-volume and maturity—to industry-level intangible capital (from the BEA). The control variables correspond to the usual determinants of corporate borrowing, but are defined at the industry level. All specifications include bank×year and borrower-MSA×year fixed effects.

The results are reported in Table 6. For each of the two dependent variables, in the first specification we only include industry-level intangible capital; in the second specification we control for average firm size within the industry (log-employment from the BEA); and in the third specification, we restrict the sample to manufacturing firms, which allows us to further control for the average firm's total factor productivity (TFP) growth and profitability (profits/sales), obtained from the U.S. Census Bureau. Across specifications, the estimates consistently indicate that small businesses from industries with more intangible capital re-

[18] Loan interest rate data are only available starting in 2008. Regressions for loan interest rates reveal expected coefficient signs of intangible capital, but these are imprecisely estimated (not shown).

ceive smaller and shorter-maturity loans. The estimates are statistically and economically significant: a one standard deviation increase in intangible capital (40.6%) is associated with loan volumes that are lower by between 4 and 7% (Columns 1–3) and with maturities that are lower by 0.2–0.3 years (Columns 4–6). Comparing these estimates with those for syndicated loans (Section 5.1.1), we find that the elasticity of small business loan volume with respect to intangible capital is smaller than that for syndicated loans (in the 6 to 11% range). The maturity effect is economically small and is similar in magnitude to that for syndicated loans.

5.2 Intangible Capital and Bank Reallocation to Real Estate Lending

Our baseline results in Section 4 show robust evidence that banks exposed to intangible capital growth offset the reduction in commercial lending opportunities by expanding into non-C&I assets, consistent with our Hypothesis 2. In Table A8, we use the baseline specification (Column 4 of Table 2) to examine in more detail which specific components of non-C&I assets are most affected, focusing on real estate lending, which accounts for 60% of total loan portfolios (on average over the sample period). The estimates confirm that higher intangible capital is positively related to overall real estate lending (Column 1), especially residential real estate lending (Column 2),[19] and imply that close to 12% of the increase in the share of residential real estate loans in bank loan portfolios since the mid-1980s can be attributed to the rise of intangible capital.[20]

However, this result, too, may be subject to the concern that exposed banks expand mortgage lending not because of reduced C&I opportunities, but because areas with faster intangible capital growth can also experience booming mortgage demand. To distinguish our story from the real estate demand channel, we use loan-level data on mortgage lending from

[19]The estimated effect on banks' commercial real estate lending is negative but statistically insignificant, suggesting that firms with intangible assets face impediments to substituting commercial real estate for the lacking collateral.

[20]We obtain this estimate similarly to the back-of-the-envelope calculation in Section 4.3. Given that residential real estate lending grew at an annual average growth rate of 1.8% over the period, we have that the portion of its increase explained by intangible capital is $(0.1183 \times 1.8\%)/1.8\% = 0.1187$ or close to 12%.

HMDA. We aggregate the loan-level data at the bank-MSA-year level by calculating, for each bank, total loan volumes and average acceptance rates in each MSA where it operates in a given year. The regression sample covers more than 3,000 commercial banks with mortgage lending operations across the U.S. between 1995 and 2016.[21]

We pursue the following identification approach. First, we include borrower-MSA×year fixed effects in all specifications, similar to our previous loan-level analyses. These fixed effects are intended to absorb time-varying real estate demand in the MSA where the bank extends mortgages. Moreover, we exploit the fact that many banks extend mortgages to borrowers across multiple MSAs. We restrict the sample to mortgages granted outside the MSA where banks are exposed to intangible capital growth (i.e., their headquarters MSAs). This strategy allows us to examine lending reallocation decisions that are free of the crowding-out concern (that intangible capital induces higher local mortgage demand).[22]

Our main empirical specification links bank exposure to intangible capital to the volume and terms of its mortgage lending and is given by:

$$Y_{ilt} = \alpha_t + \beta_1 IK_{it-1,l_{hq}} + \beta_2 X_{it-1} + \beta_3 L_{ilt} + +\delta_{lt} + \epsilon_{ilt}, \tag{5}$$

where banks are indexed by i, MSAs where the mortgage is originated by l, and years by t. Y_{ilt} are two dependent variables: the change in the log-volume of mortgages and the change in the mortgage acceptance rate. The main explanatory variable, IK_{it-1}, is the growth rate of intangible capital in the MSA of bank i's headquarters. X_{it-1} are bank-level controls and L_{ilt} are standard controls for the characteristics in banks' mortgage applicant pool in a given MSA. Both intangible capital growth and bank controls are lagged one year to allow for a delay in the bank's mortgage lending response.[23] The coefficient of interest, β_1, represents

[21]The median bank is present in 16 MSAs and originates around \$6 million worth of mortgages per year and MSA. The median mortgage loan is just over \$130,000 and the median mortgage application acceptance rate is 88%, similar to Loutskina and Strahan (2009). See Appendix A-IV for a more detailed description of the HMDA data.

[22]This strategy also sheds light on the presence of the crowding-out channel in banks' headquarters MSA. If our results were due to local real estate demand in banks' headquarters MSA, then exposed banks would pull funds from other MSAs and allocate them to meet higher mortgage demand in their headquarters MSA. By contrast, if our results reflected spare lending capacity from lower commercial lending in the headquarters MSAs, then exposed banks would increase mortgage lending in other MSAs.

[23]The specifications we report do not include bank fixed effects as the dependent variables are expressed in changes. However, adding bank fixed effects leaves the results virtually unchanged (see Table A10).

the effect of bank exposure to intangible capital growth on the bank's mortgage lending in a given MSA relative to other banks that lend in the same MSA and in the same year. Our reallocation hypothesis suggests a positive association between bank exposure and mortgage lending, i.e. $\beta_1 > 0$.

Columns 1–3 of Table 7 present the results for mortgage loan volume. The first column shows a specification with no controls. Then we add bank-level balance sheet controls (size, capital, and total asset growth), as well as controls for macroeconomic conditions in the bank's headquarters MSA which may have an independent effect on bank credit (growth in house price index, per capita income, population, firm sales, and market-to-book). In the third specification we also control for characteristics of the bank's applicant pool in the MSA where the mortgage is extended (applicants' average income, the share of female and minority loan applicants, and the average income and the share of minority applicants in the census tract of the property, all expressed in differences). These control variables follow Loutskina and Strahan (2009) and capture changes in a bank's mortgage lending that are attributed to the makeup of the applicant pool.[24]

The estimates are consistent across specifications. Banks exposed to higher growth of intangible capital (in their headquarters MSAs) expand mortgage lending in other locations.[25] The economic magnitudes are sizable. The estimates in Columns 3, for example, indicate that a one standard deviation increase in intangible capital growth is associated with an expansion of bank mortgage loan volume by close to 23% (about a quarter of the standard deviation of mortgage loan growth), or about 2% of the average bank's real estate loans.

Next, we examine the effect of intangible capital on mortgage acceptance rates. If the reallocated lending capacity relaxes exposed banks' credit rationing constraints, then acceptance rates would increase. Columns 4–6 of Table 7 show the results for the effect of intangible capital growth in headquarters MSA on the change in the mortgage acceptance rate in other MSAs. Across specifications—presented in the same order as for loan volumes—the

[24]Summary statistics for these variables are shown in Table A1.

[25]Furthermore, the control variables for changes in the characteristics of mortgage applicants have broadly anticipated signs. Greater applicant income increases loan volumes and acceptance rates. Female and minority applicants experience lower mortgage loan acceptance rates. Loans in more affluent neighborhoods have higher acceptance rates and are larger. Loans in minority neighborhoods are larger as well, possibly related to incentives provided by the Community Reinvestment Act (see Agarwal et al. (2012)).

estimates consistently show that acceptance rates are significantly higher in more exposed banks compared to other banks that lend in the same MSA. The coefficient estimates are also economically meaningful: the estimates in Columns 6 suggest that a one standard deviation increase in intangible capital growth is associated with an increase in the mortgage acceptance rate by 2 percentage points (or about one-sixth of the standard deviation).

Overall, this section provides robust evidence that banks exposed to higher growth in intangible capital increase mortgage lending. These findings are consistent with our conjecture that intangible capital reduces commercial lending opportunities and induces banks to reallocate to other types of lending, including mortgage lending. Further, the finding that exposed banks increase mortgage acceptance rates suggests that such reallocation leads to an easing of lending standards—a possibility we explore further in Section 6.2.

6 Further Evidence and Implications

6.1 Heterogeneity of Effects by Bank Constraints

Our main analysis documents that the shift from tangible to intangible capital in the real sector induces banks to reallocate from commercial lending to other types of lending, including mortgages. It is important to note that these results hold regardless of whether the underlying reason for the decline in commercial lending is the lower debt capacity of intangible capital firms (the financial frictions channel) or these firms' lower demand for external financing (the demand channel). Nevertheless, distinguishing between these two mechanisms lends insight for welfare and policy implications. A decline in commercial lending that stems from firms' lower demand for external funds is efficient. By contrast, a decline in lending that is driven by collateral-related frictions can hinder investment.

Given that firms with more intangible capital experience worse price and nonprice lending terms, our results appear to be more consistent with the financial frictions channel. To bring additional evidence on this question, in this section we exploit cross-sectional heterogeneity in bank constraints. If our main result is indeed driven by financial intermediation frictions, then it should be more pronounced in constrained banks because such banks are less able to bear risks associated with lending to firms that lack collateral. We take this prediction to the data using a wide range of proxies for bank constraints.

Our main measure of bank constraints is the capital ratio, defined as the ratio of total equity to assets. Capital enables banks to absorb loan losses without imposing costs on their depositors (Diamond and Rajan, 2000; Flannery, 2014) and to extend riskier loans without breaching regulatory requirements (Peek and Rosengren, 1995). If firms with more intangible capital have less collateral, then loans to such firms are riskier (Berger and Udell, 1990) and require more regulatory capital (Adrian and Shin, 2014). As a result, banks with more capital should be better suited to lend to these firms. Thus, banks exposed to intangible capital growth should reduce commercial lending less if they are better capitalized. We define constrained banks as those with capital ratio below the sample median.

While capital is arguably the most direct measure of bank lending ability, it may also be mismeasured when banks engage in regulatory arbitrage (Huizinga and Laeven, 2012; Acharya et al., 2013; Kisin and Manela, 2016). For this reason, we use two additional measures of bank constraints. One such measure is the dividend ratio, a standard proxy of financial constraints for non-financial firms (Fazzari et al., 1988; Campello et al., 2010). We deem banks to be constrained if their dividend ratio is below the sample median. Another proxy is based on whether a bank belongs to a bank holding company. Studies show that lending by a bank that is affiliated with a multi-bank holding company is less sensitive to its own financial position (compared to a standalone bank) because bank holding companies establish an internal capital market to allocate capital among subsidiaries (e.g., Houston et al. (1997)). Accordingly, we expect that a bank that belongs to a bank holding company is more likely to have the necessary financial resources to lend to firms with intangible capital.

Table 8 presents the results. We estimate the baseline regressions (Column 4 of Table 2) on subsamples split by bank constraints as defined above (see Panels A–C). We find that the point estimates are larger for constrained banks. For all proxies, the effects are statistically insignificant or marginally significant in less constrained banks. The coefficient difference between constrained and unconstrained banks is statistically significant at 20% for the capital and the dividend ratio splits and at 5% for the standalone bank split. Overall, across all measures of bank constraints, the results are therefore consistent with the collateral-based financial frictions channel.

Another common measure of bank constraints is bank size. Larger banks have better access to external capital markets (Albuquerque and Hopenhayn, 2004; Clementi and Hopenhayn, 2006) and more developed internal capital markets (Goetz et al., 2016; Gilje et al., 2016). Therefore, larger banks could be relatively better placed to lend to firms with intangible capital. However, to the extent that one can view intangible capital firms as an "informationally difficult credit" (Berger et al., 2005a), it is possible that large banks are less well suited to lend to such firms because they are less able to process soft information (Stein, 2002; Zarutskie, 2010). Thus, the effect of bank size on lending to intangible capital firms is a priori ambiguous. Panel D of Table 8 shows the results in subsamples of large versus small banks (above/below-median assets). The effect of intangible capital on bank C&I lending is stronger in smaller banks and the difference is statistically significant at the 20% level. This result suggests that the collateral-based financial frictions channel—insofar as bank constraints are captured by bank size—dominates the soft information channel.[26]

Finally, we examine heterogeneity by bank exposure to intrastate branching deregulation. Historically, U.S. banks faced strict regulatory restrictions on activities outside their state of incorporation. The limits on the scope of bank operations imposed by these restrictions exacerbated bank constraints by hindering the development of internal capital markets (Gilje et al., 2016) and amplifying bank exposure to idiosyncratic local risks (Goetz et al., 2016). Starting in the early 1980s, states gradually eased these restrictions until they were completely removed by the mid-1990s (Jayaratne and Strahan, 1996; Kroszner and Strahan, 1999). We use the staggered deregulation of intrastate bank branching as a shock to individual bank constraints and examine how C&I lending responds to intangible capital as banks become less constrained after deregulation.

[26]In Table A12 we report bank heterogeneity results for syndicated and small business loans, building on the specifications of Sections 5.1.1-5.1.2 and using the full set of controls and fixed effects (including borrower-MSA×year fixed effects) to account for local real estate demand. Focusing on bank capital and bank size as key dimensions of bank constraints, we document stronger links between intangible capital and bank loan volumes (in both data sets) and loan spreads (available for syndicated loans only) in constrained banks. Further, in Table A13 we explore the role of soft information using geographic diversification as an additional dimension of bank heterogeneity. We find no systematic evidence in the effect of intangible capital growth on bank lending by degree of geographic diversification, consistent with the fact that geographically-diversified banks are usually larger and hence less constrained, and that the financial frictions channel dominates the soft information channel (see Appendix A-V for details).

Following Chakraborty et al. (2018), we construct a bank-level measure of deregulation by taking the weighted average of the deregulation indicator across all states where a bank operates, with the weights given by the bank's share of deposits in that state. We classify a bank as regulated if the weighted average is zero, that is, if no state in which it operates has been deregulated. Otherwise, we deem a bank to be (at least partially) deregulated. In effect, this measure captures the banks that are most constrained by intrastate branching regulation. Panel E of Table 8 shows that regulated banks respond more strongly to intangible capital growth than do deregulated banks. The difference in the main coefficient across subsamples is both statistically and economically significant. These results lend further support to the idea that financial intermediation frictions, rather than reduced loan demand, are the dominant mechanism behind the impact of intangible capital on C&I lending.

6.2 Economic Implications

The results of our bank- and loan-level analyses provide robust support for the hypotheses that banks curb commercial lending in response to intangible capital growth and reallocate the resulting balance sheet capacity to real estate lending. As bank mortgage supply expands, banks need to attract new mortgage borrowers. As Shin (2009) points out, "the only way they can do this is to lower their lending standards" (pp. 17). In this section, we examine the effects of banks' reallocation to real estate lending on the riskiness and profitability of banks' mortgage portfolios and explore the broader implications for bank performance.

In Table 7 we showed that intangible capital leads banks to increase mortgage acceptance rates relative to other banks in the same MSA. To the extent that the newly-approved borrowers were previously credit-rationed, new mortgage loans are likely to be of lower quality than pre-existing loans. Furthermore, if banks facing a rise in intangible capital engage in riskier real estate lending, then the same banks should also incur more mortgage defaults. Finally, to the extent that the increased mortgage lending by exposed banks is the result of a credit supply shift, then these banks' mortgage profitability should decline as they would cut mortgage rates to attract new borrowers. In other words, we expect a positive link from intangible capital growth to the riskiness of mortgage lending, and a negative link to the profitability of such lending. To test these links, we first draw on HMDA data to measure applicants' LTI ratio—a loan quality indicator associated with a higher likelihood of default (see, for example, Ambrose et al. (2005) and Agarwal et al. (2012)). Given that HMDA data has no information on loan performance or pricing at the loan level, we then turn to bank balance sheet data from the U.S. Call Reports, which provides information on mortgage delinquencies.

The results are reported in Table 9. The estimates in Column 1 indicate that banks exposed to higher intangible capital growth in their headquarters MSA originate new mortgages with higher LTI ratios in other MSAs (compared to nonexposed banks operating in those MSAs). Combined with an increase in the application acceptance rate (Table 7), this result suggests that exposed banks take more ex-ante risk in their mortgage portfolio. The specification in Column 2 examines the relation between intangible growth and subsequent mortgage default rates as reported on bank balance sheets. As loan delinquencies take time to realize, we compute the dependent variable as the average NPL ratio over a five-year window following the increase in intangible capital.[27] Consistent with banks reducing mortgage lending standards as they reallocate, we find that intangible capital growth is associated with higher mortgage NPLs, and thus greater realized risk of mortgage lending.

In Columns 3–4 of Table 9 we examine the profitability of mortgage lending, defined as interest income from mortgage lending, in percent of mortgage loans. Given that the effects on profitability should materialize soon after loan pricing decisions, in Column 3 the dependent variable is defined over the year following the increase in intangible capital. The coefficient estimates indicate that higher intangible capital growth is associated with lower profitability of mortgage lending, consistent with loan supply effects. The effect of intangible capital on profitability of mortgage lending is statistically significant after one year and becomes stronger over the subsequent five years (Column 4). Given that banks increase the quantity of mortgage lending, this loss of profitability suggests that they extend new mortgages at lower interest rates and hence incur compressed profit margins.[28]

[27] NPLs went up significantly during the housing bust, therefore we examine the robustness of all our NPL and profitability results to including the financial crisis years 2008–2010 (see Table A14).

[28] We also examine how these risk-taking and profitability effects vary with bank constraints. Relatively more constrained banks arguably have a larger pool of previously credit-rationed borrowers, some of which are of better quality. Hence, such banks should be able to expand mortgage lending with a less adverse impact on its quality and profitability. We explore this intuition in Table A15, which reports the results for our main measures of bank constraints: capital and size. For both measures, we find that more constrained

These coefficient estimates are also economically sizable. One standard deviation increase in intangible capital growth is associated with an increase in loan-to-income ratios of newly granted mortgages by close to 4% of the sample mean and an increase in mortgage NPLs by close to 7.5% of the sample mean over the subsequent five years (excluding the crisis years, as in our baseline analysis). One standard deviation increase in intangible capital growth is also associated with a decline in mortgage interest income by almost 4% of the sample mean over the following year.

What are the broader implications of higher risk-taking and lower profitability in mortgage lending for bank performance? To answer this question, we examine the aggregate impact of reallocation to mortgage lending on bank balance sheet risk and profitability, as captured by the all-loan NPL ratio and return on assets, including those adjusted for risk. As shown in Columns 5–7 of Table 9, the adverse effects of expanding mortgage portfolios are sizable enough to drive up overall NPLs and reduce bank ROA, including risk-adjusted ROA. The estimates in Columns 5 and 7 indicate that one standard deviation increase in intangible capital growth is associated with an economically significant increase in total NPLs and reduction in risk-adjusted ROA, by 5% and 7.1% of the sample means, respectively.

We interpret the results of this section as suggesting that the shift in the composition of firm assets towards intangible capital has reduced bank lending efficiency, as judged from the banks' perspective. Commercial lending is curtailed by collateral-related frictions, while additional mortgage lending induced by intangible capital growth is riskier and less profitable, with adverse consequences for the riskiness and profitability of bank balance sheets. An important caveat in interpreting these findings, however, is that our analysis does not provide a gauge for the overall welfare effects of bank reallocation to the real estate sector. Estimating welfare effects would require a quantitative evaluation in a general equilibrium setting to determine whether additional mortgage lending is just marginally riskier or overly risky, and whether it benefits households though better access to credit.

banks experience either statistically small or no increases in mortgage impairments following a period of intangible capital growth, consistent with their lending being more rationed ex-ante.

7 Conclusions

Over the past few decades, U.S. firms have dramatically increased their investment in intangible capital. Yet, little is known about the effect of this shift in the real sector on financial intermediation. In this paper, we examine the impact of intangible capital on the composition of U.S. banks' loan portfolios. Using bank-level panel data and loan-level microdata, we find robust evidence that exposure to intangible capital induces banks to reduce their commercial lending and reallocate toward other assets, particularly real estate loans. By constraining banks' commercial lending opportunities, a rise in intangible capital generates supply-side pressures in real estate lending, with adverse effects for the riskiness and profitability of banks' mortgage portfolios. Overall, the evidence suggests that the long-run change in the composition of the U.S. capital stock toward intangible capital has a quantitatively large effect on financial intermediary balance sheets.

Our results have important economic policy implications. We find that firms with more intangible capital have worse lending terms, pointing to external finance frictions as a key reason for their lower borrowing. Borrowing constraints likely distort firm investment decisions. The lower efficiency of financial intermediation in an intangible capital-intensive economy may explain some of the decline in investment rates that underlies the "secular stagnation" hypothesis (Summers, 2014). Our findings thus raise the question of how policy can facilitate the financing of innovative firms. The fact that banks exposed to corporate intangible capital growth reallocate their balance sheet capacity to real estate lending is consistent with the "banking glut" observations of Shin (2012). We highlight that banks' reallocation to real estate lending is associated with higher mortgage risk and lower mortgage profitability, raising prudential concerns. The bank balance sheet reallocation identified in this paper also has monetary policy implications. As banks shift from commercial to household lending, the importance of bank net worth and of the bank credit channel of monetary policy for firm investment may diminish (Kashyap and Stein, 2000; Kishan and Opiela, 2000; Chodorow-Reich, 2013), while the impact on households may strengthen (Mishkin, 2007).

References

Acharya, V. V., Eisert, T., Eufinger, C., and Hirsch, C. W. (2018). Real effects of the sovereign debt crisis in Europe: Evidence from syndicated loans. *Review of Financial Studies*, 31(8):3366–3411.

Acharya, V. V., Schnabl, P., and Suarez, G. (2013). Securitization without risk transfer. *Journal of Financial Economics*, 107(3):515–536.

Adrian, T. and Shin, H. S. (2014). Procyclical leverage and value-at-risk. *Review of Financial Studies*, 27(2):373–403.

Agarwal, S., Benmelech, E., Bergman, N., and Seru, A. (2012). Did the Community Reinvestment Act (CRA) lead to risky lending? *NBER Working Paper No. 18609.*

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

Albuquerque, R. and Hopenhayn, H. A. (2004). Optimal lending contracts and firm dynamics. *Review of Economic Studies*, 71(2):285–315.

Ambrose, B. W., LaCour-Little, M., and Sanders, A. B. (2005). Does regulatory capital arbitrage, reputation, or asymmetric information drive securitization? *Journal of Financial Services Research*, 28:113–133.

Amel, D. F. and Brevoort, K. P. (2005). The perceived size of small business banking markets. *Journal of Competition Law and Economics*, 1(4):771–784.

Autor, D. H. and Dorn, D. (2013). The growth of low skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–1597.

Bates, T. W., Kahle, K. M., and Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to? *Journal of Finance*, 64(5):1985–2021.

Berger, A. N., Demsetz, R. S., and Strahan, P. E. (1999). The consolidation of the financial services industry: Causes, consequences, and implications for the future. *Journal of Banking & Finance*, 23(2-4):135–194.

Berger, A. N., Espinosa-Vega, M. A., Frame, W. S., and Miller, N. H. (2005a). Debt maturity, risk, and asymmetric information. *Journal of Finance*, 60(6):2895–2923.

Berger, A. N., Miller, N. H., Petersen, M. A., and Rajan, R. G. (2005b). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, 76(2):237–269.

Berger, A. N. and Udell, G. F. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, 25(1):21–42.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *American Economic Review*, 75(4):850–855.

Brevort, K. P., Holmes, J. A., and Wolken, J. D. (2010). Distance still matters: The information revolution in small business lending and the persistent role of location, 1993-2003. *FEDS Working Paper No. 2010-08.*

Brown, J. D. and Earle, J. S. (2017). Finance and growth at the firm level: Evidence from SBA loans. *Journal of Finance*, 72(3):1039–1080.

Brown, J. R., Fazzari, S. M., and Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *Journal of Finance*, 64(1):151–185.

Brown, J. R., Martinsson, G., and Petersen, B. C. (2013). Law, stock markets, and innovation. *Journal of Finance*, 68(4):1517–1549.

Caggese, A. and Perez-Orive, A. (2017). Capital misallocation and secular stagnation. *FEDS Working Paper No. 2017–009.*

Campello, M., Graham, J. R., and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Einancial Economics*, 97(3):470–487.

Cannon, C., Clark, P., Diamond, J. S., and Meisler, L. (2015). The Unlikely Cities That Will Power the U.S. Economy. https://www.bloomberg.com/graphics/2015-stem-jobs/.

Carpenter, R. E. and Petersen, B. C. (2002). Capital market imperfections, high-tech investment, and new equity financing. *Economic Journal*, 112(477):F54–F72.

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

Chan, Y.-S. and Thakor, A. V. (1987). Collateral and competitive equilibria with moral hazard and private information. *Journal of Finance*, 42(2):345–363.

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

Chodorow-Reich, G. (2013). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *Quarterly Journal of Economics*, 237(1):1–59.

Clementi, G. L. and Hopenhayn, H. A. (2006). A theory of financing constraints and firm dynamics. *Quarterly Journal of Economics*, 121(1):229–265.

Corrado, C., Hulten, C., and Sichel, D. (2009). Intangible capital and US economic growth. *Review of Income and Wealth*, 55(3):661–685.

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

Craig, B. R., Jackson, W. E., Thomson, J. B., et al. (2004). Are SBA loan guarantees desirable? *Federal Reserve Bank of Cleveland*.

De Haas, R. and Van Horen, N. (2012). Running for the exit? International bank lending during a financial crisis. *Review of Financial Studies*, 26(1):244–285.

Del Guidice, V. and Lu, W. (2019). These Are America's New Top Tech Hubs. https://www.bloomberg.com/news/articles/2019-11-18/kansas-draws-enough-brain-power-to-make-it-a-top-tech-hub/.

Den Haan, W., Sumner, S., and Yamashiro, G. (2002). Construction of aggregate and regional bank data using the call reports: Data manual. *mimeo*.

Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *Quarterly Journal of Economics*, 106(3):709–737.

Diamond, D. W. and He, Z. (2014). A theory of debt maturity: The long and short of debt overhang. *Journal of Finance*, 69(2):719–762.

Diamond, D. W. and Rajan, R. G. (2000). A theory of bank capital. *Journal of Finance*, 55(6):2431–2465.

Döttling, R. and Perotti, E. (2016). Secular financial trends and technological progress. *mimeo*.

Duchin, R. and Sosyura, D. (2014). Safer ratios, riskier portfolios: Banks' response to government aid. *Journal of Financial Economics*, 113(1):1–28.

Eisfeldt, A. L. and Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *Journal of Finance*, 68(4):1365–1406.

Falato, A., Kadyrzhanova, D., Sim, J., and Steri, R. (2018). Rising intangible capital, shrinking debt capacity, and the US corporate savings glut.

Fazzari, S., Hubbard, R. G., and Petersen, B. (1988). Investment, financing decisions, and tax policy. *American Economic Review*, 78(2):200–205.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. *Journal of Finance*, 41(1):19–37.

Flannery, M. J. (2014). Maintaining adequate bank capital. *Journal of Money, Credit and Banking*, 46(s1):157–180.

Gilje, E. P., Loutskina, E., and Strahan, P. E. (2016). Exporting liquidity: Branch banking and financial integration. *Journal of Finance*, 71(3):1159–1184.

Goetz, M. R., Laeven, L., and Levine, R. (2016). Does the geographic expansion of banks reduce risk? *Journal of Financial Economics*, 120(2):346–362.

Graham, J. R. and Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics*, 60(2-3):187–243.

Hale, G. (2012). Bank relationships, business cycles, and financial crises. *Journal of International Economics*, 88(2):312–325.

Hale, G., Kapan, M. T., and Minoiu, C. (2019). Shock Transmission Through Cross-Border Lending: Credit and Real Effects. *Review of Financial Studies (forthcoming)*.

Hart, O. and Moore, J. (1994). A theory of debt based on the inalienability of human capital. *Quarterly Journal of Economics*, 109(4):841–879.

Houston, J., James, C., and Marcus, D. (1997). Capital market frictions and the role of internal capital markets in banking. *Journal of Financial Economics*, 46(2):135–164.

Huizinga, H. and Laeven, L. (2012). Bank valuation and accounting discretion during a financial crisis. *Journal of Financial Economics*, 106(3):614–634.

Ivashina, V. and Scharfstein, D. S. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, 97(3):319–338.

Jayaratne, J. and Strahan, P. E. (1996). The finance-growth nexus: Evidence from bank branch deregulation. *Quarterly Journal of Economics*, pages 639–670.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers, and credit supply: evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy*, 125(6):2126–2177.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442.

Kishan, R. P. and Opiela, T. P. (2000). Bank size, bank capital, and the bank lending channel. *Journal of Money, Credit and Banking*, pages 121–141.

Kisin, R. and Manela, A. (2016). The shadow cost of bank capital requirements. *Review of Financial Studies*, 29(7):1780–1820.

Kroszner, R. S. and Strahan, P. E. (1999). What drives deregulation? Economics and politics of the relaxation of bank branching restrictions. *Quarterly Journal of Economics*, 114(4):1437–1467.

Lev, B. and Radhakrishnan, S. (2005). The valuation of organization capital. In *Measuring capital in the new economy*, pages 73–110. University of Chicago Press.

Loughran, T. and Ritter, J. (2004). Why has ipo underpricing changed over time? *Financial Management*, pages 5–37.

Loumioti, M. (2012). The use of intangible assets as loan collateral. *Available at SSRN 1748675*.

Loutskina, E. and Strahan, P. E. (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *Journal of Finance*, 64(2):861–889.

Mann, W. (2018). Creditor rights and innovation: Evidence from patent collateral. *Journal of Financial Economics*, 130(1):25–47.

Mian, A. and Santos, J. A. (2018). Liquidity risk and maturity management over the credit cycle. *Journal of Financial Economics*, 127(2):264–284.

Mishkin, F. S. (2007). Housing and the monetary transmission mechanism. In *Proceedings-Economic Policy Symposium-Jackson Hole*, pages 359–413. Federal Reserve Bank of Kansas City.

Morris, J. R. (1976). On corporate debt maturity strategies. *Journal of Finance*, 31(1):29–37.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2):147–175.

Peek, J. and Rosengren, E. (1995). Bank regulation and the credit crunch. *Journal of Banking & Finance*, 19(3-4):679–692.

Peters, R. H. and Taylor, L. A. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123(2):251–272.

Rajan, R. and Winton, A. (1995). Covenants and collateral as incentives to monitor. *Journal of Finance*, 50(4):1113–1146.

Rampini, A. A. and Viswanathan, S. (2013). Collateral and capital structure. *Journal of Financial Economics*, 109(2):466–492.

Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *Journal of Finance*, 67(3):897–932.

Shin, H. S. (2009). Securitisation and financial stability. *Economic Journal*, 119(536):309–332.

Shin, H. S. (2012). Global banking glut and loan risk premium. *IMF Economic Review*, 60(2):155–192.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *Journal of Finance*, 57(5):1891–1921.

Strahan, P. E. (1999). Borrower risk and the price and nonprice terms of bank loans. *FRB of New York Staff Report*, (90).

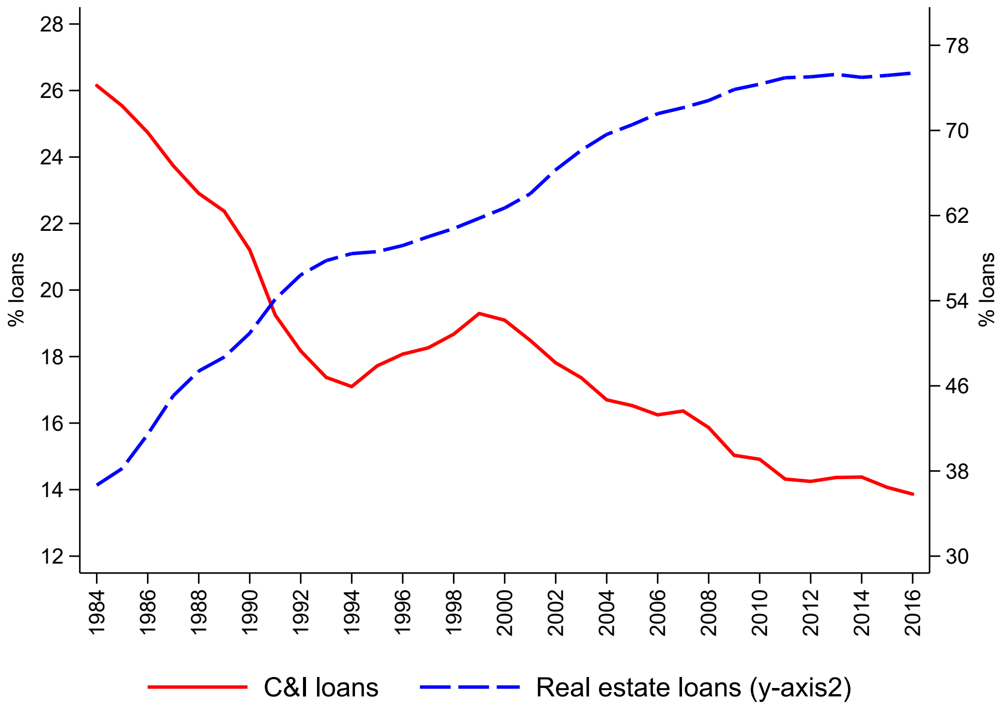
Summers, L. H. (2014). US economic prospects: Secular stagnation, hysteresis, and the zero lower bound. *Business Economics*, 49(2):65–73.

Sun, Q. and Xiaolan, M. Z. (2019). Financing intangible capital. *Journal of Financial Economics*, 133(3):564–588.

Zarutskie, R. (2010). Competition and specialization in credit markets. *Federal Reserve Bank of New York, mimeo.*

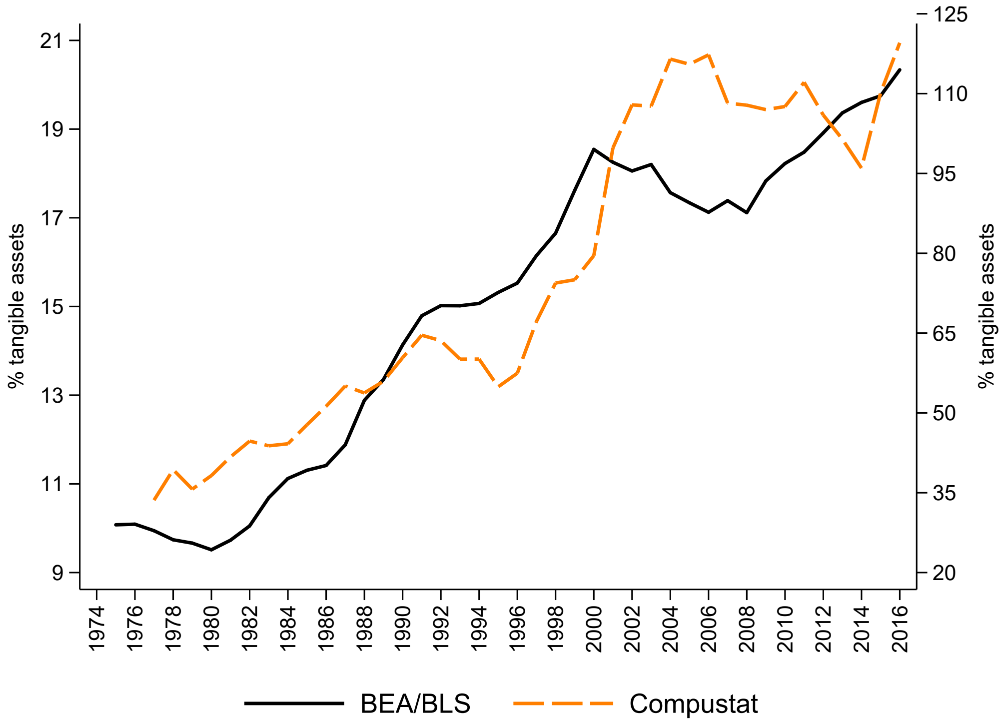
Figures and Tables

Figure 1: Bank loan portfolio composition, 1984–2016



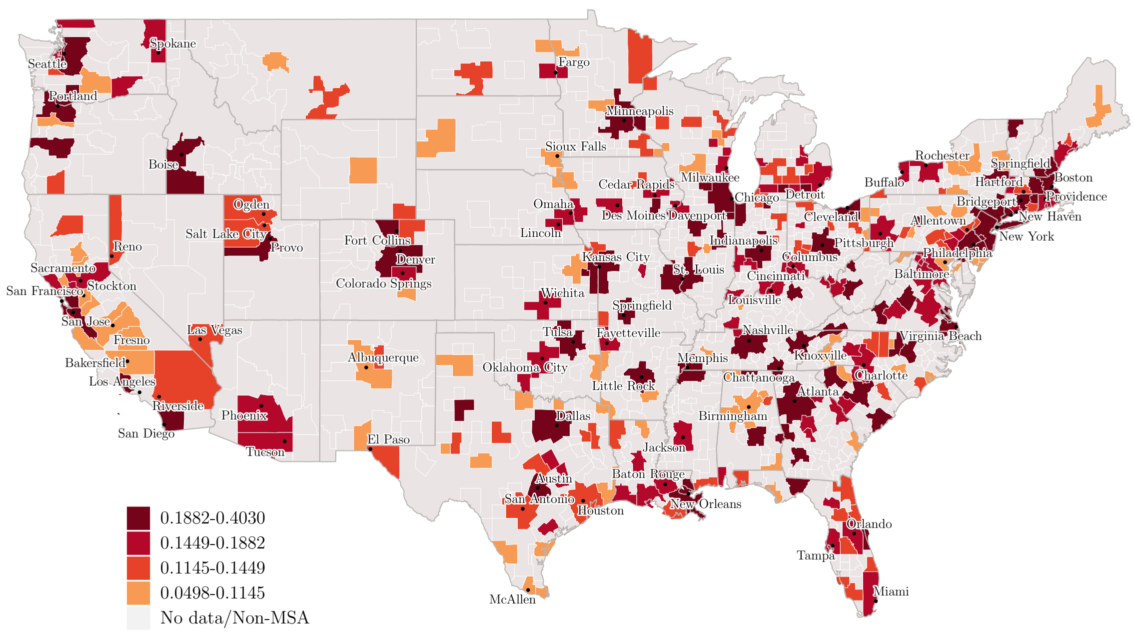
The figure depicts the average share of C&I and real estate loans in total loans across U.S. commercial banks in our sample during 1984–2016. Data sources: U.S. Call Reports.

Figure 2: Corporate intangible capital, 1975–2016

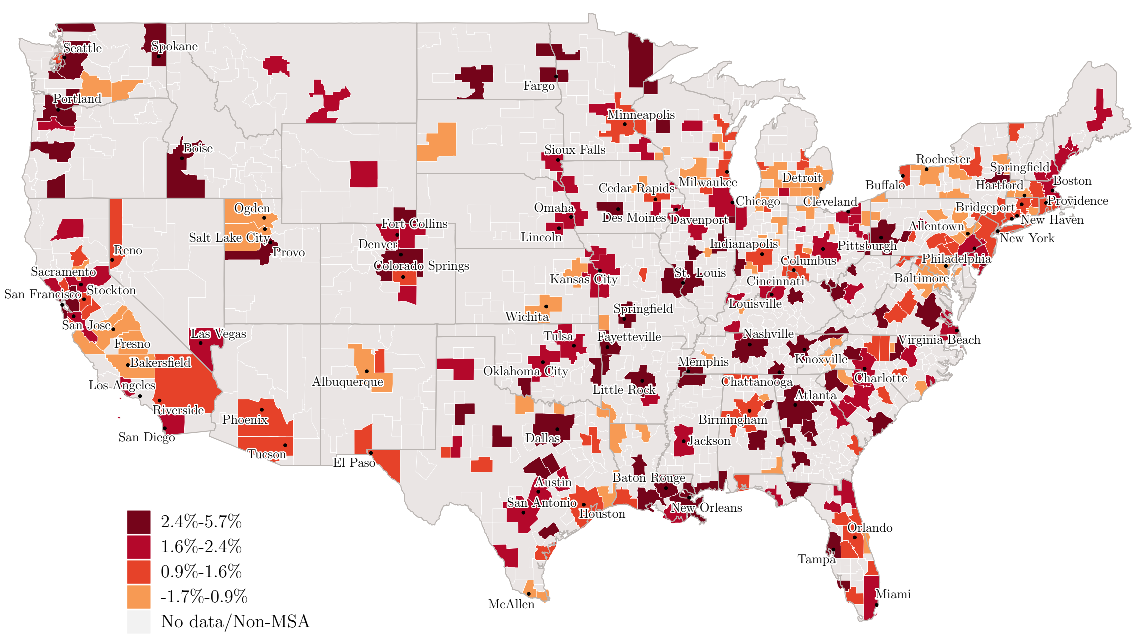


The figure depicts the long-run trend in aggregate corporate intangible capital ratio (in % of tangible capital). The BEA/BLS aggregate intangible capital ratio is computed as the weighted average of industry-level intangible-to-tangible capital ratios, with weights given by each industry's share in total U.S. employment. Industries are defined at the three-digit NAICS industry level, and the sample period is 1975–2016. The Compustat aggregate intangible capital ratio (shown on the secondary y-axis) is the unweighted average ratio across firms. Intangible capital is computed from financial statement data as the sum of accumulated knowledge capital, organizational capital, and informational capital. It is available over 1977–2016. See Section 3 for details on the construction of both measures. Data sources: BEA, BLS, Compustat, Falato et al. (2018).

Figure 3: Corporate intangible capital across U.S. MSAs



(a) Level, 2016



(b) Average growth, 1984–2016

The maps depict spatial variation across MSAs in the level of intangible capital in 2016 (top) and in the growth rate of intangible capital over 1984–2016 (bottom). Data sources: BEA, BLS.

Table 1: Descriptive statistics for selected regression variables

	Obs.	Mean	St. Dev.	p25	Median	p75
A. Bank-level analysis						
C&I loan growth	82220	6.5%	24.5%	-10.0%	3.6%	19.1%
Non C&I asset growth	87258	5.5%	9.6%	-1.3%	3.9%	10.6%
Bank asset growth	89164	5.3%	9.2%	-1.1%	3.7%	10.0%
Real estate loan growth	84171	9.4%	16.2%	-1.5%	6.8%	17.4%
C&I loans (% assets)	78986	11.6%	87%	5.5%	9.7%	15.6%
Real estate loans (% assets)	78986	35.2%	16.8%	22.8%	33.8%	46.4%
Bank size (log-assets)	89028	18.07	1.24	17.21	17.95	18.76
Bank capital	89091	15.4%	8.0%	10.1%	13.7%	18.9%
B. MSA-level variables						
IK level	89011	14.2%	5.7%	10.9%	13.5%	17.2%
IK growth	89011	4.3%	3.9%	1.4%	4.3%	7.4%
Mortgage NPL ratio	47535	4.3%	7.7%	0.0%	0.0%	5.9%
Mortgage profitability	103977	8.2%	9.6%	0.0%	0.0%	16.8%
Overall NPL ratio	47528	1.5%	1.7%	0.5%	1.0%	2.0%
Return on assets (ROA)	50358	2.7%	3.4%	1.7%	3.0%	4.3%
Risk-adjusted ROA	30684	2.8%	2.6%	1.6%	2.9%	4.1%
C. Syndicated loan analysis						
Firm-level IK	82509	32.2%	44.6%	8.8%	21.5%	41.2%
Loan volume (log)	82509	21.7	2.3	21.1	21.8	22.5
Spread (bps)	75602	135.6	102.1	60.0	116.7	183.9
Maturity (years)	80425	4.2	2.0	3.0	5.0	5.0
D. Small business loan analysis						
Industry-level IK	514116	14.9%	40.6%	1.6%	2.7%	9.1%
Loan volume (log)	514116	12.0	1.4	11.0	11.9	13.0
Maturity (years)	513827	9.5	6.3	5.5	7.0	10.3
E. Mortgage analysis						
Loan volume (log)	83076	8.75	1.56	7.70	8.68	9.77
Acceptance rate	83076	0.83	0.16	0.77	0.88	0.94
Δ log(loan volume)	83076	0.20	0.83	-0.25	0.13	0.56
Δ acceptance rate	83076	0.00	0.12	-0.05	0.00	0.05
Δ applicants' loan-to-income ratio	83076	0.04	2.02	-0.18	0.03	0.25

The table presents descriptive statistics for selected regression variables. Growth rates of U.S. Call Report variables are winsorized at 5% of the distribution. The variable "IK level" refers to the MSA-level intangible capital ratio using employment shares lagged at $t-3$ (see Section 3 for details.) IK growth is winsorized at 1% of the MSA-level distribution. Firms' sales growth and market-to-book ratio (original variables are winsorized at the 5% of the distribution) are computed at the MSA level as unweighted averages across the firms in each MSA. The variables in panels A and B refer to the bank-level panel in the baseline analysis; panels C–E refer to loan-level analyses. Sample periods are 1984–2016 for bank- and macro-level variables in the baseline regressions, 1990–2016 for DealScan, 1990–2016 for SBA, and 1995–2016 for HMDA analysis. See Data Appendices A-II–A-IV for details and Table A2 for additional descriptive statistics.

Table 2: Intangible capital and bank asset allocations—Baseline

	C&I loans (1)	C&I loans (2)	C&I loans (3)	C&I loans (4)	Bank assets (5)	Non C&I assets (6)
IK growth	-0.3349***	-0.1803***	-0.1853***	-0.2107***	0.0330	0.0447***
	(0.023)	(0.027)	(0.072)	(0.068)	(0.030)	(0.012)
House price growth		0.3054***	0.2877***	0.1400***	0.1970***	-0.0244***
		(0.020)	(0.023)	(0.022)	(0.009)	(0.004)
Pc income growth		0.2470***	0.2085***	0.0896**	0.1556***	-0.0316***
		(0.036)	(0.045)	(0.043)	(0.016)	(0.008)
Population growth		0.7130***	0.5589***	-0.0229	0.7874***	0.0278**
		(0.076)	(0.078)	(0.071)	(0.040)	(0.013)
Firm sales growth		0.0475***	0.0082	0.0012	0.0098***	-0.0006
		(0.006)	(0.006)	(0.006)	(0.003)	(0.001)
Firm market-to-book		0.0003	0.0009	-0.0042***	0.0068***	0.0008***
		(0.002)	(0.002)	(0.002)	(0.001)	(0.000)
Bank size		-0.0016**	-0.0011	-0.0026***	0.0018***	0.0002
		(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Bank capital		0.1972***	0.1986***	0.1447***	0.0680***	-0.0205***
		(0.018)	(0.025)	(0.021)	(0.010)	(0.003)
Bank asset growth				0.7323***		0.9823***
				(0.011)		(0.002)
Observations	81,953	80,448	80,448	80,448	87,408	85,456
R-squared	0.003	0.013	0.027	0.094	0.081	0.833
Year fixed effects	No	No	Yes	Yes	Yes	Yes

The dependent variables are bank-level C&I loan growth (Columns 1–4), total asset growth (Column 5), and non-C&I asset growth (Column 6). Macro controls include house price growth, per capita income growth, population growth, firm sales growth, and firm market-to-book ratio. Bank controls include bank size, capital, and, in Columns 4 and 6, total bank asset growth. IK growth and macro controls correspond to the MSA of the bank's headquarters. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 3: Intangible capital and bank asset allocations—IK measure based on alternative lags of employment shares

	C&I loans	Bank assets	Non C&I assets
	(1)	(2)	(3)
	IK: Employment shares at $t-1$		
IK growth	-0.1365**	-0.0091	0.0257***
	(0.063)	(0.026)	(0.010)
Observations	80,448	87,408	85,456
R-squared	0.094	0.081	0.833
	IK: Employment shares at $t-5$		
IK growth	-0.2075***	0.0349	0.0362***
	(0.070)	(0.032)	(0.012)
Observations	80,448	87,408	85,456
R-squared	0.094	0.081	0.833
	IK: Employment shares at $t-10$		
IK growth	-0.2450***	-0.0364	0.0488***
	(0.069)	(0.032)	(0.011)
Observations	80,448	87,408	85,456
R-squared	0.094	0.081	0.833
	IK: Employment shares in 1975		
IK growth	-0.1676***	-0.0305	0.0303***
	(0.062)	(0.032)	(0.010)
Observations	80,448	87,408	85,456
R-squared	0.094	0.081	0.833
Macro controls	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

The table reports coefficient estimates for the variable "IK growth" from regressions using the baseline specification in Column 4 of Table 2. The dependent variables are bank-level C&I loan growth, total asset growth, and non-C&I asset growth. Panel headings indicate the lag structure for employment shares used in constructing corporate IK growth. Macro controls and bank controls are defined as in Table 2 and are included in all specifications (coefficients not shown). Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 4: Intangible capital and bank asset allocations—IK measure based on banks' geographic footprint

	C&I loans (1)	Bank assets (2)	Non C&I assets (3)
		IK: weighted by deposits	
IK growth	-0.1597**	0.0095	0.0370***
	(0.071)	(0.032)	(0.012)
Observations	46,582	49,153	48,475
R-squared	0.107	0.080	0.870
		IK: weighted by number of mortgage applications	
IK growth	-0.2822***	-0.0339	0.0441***
	(0.095)	(0.047)	(0.016)
Observations	46,582	49,153	48,475
R-squared	0.107	0.080	0.870
		IK: weighted by volume of mortgage applications	
IK growth	-0.2827***	-0.0315	0.0446***
	(0.095)	(0.047)	(0.016)
Observations	73,503	79,331	77,875
R-squared	0.094	0.080	0.849
Macro controls	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

The table reports coefficient estimates for the variable "IK growth" from regressions using the baseline specification in Column 4 of Table 2. The dependent variables are bank-level C&I loan growth, total asset growth, and non-C&I asset growth. Unlike in the baseline analysis, the IK growth variable is constructed at the bank level using the bank's geographic footprint across MSAs and years, based on bank's deposit-taking and mortgage-lending activities. Macro controls are also computed at the bank level using the same approach as for IK growth. Macro controls and bank-level controls are included in all specifications (coefficients not shown). Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5: Intangible capital and commercial lending terms—Evidence from DealScan syndicated loan data

	Loan volume (log)			Loan spread			Loan maturity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm-level IK	-0.2569***	-0.2215***	-0.1506***	19.9089***	15.2085***	11.2265***	-0.0644***	-0.0710***	-0.0708***
	(0.028)	(0.027)	(0.027)	(1.537)	(1.765)	(1.674)	(0.022)	(0.022)	(0.024)
Firm size (large firm)		0.5162***	0.4099***		-58.4775***	-61.1675***		-0.0063	0.0812*
		(0.029)	(0.051)		(1.165)	(2.443)		(0.028)	(0.045)
Firm market-to-book		0.0320***	-0.0018		-3.5269***	-0.1474		-0.0554***	-0.0341*
		(0.011)	(0.020)		(0.544)	(1.230)		(0.010)	(0.018)
Firm ROA		0.0069***	0.0065***		-3.2093***	-2.9607***		0.0157***	0.0197***
		(0.001)	(0.002)		(0.083)	(0.150)		(0.002)	(0.003)
Firm cash ratio		-0.0005	-0.0004		0.0433	-0.3416***		0.0035***	0.0015
		(0.001)	(0.002)		(0.052)	(0.111)		(0.001)	(0.001)
Observations	82,557	82,557	80,945	75,351	75,351	73,940	80,372	80,372	78,936
R-squared	0.303	0.308	0.507	0.563	0.625	0.884	0.596	0.598	0.881
Bank×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Rating×Year fixed effects			Yes			Yes			Yes

The dependent variables are log(loan amount) (Columns 1–3), loan spreads (Columns 4–6), and loan maturity (Columns 7–9). The data are at the bank-firm-year level and are aggregated from loan-level data on syndicated loan deals. Firm-level IK is constructed following Falato et al. (2018). Firm industry refers to four-digit SIC industries. Firm rating category refers to 23 S&P firm rating categories (including unrated category). All regressions include bank×year, borrower-MSA×year fixed effects, and borrower industry fixed effects. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6: Intangible capital and commercial lending terms—Evidence from SBA data

	Loan volume (log)			Loan maturity		
	All industries		Manufacturing	All industries		Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
Industry-level IK	-0.0936***	-0.0852***	-0.1729***	-0.4540***	-0.4801***	-0.9298***
	(0.013)	(0.013)	(0.040)	(0.049)	(0.051)	(0.153)
Industry size		0.1423***	0.1891***		0.1109***	0.1484***
		(0.019)	(0.017)		(0.036)	(0.043)
Industry TFP growth			0.7337**			2.3495*
			(0.328)			(1.390)
Industry profitability			0.4412***			0.1249
			(0.142)			(0.305)
Observations	514,116	482,400	43,237	513,822	482,139	43,194
R-squared	0.372	0.385	0.470	0.369	0.375	0.428
Bank×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variables are log(loan amount) (Columns 1–3) and loan maturity (Columns 4–6). The data are at the bank-industry-MSA-year level and are aggregated from loan-level data for small business lending. Industry-level IK comes from the BEA based on the three-digit NAICS classification. All regressions include bank×year and borrower-MSA×year fixed effects. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: Intangible capital and bank mortgage lending—Evidence from HMDA data

	Δ log(loan volume)			Δ acceptance rate		
	(1)	(2)	(3)	(4)	(5)	(6)
IK growth	7.5530**	8.2144**	8.1477**	0.7120***	0.6753***	0.6550***
	(3.3769)	(3.4207)	(3.4010)	(0.1635)	(0.1693)	(0.1655)
House price growth		-0.4816	-0.4696		0.1484	0.1517
		(0.4583)	(0.4586)		(0.1208)	(0.1216)
Pc income growth		1.0618	1.0298		0.0923	0.0811
		(0.7019)	(0.7160)		(0.0679)	(0.0675)
Population growth		-2.3237	-2.3991		-0.6086	-0.6246
		(2.3874)	(2.4148)		(0.4900)	(0.4937)
Firm sales growth		-0.0384**	-0.0381**		0.0014	0.0015
		(0.0152)	(0.0151)		(0.0024)	(0.0024)
Firm market-to-book		-0.5046	-0.5172		-0.0432	-0.0462
		(0.4193)	(0.4185)		(0.0625)	(0.0623)
Bank size		1.2141***	1.2247***		0.0741**	0.0772**
		(0.1668)	(0.1688)		(0.0354)	(0.0354)
Bank capital		-0.1638	-0.1596		0.0029	0.0048
		(0.1174)	(0.1186)		(0.0147)	(0.0144)
Bank asset growth		-0.0306	-0.0316		-0.0033	-0.0037
		(0.0226)	(0.0224)		(0.0057)	(0.0056)
Δ applicants' log income			0.2643***			0.0677***
			(0.0317)			(0.0050)
Δ share of female applicants			-0.0460			-0.0181***
			(0.0405)			(0.0060)
Δ share of minority applicants			-0.0592			-0.0898***
			(0.0645)			(0.0116)
Δ share of minority residents			0.0064***			0.0004
			(0.0018)			(0.0003)
Δ log(personal income)			0.7220***			0.1038***
			(0.1393)			(0.0232)
Observations	52,085	52,085	52,085	52,912	52,912	52,912
R-squared	0.1967	0.2195	0.2276	0.1337	0.1391	0.1614
MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variables are the growth rate in mortgage lending volume (Columns 1–3) and the change in the acceptance rate for mortgage applications (Columns 4–6). The data are at the bank-MSA-year level and are aggregated from loan-level data on individual mortgages. IK growth, macro controls, and bank controls are as in the baseline specification in Column 4 of Table 2. All regressions include borrower-MSA×year fixed effects. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8: Intangible capital and bank commercial lending—Heterogeneity by bank constraints

	Constrained	Unconstrained	p-value
	(1)	(2)	(3)
	A. Capital		
IK growth	-0.2694***	-0.0740	0.156
	(0.095)	(0.099)	
Observations	40,028	40,420	
R-squared	0.099	0.092	
	B. Dividend policy		
IK growth	-0.3028***	-0.0924	0.114
	(0.102)	(0.088)	
Observations	40,125	40,323	
R-squared	0.116	0.066	
	C. Internal capital markets		
IK growth	-0.5177***	-0.1128#	0.0160
	(0.150)	(0.075)	
Observations	18,685	61,763	
R-squared	0.075	0.102	
	D. Size		
IK growth	-0.3086***	-0.1166#	0.152
	(0.099)	(0.090)	
Observations	39,854	40,594	
R-squared	0.073	0.125	
	E. Regulation		
IK growth	-0.5804***	-0.1595**	0.0470
	(0.202)	(0.072)	
Observations	19,081	61,366	
R-squared	0.088	0.096	

The table explores heterogeneity in the effect of intangible capital on bank C&I loan growth (from Column 4 in Table 2) by bank constraints. Banks are classified as constrained if they have below-median capital, below-median dividend payouts, no access to internal capital markets (standalone bank as opposed to in a BHC), below-median assets, or if they are located in a regulated state before the removal of intra-state branching restrictions. Columns 1–2 report the coefficients for the "IK growth" variable in the constrained and unconstrained samples of banks. Column 3 reports the p-value of a two-sided t-test of equality of coefficients across constrained and unconstrained banks. All specifications include macro and bank controls, and year fixed effects. Standard errors are clustered on bank. # indicates statistical significance at the 20% level, *** at the 1% level, ** at the 5% level, and * at the 10% level.

Table 9: Intangible capital and bank risk-taking and profitability

	Δ LTI ratio (t, t+5)	Mortgage NPL ratio (t, t+5)	Mortgage profitability (t, t+1)	Mortgage profitability (t, t+5)	Overall NPL ratio (t, t+5)	Overall ROA (t, t+5)	Risk-adj. overall ROA (t, t+5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IK growth	3.6779*	0.0825***	-0.0554*	-0.0672**	0.0194***	-0.0189***	-0.0510***
	(1.8841)	(0.026)	(0.028)	(0.027)	(0.007)	(0.007)	(0.015)
Observations	52,912	37,139	79,551	55,377	37,373	55,492	21,345
R-squared	0.1199	0.304	0.647	0.701	0.110	0.138	0.119
MSA controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year fixed effects	Yes						
Borrower controls	Yes						

The dependent variables are risk and profitability of mortgage lending (Columns 1–3) and respectively of overall balance sheets (Columns 4–6). All dependent variables are averaged over $t, t+5$ except Column 3 where mortgage profitability is averaged over $t, t+1$. The specification in Column 1 uses HMDA data and all controls are as in Columns 3 and 6 of Table 7. The specifications in Columns 2–6 use U.S. Call Report data and all controls are as Columns 4 and 6 of baseline Table 2. Across all specifications, IK growth and macro controls correspond to the MSA of the bank's headquarters. In line with the baseline analysis, crisis year observations (2008–2010) are excluded from the sample. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Online Appendix

This document contains data appendices with details on our data sources, merges, and transformations for the regression samples; and additional results.

A-I Data Appendix: Intangible Capital Data

Our main explanatory variable—the growth of MSA-level intangible capital—is constructed using two data sources: industry-level estimates of intangible capital from Bureau of Economic Analysis' (BEA) Fixed Assets data and MSA-level distribution of employment by industry from the Bureau of Labor Statistics' (BLS) Quarterly Census of Employment and Wages (QCEW).

Intangible assets are more difficult to measure than physical (tangible) assets such as property, plant, and equipment (PP&E). In general, the literature recognizes three types of investment as important for the accumulation of intangible capital: investment in knowledge capital, organizational capital, and informational capital (see, for example, Corrado et al. (2009)). In 2013, BEA revised the national income and product accounts (NIPAs) to explicitly recognize R&D spending as intangible capital to be included in estimates of fixed assets. Previously, R&D spending was treated as expenditures, similar to the way it is treated in companies' financial statements. The 2013 revision's measure of intangible capital, which includes software and capitalized private expenditures on R&D, entertainment, literary, and artistic originals, is estimated starting in 1947 and is available at the industry level. For R&D expenditures at the establishment level, BEA relies on NSF's R&D Survey administered by the U.S. Census. For our measure of industry-level corporate intangible capital, we take the ratio of intangible capital to tangible capital stock (equipment and structures) from BEA's revised Fixed Assets data.

For industry employment shares we use data from the BLS' QCEW over the 1984–2016 period. We use data at the three-digit NAICS classification and MSA level. To map employment shares from QCEW to intangible capital from BEA, we use the BEA-provided crosswalk from the BEA industry definitions to three-digit NAICS codes.

A-II Data Appendix: U.S. Call Reports

We construct our bank-year panel for the baseline analysis as follows. Bank financial information comes from the U.S. Call Reports (available for all the banks regulated by the

Federal Reserve System, Federal Deposit Insurance Corporation, and the Comptroller of the Currency) that are publicly available on the website of the Federal Reserve Bank of Chicago. The sample period in our baseline analysis is 1984–2016. Starting our sample in 1984 ensures time-series consistency in regards to the definitions of several key variables, including total assets, C&I loans, and total equity (as discussed in Kashyap and Stein (2000) and Den Haan et al. (2002)). The data refer to non-consolidated accounts (that is, on an "individual bank basis") that reflect domestic operations and ignore banks' foreign activities.

We restrict the sample to commercial banks (variable RSSD9331 takes value 1) by dropping state-chartered savings banks, federal savings banks, cooperative banks, industrial banks, and foreign banking organizations. Following Den Haan et al. (2002), we also limit the sample to insured banks (RSSD9424 takes values 1, 2 or 6) and banks that are located in the 50 states and District of Columbia. For each bank we observe the MSA of its headquarters (variable RSSD9180). The bank-level panel covers about 7,800 commercial banks with headquarters in 271 MSAs.

Main variable definitions and transformations are listed below:

- **Commercial and industrial (C&I) loans**. Commercial and industrial loans in USD or divided by total assets (RCON2170). For years 1984-2000, we use RCON1600. For years 2001-2008, we use (RCON1755+RCON1766). If RCON1755 is missing, we only use RCON1766.
- **Non-C&I assets**. Difference between total assets (RCON2170) and C&I loans.
- **Real estate loans**. Loans secured by real estate in USD (RCON1410) or divided by total assets (RCON2170). This variable is split into its components: residential real estate loans (RCON1430+RCON1460) and commercial real estate loans (the difference between total and residential real estate loans).
- **Real estate loan profitability**. Interest and fees on loans secured primarily by real estate (RIAD4011) divided by loans secured by real estate (RCON1410). Available starting in 1985.
- **NPL ratio**. Sum of loans and leases past-due 90 days or more (still accruing) plus non-accruing loans (RCFD1407+RCFD1403), divided by total gross loans (RCFD2122).
- **Real estate NPL ratio**. Sum of loans and leases past-due 90 days or more (still accruing) plus non-accruing revolving, open-end mortgage loans secured by 1–4 family residential properties (RCON5399 + RCON5400), divided by loans secured by real estate (RCON1410). Available starting in 1991.
- **Return on assets (ROA)**. Net income (RIAD4340) divided by total assets (RCON2170).
- **Risk-adjusted ROA**. Net income (RIAD4340) divided by risk-weighted assets (RCONA223).
- **Bank size**: Log of total bank assets (RCON2170).
- **Bank equity**: Total bank equity (RCON3210) divided by total assets (RCON2170).

A-III Data Appendix: Dealscan and SBA

DealScan. In Section 5.1.1 we use detailed loan-level data on originations of large corporate loans from Refinitiv's DealScan Loan Pricing Corporation (LPC). We start with information on 92,687 individual loan deals, structured in 136,020 loan facilities, signed between January 1990 and December 2016. These loans deals involve 6,779 U.S. banks and 33,948 U.S. borrowers. We drop loans signed before 1990 due to the sparseness of the data and the fact that sovereigns (rather than firms) were the main borrowers in the syndicated loan market during the 1980s. From these data we construct an unbalanced bank-borrowing firm-year panel. Loan volumes at the bank-firm-year level are summed up across multiple loans for any given bank-firm pair and year. For loan spreads we calculate the weighted average of the "all-in-spread drawn" (which refers to the spread over the reference rate, usually the London Interbank Offered Rate (LIBOR), expressed in basis points, plus the facility fee associated with granting the loan) where the weights are given by loan size. For loan maturities, we calculate the weighted average maturity (similarly weighted by loan size).

Loan volumes are obtained from the raw data by multiplying loan shares (contributed by individual banks to each loan deal) with the loan amount. We use the actual loan shares as reported in DealScan when available. When loan shares are not available, we estimate them following the regression-based approaches suggested by De Haas and Van Horen (2012) and Hale et al. (2019). More precisely, we predict these shares using a regression model estimated on the sample of loans with reported shares. The dependent variable is the loan share and the regressors are log(loan amount), syndicate size (number of banks in the syndicate), number of lead banks in the syndicate, dummies for loan currency, lead banks, bank country, loan type (term loan, letter of credit, bond, etc.), deal purpose (corporate purposes, working capital, debt repayment, LBO, etc.), firm country, firm industry (four-digit SIC code), and time (year×quarter dummies). The model has an adjusted R-squared of 74.8%. Our regression results are robust to two additional approaches to imputing the missing loan shares from previous studies.[29]

Merge DealScan with Compustat. We merge the bank-firm-year level panel from DealScan with borrowing firms' financial information from Compustat using the Dealscan-Compustat link (which contains matches through the end of 2017) from Chava and Roberts (2008). We drop firms with missing industry information and financial firms (with four-digit SIC industry codes between 6000 and 6799). We find a total number of 10,730 firms (with GVKEY identifier in Compustat) at the intersection of DealScan and Compustat during the 1990–2016 period. We have information on borrowing activities and firm-level intangible capital on a yearly basis (from Falato et al. (2018)) for 6,545 firms.

Merge DealScan with U.S. Call Reports. For the bank heterogeneity analysis (Table

[29]In the first approach, advocated by Duchin and Sosyura (2014), missing shares are imputed as follows: for lead banks, we use the average share for lead banks in the sample of loans with non-missing shares, and for other syndicate participants, we split the remainder of the loan in equal shares. In the second approach, used in Hale (2012), missing loan shares are distributed equally across deal participants, regardless of their role in the syndicate.

A14), we merge the bank-firm-year level panel from DealScan with bank balance sheet information from the U.S. Call Reports. Given that there is no common identifier across the two datasets, we perform a careful manual match based on bank name (supplemented by information on location, as needed). Out of 4,492 banks that appear as lenders in DealScan, we are able to unambiguously assign a Federal Reserve identification number (RSSD ID) to 519 banks. To be conservative, we ignore all ambiguous matches. The dataset that represents the intersection of DealScan, Compustat, U.S. Call Reports, with non-missing information on the location and balance sheets of banks and firms spanning the sample period 1990–2016, comprises bank-borrower pairs involving 503 banks and 6,124 non-financial firms.

SBA. In Section 5.1.2 we use detailed loan-level data on small business loans guaranteed by the U.S. Small Business Administration (SBA) and granted under the 7(a) program by more than 5,000 U.S. banks during the 1990–2016 period. For the analysis, we retain non-financial firms (by dropping firms in the two-digit NAICS industry category of 52) and identify manufacturing firms as those in the three-digit NAICS industry categories between 300 and 400. From these data we construct an unbalanced bank-industry-MSA-year panel where the industry and MSA correspond to the borrower. Loan volumes at the bank-industry-MSA-year level are summed up across multiple loans for any given bank-industry-MSA combination and year. For loan maturity, we calculate the weighted average maturity, weighted by loan size. Loan interest rates (not used in the analysis) are available starting in 2008. In the regression dataset, which matches borrower industries to our baseline BEA/BLS measure of intangible capital, we have lending information from 3,998 U.S. banks to enterprises in 94 industries (at the three-digit NAICS level) and located in 421 metropolitan and non-metropolitan areas.

Merge SBA with U.S. Call Reports. For the bank heterogeneity analysis (Table A14), we merge the bank-industry-MSA-year level panel from SBA with bank balance sheet information from the U.S. Call Reports. Given that there is no common identifier across the two datasets, we perform a fuzzy-match based on bank name and location. Out of 5,200 banks that appear as lenders in the SBA data set, we are able to assign a Federal Reserve identification number (RSSD ID) to 3,161 banks. To be conservative, we retain only matches with the highest two matching quality scores after a careful manual check of all matches.

A-IV Data Appendix: HMDA

HMDA data. In Section 5.2, we use data on banks' lending activities from the HMDA data set—a comprehensive source of information on mortgage market activity—to analyze the link between intangible capital and bank mortgage lending. These data are collected by the Federal Financial Institutions Examinations Council (FFIEC) under the provisions of the Home Mortgage Disclosure Act (HMDA). Covered institutions include banks, savings associations, credit unions, and mortgage companies which report mortgage lending transactions to the FFIEC on a yearly basis. Loan-level data covers the near-universe of mortgage loan applications and originations, except those from the institutions with assets below $30 million. Reliable data starts in 1995.

For each mortgage loan, we observe its volume, characteristics such as property location (down to the zipcode), type of originating institution, whether the loan is insured, etc., and borrower characteristics (such as income, race, and gender). From the raw data we drop loans that are originated by non-bank institutions, loans that are not conventional (that is, loans that are insured by the Federal Housing Administration, Veterans Administration, Farm Service Agency, or Rural Housing Service), and loans that have incorrect or missing coding. We aggregate the data at the bank-MSA-year level by adding up loan volumes and calculating the acceptance rate as the share of accepted loan applications relative to the total number of applications. The resulting dataset covers 3,372 commercial banks with lending operations in 408 metropolitan and non-metropolitan areas during the 1995–2016 period. In the regression sample, we drop bank-MSA-year observations with fewer than 10 mortgage loan applications as they do not reflect sufficiently active banks in an MSA.

Merge HMDA with U.S. Call Reports.We use HMDA Reporter Panel data, also provided by FFIEC, to link HMDA reporting entities, through their RSSD ID, to the U.S. Call Report data. We match property zipcodes and counties to MSAs using crosswalks from the U.S. Census Bureau.

Banks' geographic footprint. In Section 4.4, we use FDIC Summary of Deposits data and HMDA data to construct several measures of banks' geographic presence and intangible capital variables that are weighted by these measures. We capture banks' geographic footprint using the distribution of deposit-taking activities from the FDIC Summary of Deposits data set; and that of mortgage lending—both mortgage lending volumes and numbers of mortgage applications—from the HMDA data set. To aggregate deposit volumes at the MSA level using FDIC data, we match branch locations at the zipcode level to MSAs using the crosswalk from the U.S. Census Bureau. Given that reliable HMDA data start in 1995 and FDIC Summary of Deposits data are available starting in 1994, we backfill the data to the beginning of our sample (1984) using the earliest available year in each data set.

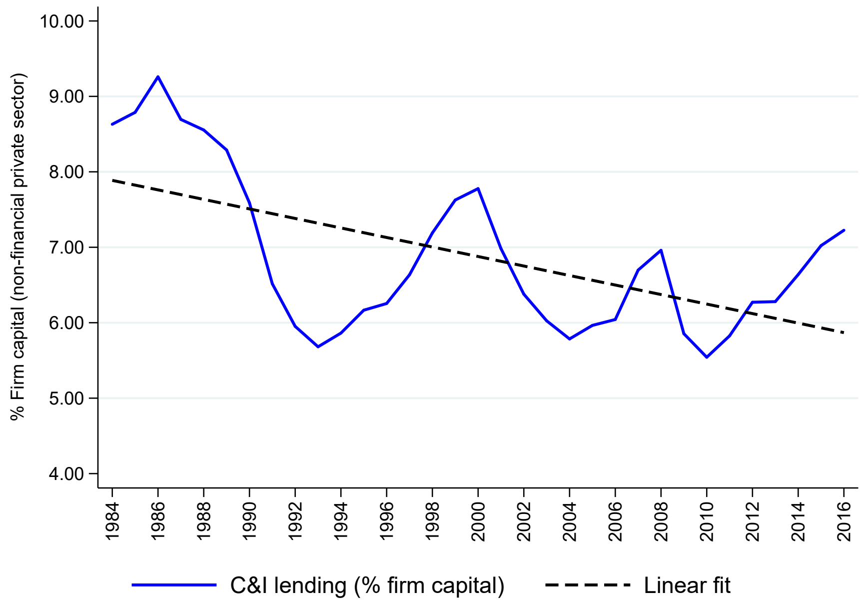
A-V Results Appendix: Role of Bank Soft Information

In this appendix we provide additional results that explore the role of soft information. Specifically, we examine two additional dimensions of bank heterogeneity: geographic diversification and specialized knowledge in lending to intangible capital-intensive firms. We measure geographic diversification based on banks' deposit-taking locations (using FDIC Summary of Deposits data) with the Herfindahl-Hirschman Index (HHI) of a bank's deposit drawing from each MSA. Berger et al. (2005a) argue that geographically diversified banks are less well suited to lend to "informationally-difficult credits" such as intangible capital firms as larger distances between borrowers and bank headquarters reduce banks' ability to process soft information (Agarwal and Hauswald, 2010).

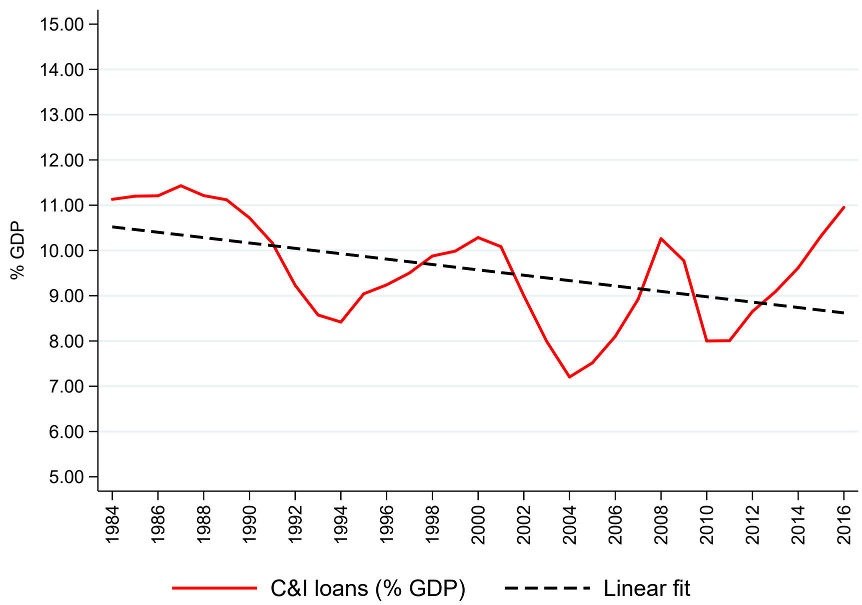
We estimate the impact of intangible capital on C&I loan volumes in panels A–C of Table A13, where each panel corresponding to a different data set: U.S. Call Reports, DealScan, and respectively, SBA. As indicated by the p-values of a two-sided t-test of equality of coefficients across subsamples of more vs. less diversified banks (defined as having above/below-median HHI of deposits), shown in Column 3, there is no systematic difference in the effects of intangible asset growth on commercial lending across banks with different levels of geographic diversification. However, geographically diversified banks also tend to be larger—the sample correlation between deposit-based geographic diversification HHI and size is 0.47—and it is possible that the benefits of larger size of these banks offset their soft information disadvantage in lending to firms with intangible capital.

We measure banks' specialized knowledge in lending to industries with intensive use of intangible capital using DealScan data. Banks that specialize in such industries, say due to superior knowledge or information, should be able to offer better lending terms to firms in these industries. We define bank expertise in intangibles-intensive industries based on lending concentration in those industries, as follows. First, we rank industries (using the four-digit SIC classification) by average level of corporate intangible capital over the sample period (1990–2016), and define intangibles-intensive industries as those above the median. Second, we compute, for each bank, the share of total syndicated loan volumes to intangibles-intensive industries. As shown in Panel D in Table A13, when we re-estimate our main DealScan specification for loan spreads (from Column 5 of Table 5), we find that specialized banks systematically charge firms with more intangible capital relatively smaller loan spreads. This result suggests that banks with expertise in lending to intangible capital firms can partly offset the adverse effects of collateral-based frictions on lending terms.

Figure A1: Banking lending and economic activity, 1984–2016



(a) Bank C&I lending, % total capital



(b) Bank total assets, % GDP

The figure depicts the long-run trend in U.S.-chartered depository institutions' C&I lending (to domestic businesses) relative to total capital of the nonfinancial private sector (panel a) and GDP (panel b). Total capital refers to the current-cost net stock of private nonresidential fixed assets: equipment, structures, and intellectual property products. Sources: FRED Economic Data.

Table A1: Descriptive statistics for additional variables

	Obs.	Mean	St. Dev.	p25	Median	p75
A. Additional IK measures						
IK growth: Employment shares at $t-1$	78986	4.46%	4.35%	1.44%	5.05%	7.80%
IK growth: Employment shares at $t-5$	78986	4.40%	4.26%	1.55%	4.82%	7.74%
IK growth: Employment shares at $t-10$	78986	4.46%	4.27%	1.62%	4.95%	7.66%
IK growth: Employment shares in 1975	78986	4.43%	4.20%	1.65%	4.78%	7.44%
IK growth: Deposits	69218	4.14%	4.35%	1.05%	4.56%	7.74%
IK growth: Mortgages, volume	40030	3.10%	4.36%	-0.99%	3.01%	6.77%
IK growth: Mortgages, number	40030	3.10%	4.36%	-0.99%	3.00%	6.77%
B. Bank-level analysis						
Residential real estate loan - growth	82963	8.2%	19.6%	-4.7%	4.7%	16.9%
Commercial real estate loan - growth	82663	11.7%	24.1%	-4.0%	7.8%	22.7%
House price growth	89164	4.0%	4.8%	1.8%	3.9%	5.8%
Pc income growth	89164	4.5%	2.5%	3.0%	4.5%	6.0%
Population growth	89164	1.3%	1.3%	0.5%	1.2%	2.0%
Firms' sales growth	89164	11.4%	14.3%	4.4%	10.8%	17.0%
Firms' market-to-book	87560	1.84	0.59	1.49	1.77	2.11
C. Syndicated loan analysis						
Firm size (large firm)	82557	73.0%	44.4%	0.0%	0.0%	100.0%
Firm market-to-book	82557	175.5%	95.8%	115.5%	148.1%	200.8%
Firm ROA	82557	13.9%	7.8%	9.5%	13.3%	17.7%
Firm cash ratio	82557	7.6%	10.3%	1.4%	3.7%	9.8%
Firm patents (no. patents/assets, unweighted)	25729	0.10	0.25	0.01	0.04	0.11
Firm patents (no. patents/assets, citation-weighted)	25729	2.11	15.82	0.12	0.53	1.71
D. Small business loan analysis						
Industry size (log-employment)	483540	14.4	1.1	13.7	14.2	15.2
Industry TFP growth	49332	0.6%	2.6%	-0.8%	0.9%	2.2%
Industry profitability (profits/sales)	49332	51.8%	8.0%	46.8%	53.4%	57.2%
C. Mortgage analysis						
Δ applicants' log income	83076	0.02	0.27	-0.09	0.02	0.13
Δ share of female applicants	83076	0.01	0.14	-0.05	0.01	0.07
Δ share of minority applicants	83076	0.00	0.10	-0.01	0.00	0.01
Δ share of minority residents	83076	-0.13	4.67	-0.28	0.28	0.91
Δ log(personal income)	83076	0.04	0.05	0.02	0.04	0.06

The table presents descriptive statistics for additional regression variables. Panel A refers to additional measures of IK growth with different lag structure for industry-level employment shares (Table 3); or using bank's geographic footprint (Table 4). Panel B includes more U.S. Call Reports variables, such as the dependent variables in Table 9. Panel C includes variables from the DealScan analysis (Table 5), where firm size is a dummy variable for firms with above-median total assets. Panel D includes variables from the SBA analysis (Table 6). Panel E shows control variables in the HMDA analysis (Tables 6-7).

Table A2: Robustness—Baseline Regressions—Without Bank Asset Growth as Control

	C&I loans	Bank assets	Non C&I assets
	(1)	(2)	(3)
IK growth	-0.1853***	0.0330	0.0815***
	(0.072)	(0.030)	(0.031)
House price growth	0.2877***	0.1970***	0.1684***
	(0.023)	(0.009)	(0.010)
Pc income growth	0.2085***	0.1556***	0.1251***
	(0.045)	(0.016)	(0.017)
Population growth	0.5589***	0.7874***	0.7654***
	(0.078)	(0.040)	(0.041)
Firm sales growth	0.0082	0.0098***	0.0087***
	(0.006)	(0.003)	(0.003)
Firm market-to-book	0.0009	0.0068***	0.0075***
	(0.002)	(0.001)	(0.001)
Bank size	-0.0011	0.0018***	0.0021***
	(0.001)	(0.000)	(0.000)
Bank capital	0.1986***	0.0680***	0.0417***
	(0.025)	(0.010)	(0.010)
Observations	80,448	87,408	85,456
R-squared	0.027	0.081	0.066
Year fixed effects	Yes	Yes	Yes

This table examines the robustness of our main baseline results (columns 4-6 in Table 2 and columns 1-4 in Table 8) to dropping total asset growth as a control variable. The dependent variables are indicated as column headings. IK growth, house price growth, per capital income growth, population growth, firm sales growth, and firm market-to-book ratio, are at the MSA level, for the MSA where the bank is headquartered. Bank size, capital, and total asset growth are at the bank level. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A3: Robustness—Baseline Regressions—Including Crisis Years

	C&I loans	Bank assets	Non C&I assets
	(1)	(2)	(3)
IK growth	-0.1821***	0.0261	0.0401***
	(0.067)	(0.029)	(0.011)
House price growth	0.1415***	0.1785***	-0.0240***
	(0.021)	(0.009)	(0.004)
Pc income growth	0.0876**	0.1468***	-0.0295***
	(0.041)	(0.016)	(0.007)
Population growth	-0.0576	0.7991***	0.0302**
	(0.070)	(0.040)	(0.013)
Firm sales growth	-0.0007	0.0102***	-0.0006
	(0.006)	(0.002)	(0.001)
Firm market-to-book	-0.0043***	0.0065***	0.0008***
	(0.001)	(0.001)	(0.000)
Bank size	-0.0031***	0.0019***	0.0001
	(0.001)	(0.000)	(0.000)
Bank capital	0.1331***	0.0784***	-0.0213***
	(0.020)	(0.010)	(0.003)
Bank asset growth	0.7312***		0.9831***
	(0.011)		(0.002)
Observations	86,389	93,818	91,751
R-squared	0.099	0.079	0.835
Year fixed effects	Yes	Yes	Yes

This table examines the robustness of our main baseline results (Columns 4–6 Table 2) to including the crisis years in the regression sample. The dependent variable is bank-level C&I loan growth (Column 1), total asset growth (Column 2), and the growth rate of assets other than C&I loans (Column 3). IK growth, house price growth, per capital income growth, population growth, firm sales growth, and firm market-to-book ratio, are at the MSA level, for the MSA where the bank is headquartered. Bank size, capital, and total asset growth are at the bank level. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A4: Robustness—Baseline Regressions with Additional Fixed Effects

	C&I loans	Bank assets	Non C&I assets	C&I loans	Bank assets	Non C&I assets
	(1)	(2)	(3)	(4)	(5)	(6)
	With Bank FE			**With Bank MSA FE**		
IK growth	-0.2056**	-0.0289	0.0491***	-0.2007***	-0.0158	0.0426***
	(0.082)	(0.028)	(0.013)	(0.076)	(0.029)	(0.013)
House price growth	0.0869***	0.1897***	-0.0120**	0.0964***	0.1633***	-0.0193***
	(0.026)	(0.010)	(0.005)	(0.023)	(0.010)	(0.004)
Pc income growth	0.0999**	0.1576***	-0.0239***	0.1106**	0.1432***	-0.0333***
	(0.044)	(0.015)	(0.008)	(0.043)	(0.016)	(0.008)
Population growth	0.5738***	0.6036***	-0.0690***	0.4267***	0.5727***	-0.0559***
	(0.129)	(0.053)	(0.024)	(0.115)	(0.052)	(0.022)
Firm sales growth	0.0072	0.0039	-0.0010	0.0113*	0.0041*	-0.0019*
	(0.007)	(0.002)	(0.001)	(0.007)	(0.002)	(0.001)
Firm market-to-book	-0.0024	0.0009	-0.0000	-0.0020	0.0013	0.0004
	(0.002)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)
Bank size	-0.0102***	-0.0268***	0.0016***	-0.0031***	-0.0015***	0.0002
	(0.003)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)
Bank capital	0.2264***	0.1760***	-0.0283***	0.1400***	0.0538***	-0.0193***
	(0.035)	(0.016)	(0.005)	(0.021)	(0.011)	(0.003)
Bank asset growth	0.6667***		0.9862***	0.7335***		0.9812***
	(0.013)		(0.002)	(0.011)		(0.002)
Observations	80,041	87,035	85,049	80,447	87,407	85,455
R-squared	0.191	0.353	0.853	0.099	0.112	0.834
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes			
Bank-MSA fixed effects				Yes	Yes	Yes

This table examines the robustness of our main baseline results (Columns 4–6 in Table 2) to including additional fixed effects (bank fixed effects in Columns 1–3 and bank-MSA fixed effects in Columns 4–6). The dependent variable is bank-level C&I loan growth (Columns 1, 4), total asset growth (Columns 2, 5), and the growth rate of assets other than C&I loans (Columns 3, 6). IK growth, house price growth, per capital income growth, population growth, firm sales growth, and firm market-to-book ratio, are at the MSA level, for the MSA where the bank is headquartered. Bank size, capital, and total asset growth are at the bank level. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A5: Robustness—Baseline Regressions with Alternative Clustering

	C&I loans	Bank assets	Non C&I assets	C&I loans	Bank assets	Non C&I assets	C&I loans	Bank assets	Non C&I assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Cluster on bank and year			**Cluster on MSA**			**Cluster on MSA and year**		
IK growth	-0.2107**	0.0330	0.0447**	-0.2107***	0.0330	0.0447***	-0.2107**	0.0330	0.0447**
	(0.094)	(0.039)	(0.019)	(0.074)	(0.054)	(0.015)	(0.094)	(0.053)	(0.019)
House price growth	0.1400**	0.1970***	-0.0244**	0.1400***	0.1970***	-0.0244***	0.1400**	0.1970***	-0.0244**
	(0.059)	(0.033)	(0.011)	(0.035)	(0.016)	(0.007)	(0.062)	(0.034)	(0.011)
Pc income growth	0.0896	0.1556***	-0.0316*	0.0896	0.1556***	-0.0316***	0.0896	0.1556***	-0.0316*
	(0.082)	(0.038)	(0.017)	(0.056)	(0.028)	(0.011)	(0.081)	(0.039)	(0.017)
Population growth	-0.0229	0.7874***	0.0278	-0.0229	0.7874***	0.0278	-0.0229	0.7874***	0.0278
	(0.100)	(0.055)	(0.022)	(0.144)	(0.103)	(0.027)	(0.143)	(0.103)	(0.029)
Firm sales growth	0.0012	0.0098***	-0.0006	0.0012	0.0098***	-0.0006	0.0012	0.0098**	-0.0006
	(0.010)	(0.003)	(0.002)	(0.008)	(0.004)	(0.001)	(0.010)	(0.004)	(0.002)
Firm market-to-book	-0.0042**	0.0068***	0.0008**	-0.0042**	0.0068***	0.0008***	-0.0042**	0.0068***	0.0008**
	(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)
Bank size	-0.0026*	0.0018*	0.0002	-0.0026***	0.0018**	0.0002	-0.0026*	0.0018	0.0002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Bank capital	0.1447***	0.0680**	-0.0205***	0.1447***	0.0680***	-0.0205***	0.1447***	0.0680*	-0.0205***
	(0.039)	(0.031)	(0.005)	(0.023)	(0.016)	(0.003)	(0.039)	(0.034)	(0.006)
Bank asset growth	0.7323***		0.9823***	0.7323***		0.9823***	0.7323***		0.9823***
	(0.033)		(0.006)	(0.013)		(0.002)	(0.033)		(0.006)
Observations	80,448	87,408	85,456	80,448	87,408	85,456	80,448	87,408	85,456
R-squared	0.094	0.081	0.833	0.094	0.081	0.833	0.094	0.081	0.833
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table examines the robustness of our main baseline results (Columns 4–6 in Table 2) to alternative clustering estimators for the standard errors. The standard errors are clustered on bank and year in Columns 1–3, on bank's MSA in Columns 4–6, and on MSA and year in Columns 7–9. The data are at the bank-year level. All controls are as in Table 2. IK growth and macro controls correspond to the MSA of the bank's headquarters. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A6: Intangible capital and bank real estate lending—By loan type

	Real estate loans	Residential real estate loans	Commercial real estate loans
	(1)	(2)	(3)
IK growth	0.0852**	0.1153**	0.0680
	(0.043)	(0.056)	(0.069)
House price growth	0.3871***	0.3047***	0.4031***
	(0.014)	(0.019)	(0.022)
Pc income growth	0.1320***	0.0366	0.1953***
	(0.027)	(0.036)	(0.041)
Population growth	0.4338***	0.4481***	0.1918***
	(0.050)	(0.067)	(0.072)
Firm sales growth	0.0008	-0.0054	0.0052
	(0.004)	(0.006)	(0.006)
Firm market-to-book	-0.0018*	-0.0025*	0.0008
	(0.001)	(0.001)	(0.001)
Bank size	-0.0022***	-0.0025***	-0.0037***
	(0.000)	(0.001)	(0.001)
Bank capital	0.0320**	0.0354**	0.0416**
	(0.016)	(0.018)	(0.020)
Bank asset growth	0.7764***	0.6823***	0.7839***
	(0.008)	(0.010)	(0.011)
Observations	81,278	78,114	77,813
R-squared	0.245	0.133	0.133
Year fixed effects	Yes	Yes	Yes

In this table we examine the relation between intangible capital growth and specific components of bank non-C&I assets using the same specification as Column 2 in baseline Table 2. The dependent variables are real estate loan growth (Column 1), residential real estate loan growth (Column 2) and commercial real estate loan growth (Column 3). The data are at the bank-year level. All controls are as in Table 2. IK growth and macro controls correspond to the MSA of the bank's headquarters. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A7: Robustness—Intangible capital and patents in DealScan regressions

	Loan volume (log)		Loan spread		Loan maturity	
Patent measure:	unweighted	citation weighted	unweighted	citation weighted	unweighted	citation weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Firm-level IK	-0.1443***	-0.1440***	9.3132***	9.1281***	-0.0494*	-0.0444*
	(0.029)	(0.028)	(1.631)	(1.668)	(0.027)	(0.026)
Firm-level patents	-0.3772***	-0.0105***	37.1087***	1.3763***	-0.3511***	-0.0135***
	(0.123)	(0.003)	(8.757)	(0.263)	(0.129)	(0.005)
Firm-level IK×patents	0.0755*	0.0026***	-9.5363***	-0.3982***	0.1102**	0.0038**
	(0.041)	(0.001)	(2.682)	(0.094)	(0.048)	(0.002)
Observations	60,901	60,901	55,293	55,293	58,934	58,934
R-squared	0.485	0.485	0.888	0.888	0.886	0.886
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Rating×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

In this table we report DealScan specifications that interact intangible capital with two measures of firm-level patents (nonweighted and citation-weighted, in % of assets), using the most complete set of fixed effects (akin to the specification in Columns 3, 6, and 9 in Table 5. The dependent variables are log(loan amount) (Columns 1–2), loan spreads (Columns 3–4), and loan maturity (Columns 5–6). The data are at the bank-firm-year level and are aggregated from loan-level data on syndicated loan deals. Firm-level IK is constructed following Falato et al. (2018). Firm industry refers to four-digit SIC industries. Firm rating category refers to 23 S&P firm rating categories (including unrated category). Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A8: Robustness—Adding bank×MSA×year fixed effects in DealScan regressions

	Loan volume (log)			Loan spread			Loan maturity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Firm-level IK	-0.3002***	-0.2513***	-0.1688***	20.2429***	16.5259***	11.7044***	-0.0773***	-0.1167***	-0.1476***
	(0.032)	(0.031)	(0.028)	(1.746)	(2.272)	(2.633)	(0.026)	(0.027)	(0.034)
Firm size (large firm)		0.5650***	0.4475***		-59.4906***	-59.3359***		-0.0252	0.0958*
		(0.024)	(0.034)		(1.461)	(3.036)		(0.032)	(0.055)
Firm market-to-book		0.0293***	0.0043		-3.4571***	-0.3083		-0.0541***	-0.0411*
		(0.011)	(0.018)		(0.690)	(1.647)		(0.012)	(0.023)
Firm ROA		0.0091***	0.0063**		-3.2953***	-2.7836***		0.0143***	0.0213***
		(0.001)	(0.003)		(0.102)	(0.224)		(0.002)	(0.003)
Firm cash ratio		-0.0023***	-0.0020		0.0405	-0.3850***		0.0073***	0.0041**
		(0.001)	(0.002)		(0.070)	(0.138)		(0.001)	(0.002)
Observations	46,868	46,868	44,405	42,569	42,569	40,364	45,236	45,236	42,973
R-squared	0.507	0.525	0.752	0.551	0.624	0.904	0.572	0.574	0.909
Bank×firm MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Rating×Year fixed effects			Yes			Yes			Yes

This table examines robustness of our baseline DealScan results in Table 5 to including bank×borrower MSA×year fixed effects. The dependent variables are log(loan amount) (Columns 1–3), loan spreads (Columns 4–6), and loan maturity (Columns 7–9). The data are at the bank-firm-year level and are aggregated from loan-level data on syndicated loan deals. Firm-level IK is constructed following Falato et al. (2018). Firm industry refers to four-digit SIC industries. Firm rating category refers to 23 S&P firm rating categories (including unrated category). Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A9: Robustness—Adding bank×MSA×year fixed effects in SBA regressions

	Loan volume (log)			Loan maturity		
	All industries		Manufacturing	All industries		Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
Industry-level IK	-0.0960***	-0.0831***	-0.1897***	-0.4031***	-0.4269***	-0.8160***
	(0.012)	(0.012)	(0.041)	(0.041)	(0.043)	(0.142)
Industry size		0.1996***	0.2251***		0.1003***	0.1443***
		(0.022)	(0.021)		(0.031)	(0.044)
Industry TFP growth			0.1060			2.1013
			(0.459)			(1.618)
Industry profitability			0.8831***			0.3968
			(0.182)			(0.431)
Observations	457,075	426,259	31,227	456,787	426,000	31,198
R-squared	0.460	0.480	0.571	0.477	0.482	0.559
Bank×MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table examines the robustness of our baseline SBA results in Table 6 to including bank×borrower-MSA×year fixed effects. The dependent variables are log(loan amount) (Columns 1–3) and loan maturity (Columns 4–6). The data are at the bank-industry-MSA-year level and are aggregated from loan-level data for small business lending. Industry-level IK comes from the BEA based on the three-digit NAICS classification. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A10: Robustness—Adding bank fixed effects in HMDA regressions

	Δ log(loan volume)			Δ acceptance rate		
	(1)	(2)	(3)	(4)	(5)	(6)
IK growth	7.8457**	7.7591**	7.6370**	0.9328***	0.9060***	0.8889***
	(3.7283)	(3.5235)	(3.4817)	(0.1939)	(0.1821)	(0.1821)
House price growth		-0.1181	-0.1358		0.0945	0.0904
		(0.6630)	(0.6509)		(0.1538)	(0.1510)
Pc income growth		0.8551	0.8401		0.0002	-0.0088
		(0.6555)	(0.6680)		(0.0688)	(0.0689)
Population growth		-5.2926***	-5.3913***		-0.6745	-0.7062
		(1.9902)	(1.9776)		(0.7081)	(0.6976)
Firm sales growth		-0.1520***	-0.1486***		-0.0072	-0.0064
		(0.0523)	(0.0523)		(0.0106)	(0.0102)
Firm market-to-book		0.2743	0.2772		0.0418	0.0372
		(0.4863)	(0.4777)		(0.1544)	(0.1534)
Bank size		1.2266***	1.2466***		0.0541	0.0589
		(0.1943)	(0.1933)		(0.0418)	(0.0415)
Bank capital		-0.2133*	-0.2090*		-0.0004	0.0009
		(0.1256)	(0.1259)		(0.0137)	(0.0133)
Bank asset growth		-0.0181	-0.0199		0.0015	0.0009
		(0.0236)	(0.0235)		(0.0029)	(0.0028)
Δ applicants' log income			0.3209***			0.0654***
			(0.0331)			(0.0048)
Δ share of female applicants			-0.0371			-0.0159***
			(0.0394)			(0.0060)
Δ share of minority applicants			-0.0141			-0.0868***
			(0.0601)			(0.0121)
Δ share of minority residents			0.0068***			0.0005
			(0.0018)			(0.0003)
Δ log(personal income)			0.6332***			0.1005***
			(0.1348)			(0.0230)
Observations	51,823	51,823	51,823	52,650	52,650	52,650
R-squared	0.2913	0.3074	0.3180	0.2102	0.2121	0.2326
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
MSA×Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table examines the robustness of our baseline HMDA results in Table 7 to including bank fixed effects. The dependent variables are the growth rate in mortgage lending volume (Columns 1–3) and the change in the acceptance rate for mortgage applications (Columns 4–6). The data are at the bank-MSA-year level and are aggregated from loan-level data on individual mortgages. IK growth, macro controls, and bank controls are as in the baseline specification in Column 4 of Table 2. All regressions include borrower-MSA×year fixed effects. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A11: Intangible capital and bank mortgage lending—Evidence from HMDA data—IK based on banks' geographic footprint

	Δ log(loan volume)	Δ acceptance rate
	(1)	(2)
	IK: weighted by deposits	
IK growth	6.6875**	0.6050***
	(2.8095)	(0.2129)
Observations	52,912	52,873
R-squared	0.1583	0.1612
	IK: weighted by volume of mortgage applications	
IK growth	6.4986***	0.3994**
	(1.8790)	(0.1982)
Observations	52,085	52,085
R-squared	0.2231	0.2233
	IK: weighted by number of mortgage applications	
IK growth	6.6137***	0.4005**
	(1.8535)	(0.2017)
Observations	52,046	52,912
R-squared	0.2282	0.1585
Macro controls	Yes	Yes
Bank controls	Yes	Yes
Bank-borrower pool controls	Yes	Yes
MSA×Year fixed effects	Yes	Yes

The table reports coefficient estimates for the "IK growth" variables from regressions using the main specifications in Columns 2 and 5 of Table 7. The dependent variables are the growth rate in mortgage lending volume (Columns 1–3) and the change in the acceptance rate for mortgage applications (Columns 4–6). The data are at the bank-MSA-year level and are aggregated from loan-level data on individual mortgages. Unlike in the baseline analysis, the IK growth variable is constructed at the bank level using the bank's geographic footprint across MSAs and years, based on bank's deposit-taking and mortgage-lending activities. Macro controls and bank controls are as in the baseline specification in Column 4 of Table 2. All regressions include borrower-MSA×year fixed effects. Standard errors are clustered on bank. # indicates statistical significance at the 20% level, *** at the 1% level, ** at the 5% level, and * at the 10% level.

Table A12: Intangible capital and bank commercial lending—Heterogeneity by bank constraints in DealScan and SBA regressions

	Constrained	Unconstrained	p-value	Constrained	Unconstrained	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
	A. DealScan: Loan volume (log)					
	(a) Capital			**(b) Size**		
Firm-level IK	-0.1348***	-0.1193	0.1530	-0.2253***	-0.1045*	0.1080
	(0.036)	(0.074)		(0.047)	(0.061)	
Observations	1687	9300		1240	9617	
R-squared	0.5156	0.3819		0.6425	0.3647	
	B. DealScan: Loan spread					
	(c) Capital			**(d) Size**		
Firm-level IK	24.0676***	7.9935***	0.0010	13.5333***	14.0674***	0.7380
	(5.913)	(2.384)		(1.793)	(3.419)	
Observations	1498	8756		1100	9009	
R-squared	0.7963	0.6264		0.8055	0.6043	
	C. SBA: Loan volume (log)					
	(e) Capital			**(f) Size**		
Industry-level IK	-0.0902***	-0.0677***	0.3570	-0.0926***	-0.0419*	0.0756
	(0.013)	(0.022)		(0.016)	(0.023)	
Observations	33,121	135,970		21,429	108,016	
R-squared	0.4161	0.4226		0.5475	0.4132	

The table explores heterogeneity in the effect of firm-level intangible capital on the volume and terms of lending by bank capital and size. Banks are classified as constrained if they have below-median capital or below-median assets. Panels A and B report the results of DealScan regressions similar to Columns 2 and 5 in Table 5 and Panel C reports the results of SBA regressions similar to Column 2 in Table 6. Columns 1–2 and 4–5 report the coefficients for the "IK" variable in the constrained and unconstrained samples of banks. Columns 3 and 6 reports the p-value of a two-sided t-test of equality of coefficients across constrained and unconstrained banks. In panels A and B, all specifications include firm controls and industry fixed effects, bank×year fixed effects, and borrower-MSA×year fixed effects. In panel C, all specifications include industry size, bank×year fixed effects, and borrower-MSA×year fixed effects. Standard errors are clustered on bank. # indicates statistical significance at the 20% level, *** at the 1% level, ** at the 5% level, and * at the 10% level.

Table A13: Intangible capital and bank commercial lending—Heterogeneity by bank geographic diversification and specialization

	(1)	(2)	(3)	(4)	(5)	(6)
	A. U.S. Call Reports: C&I loan growth			**C. SBA: Loan volume (log)**		
	Diversification			**Diversification**		
	Less diversified	More diversified	p-value	Less diversified	More diversified	p-value
IK	-0.1497*	-0.2543#	0.599	-0.0974***	-0.0863***	0.692
	(0.077)	(0.184)		(0.020)	(0.020)	
Observations	62,117	9,908		59,413	58,653	
R-squared	0.0860	0.1610		0.3922	0.4835	
	B. DealScan: Loan volume (log)			**D. DealScan: Loan spread**		
	Diversification			**Specialization**		
	Less diversified	More diversified	p-value	Specialized	Not specialized	p-value
IK	-0.1689***	−0.1183#	0.534	10.9224***	16.9281***	0.006
	(0.031)	(0.076)		(1.256)	(1.922)	
Observations	4,917	5,600		2,845	71,527	
R-squared	0.4565	0.4302		0.8566	0.6095	

The table explores heterogeneity in the effect of intangible capital on commercial lending volumes and terms by bank geographic diversification and specialization in lending to intangible capital-intensive industries. Banks are classified as more geographically diversified if they have above-median HHI of deposits. Column 3 reports the p-value of a two-sided t-test of equality of coefficients across the two subsamples of banks. All specifications include the IK variable, controls, and fixed effects as in the corresponding U.S. Call Report baseline (Column 3 of Table 2, DealScan (Columns 2, 5 of Table 5), and SBA regressions (Column 2 of Table 6). See Appendix A-V for defintions of bank diversification and specialization. Standard errors are clustered on bank. # indicates statistical significance at the 20% level, *** at the 1% level, ** at the 5% level, and * at the 10% level.

Table A14: Robustness—Intangible capital and bank risk-taking and profitability—Including crisis years

	Mortgage NPL ratio (t, t+5)	Mortgage profitability (t, t+1)	Mortgage profitability (t, t+5)	Overall NPL ratio (t, t+5)	Overall ROA (t, t+5)	Risk-adj. overall ROA (t, t+5)
	(1)	(2)	(2)	(4)	(5)	(6)
IK growth	0.1183***	-0.0623**	-0.0770***	0.0246***	-0.0203***	-0.0602***
	(0.030)	(0.028)	(0.027)	(0.007)	(0.007)	(0.016)
Observations	41,903	85,555	60,152	42,162	60,278	26,130
R-squared	0.328	0.646	0.696	0.136	0.159	0.111
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

The table examines robustness of the results in Table 9 to including crisis-year observations (2008–2010). The dependent variables capture risk and profitability of mortgage lending (Columns 1–2) and of overall balance sheets (Columns 3–5). All dependent variables are averaged over $t, t+5$ except Column 2 where mortgage profitability is averaged over $t, t+1$. All specifications use U.S. Call Report data and controls as in Columns 4 and 6 of baseline Table 2. Across all specifications, IK growth and macro controls correspond to the MSA of the bank's headquarters. Standard errors are clustered on bank. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A15: Intangible capital and bank risk and profitability—Heterogeneity by bank constraints in U.S. Call Report regressions

	Constrained	Unconstrained	p-value	Constrained	Unconstrained	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Mortgage NPL ratio $(t, t+5)$					
	(a) Capital			**(b) Size**		
IK growth	0.0042	0.1427***	0.0010	0.0146	0.1496***	0.0117
	(0.033)	(0.035)		(0.020)	(0.051)	
Observations	13,415	23,724		18,998	18,141	
R-squared	0.2624	0.3013		0.1618	0.2735	
	B. Mortgage profitability $(t, t+1)$					
	(c) Capital			**(d) Size**		
IK growth	0.0242	-0.0988***	0.0058	-0.0077	-0.0625	0.3120
	(0.038)	(0.028)		(0.009)	(0.054)	
Observations	43,006	36,545		41,239	38,312	
R-squared	0.5740	0.752		0.9337	0.4846	
	C. Mortgage profitability $(t, t+5)$					
	(e) Capital			**(f) Size**		
IK growth	0.0132	-0.0988***	0.0087	0.0025	-0.0806	0.1240
	(0.038)	(0.023)		(0.009)	(0.053)	
Observations	31,842	23,535		30,726	24,651	
R-squared	0.6355	0.8235		0.9665	0.5508	

The table explores heterogeneity by bank constraints in the effect of intangible capital on bank mortgage risk and profitability, using the same specifications as in Columns 2–4 in Table 9. Banks are classified as constrained if they have below-median capital or below-median assets. Columns 1–2 and 4–5 report the coefficients for the "IK" variable in the constrained and unconstrained samples of banks. Columns 3 and 6 reports the p-value of a two-sided t-test of equality of coefficients across constrained and unconstrained banks. All regressions include macro controls, bank controls, and year fixed effects. IK growth and macro controls correspond to the MSA of the bank's headquarters. Standard errors are clustered on bank. # indicates statistical significance at the 20% level, *** at the 1% level, ** at the 5% level, and * at the 10% level.