Does IT help startups? Information Technology in Banking and Entrepreneurship

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Abstract

This paper analyzes the increasingly important role of information technology (IT) in banking for entrepreneurship. We show that IT in banking spurs entrepreneurship. Job creation by young firms is stronger in US counties which are more exposed to IT-intensive banks through their historical geographical footprint, especially for firms in industries that rely more on external finance and have low startup capital. Entrepreneurs that use their homes as collateral benefit disproportionately more from IT in banking when house prices rise. We also show that IT adoption of banks reduces the role of distance between the headquarter and lending location in small business lending, suggesting that IT adoption can mitigate information frictions.

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1 Introduction

The United States have witnessed an anemic rate of firm creation since the 1980s that has continued in the 2000s (Decker et al., 2014), dragging productivity growth down (Decker et al., 2016; Klenow and Li, 2020). Yet, the reasons for this decline in entrepreneurship are far from completely understood. One possible explanation could be that banks have massively invested in Information Technology (IT) over the same period (see Figure 1). Banks' use of IT may have increased the importance of hard information – which can be easily gathered, transmitted, and analyzed–diminishing banks' incentives to acquire soft information. However, better technology could also help banks in evaluating borrowers by relying on non-traditional information. So far, evidence on whether there is a link between the two is scarce.

In this paper, we investigate how the rise of IT in the financial sector affects entrepreneurship. Young firms are usually opaque borrowers that have produced limited hard information. Their financing is therefore sensitive to the informational environment in which they operate and to lenders' incentives to gather and use soft information. If IT adoption leads to a reduction in banks' efforts to gather soft information, it could have contributed to the decline in firm formation.

We find no evidence of such a detrimental effect. Conversely, we show that IT in banking is associated with higher levels of entrepreneurship and could therefore serve as a driver for productivity growth. Our analysis relies on detailed data on IT adoption of commercial banks across the United States. We show that US counties which are more exposed to IT-intensive banks through banks' historical geographical footprint experience stronger job creation by young firms during the years prior to the Great Financial Crisis (GFC), i.e. when dynamism and productivity growth declined. This is especially so in industries which rely more on external financing. We also document that IT adoption makes banks' small business lending and startup employment more sensitive to changes in collateral values.This suggests that IT enhances the gains from available hard information on startups. We finally study how distance impacts lending for high- and low- IT banks to provide additional evidence that IT helps ameliorate information frictions.

Our measure of IT adoption in banking is closely related to several seminal papers on IT adoption for non-financial firms, for example Bloom et al. (2012), Beaudry et al. (2010), Bresnahan et al. (2002), and Brynjolfsson and Hitt (2003). Following the literature, we use the ratio of PCs per employee within each bank as the relevant measure of bank-level IT adoption. This measure, while simple and based only on hardware availability, is a strong predictor of other measures of IT adoption, such as IT budget or adoption of frontier technologies in 2016, which are unfortunately unavailable in our data for the pre-2007 years.[1]

We find a positive correlation between the local adoption of IT in banking and entrepreneurial activity across US counties, which–following previous literature (Adelino et al., 2017)–is measured by the share of workers employed in new firms. A concern with identification is that confounding factors could spuriously drive the association between IT and local entrepreneurship. For instance, a high level of education of the workforce may both make it easier for bank to hire IT-savvy staff and also create more frequent business opportunities for new startups. In our baseline specification we therefore calculate the exposure of US counties to banks' overall IT adoption. The county-level exposure to banks' IT is the weighted average bank-level IT adoption of banks present in this region, with weights given by the historical share of local branches. This approach bears similarities with a typical shift-share analysis, where the IT adoption at the bank-level is the shifter and as the historical location of the branches determines the shares. The results are also robust to including a wide set of control for differences in local characteristics, for instance by controlling by industrial composition.

To further control for confounding factors, we exploit the granularity of our county-industry level data. First, we show that the relation between local IT adoption and startup activity is particularly pronounced in industries that depend more on external financing (Rajan and Zingales, 1998) or in which the required startup capital is lower (Hurst and Lusardi, 2004; Adelino et al., 2015). These interaction specifications allow us to include granular fixed effects. For example, we can control for local observable and unobservable characteristics by including county fixed effects, as well as for unobservable industry factors through industry fixed effects. Irrespective of the level of fixed effects we include, startup activity is higher in counties with higher IT adoption and especially in industries that are more dependent on external finance or require lower startup capital.

What drives the relationship between IT and entrepreneurship? We investigate the

[1] In fact, later waves of the same data set provide additional information on IT-budget and adoption of Cloud Computing at the establishment level: the number of PCs per employee is a strong predictor of these other measures of IT adoption. For example, the correlation between the per capita share of PCs and the IT budget is 65%. These correlations are likely understating the correlation in the pre-crisis period.The measure has also been shown to be a valid proxy in the non-financial sector, for instance to predict firm productivity or local wage growth. During the GFC, this measure strongly predicts the performance of mortgage originated by each bank (Pierri and Timmer, 2020).

role of collateral as a source of hard information in lending decisions. Banks' IT adoption can alter the way information is processed in several ways. On the one hand, banks that adopt more IT may be more inclined to rely on hard information on whether to reject a borrower or grant a loan. While startups often do not have pre-existing collateral available to post against the loan, young entrepreneurs often post their home equity as collateral. Home value increases increase collateral values, which enables borrowers to take on more debt (Mian and Sufi, 2011; Adelino et al., 2015). If IT-intensive banks rely more on collateral values, young entrepreneurs would post their home equity when house prices rise, and IT-intensive banks would be more willing to grant a loan than less IT-intensive banks, which rely more on soft information. On the other hand, traditional hard information such as collateral values may become less relevant for banks that adopt more IT, as IT-intensive banks are able to gather additional information over and above collateral values. In this case, in regions where more IT-intensive banks are present, collateral values would be less relevant as these additional acquired information serve as substitutes for collateral values, making young firms less opaque.

We show that the presence of IT-intensive banks spurs entrepreneurship *more* when collateral values rise, pointing toward the former explanation. Combining heterogeneity across industries in their propensity to use home equity as collateral with house price increases across counties, we provide evidence in favor of a strengthened collateral value channel due to a more IT-intensive banking sector. Moreover, we find the effect of IT in banking on entrepreneurship is strongest in industries where collateral is of high importance and where these collateral values rose more. Exploiting heterogeneity in the importance of collateral across regions and industries allows us to control for observed and unobserved variation at the county and industry level through granular fixed effects, mitigating the concern that unobservable factors explain the correlation between IT in banking and entrepreneurship.

To shed further light on the role of hard information, we investigate how IT adoption affects the importance of bank-borrower distance in lending. Physical distance can increase informational frictions between borrowers and lenders, thereby increasing the importance of hard information that can be easily transmitted from local branches to the (distant) headquarters (Petersen and Rajan, 2002; Liberti and Petersen, 2017). To this end, we study how distance affects banks' lending in response to a local increase in business opportunities (ie demand for credit), measured by local growth in income per capita. We show that, first, banks' small business lending is less sensitive to a local income shock in a county that is further away from the banks' headquarter – in line with the interpretation that a greater distance implies higher frictions. Second, we show that banks' IT adoption mitigates the effect of distance on the sensitivity of lending to a rise in business opportunities. These results suggest that IT mitigates information friction and enables banks to lend in times when business opportunities even if they arise distant from the headquarter.

The overall picture emerging from the results presented in this paper indicates that a stronger reliance on information technology in the financial sector decreases the extent of informational frictions in lending markets, at least partly through encouraging the use of collateral. This ameliorated environment, in turn, ends up benefiting disproportionally more the most opaque borrowers, such as startups.

Another potential concern with our empirical approach is that bank-level technology adoption may be correlated with other bank characteristics. Most importantly, demand for IT equipment and its productivity have been associated with firms' organizational forms and managerial quality (Bresnahan et al., 2002; Bloom et al., 2012; McElheran and Forman, 2019). However, Pierri and Timmer (2020) provide comprehensive evidence that bank-level IT adoption, during the pre-GFC period, is uncorrelated with other important bank characteristics. Most importantly, high IT-adoption banks are not found to be more profitable or to have employees with higher human capital, rejecting the idea that these are better run banks. These results are also in line with Beccalli (2007), who finds IT does not lead to sizeable improvements in banks' profitability; with Hernández-Murillo et al. (2010), who find that ROA is negatively related to adoption of online banking; and Hannan and McDowell (1984), who find no correlation between profitability and deployment of ATM. In fact, when we control for regional exposure to other bank characteristics, our baseline coefficient remains virtually unaffected.

Literature and Contribution. Our results relate to literature that investigates the effects of information technology in the financial sector on credit provision and small businesses. Banks' increasing technological sophistication could enable them to more effectively screen and monitor new clients (Hauswald and Marquez, 2003; Ahnert and Kuncl, 2020). On the other hand, more IT adoption could also increase banks' reliance on hard information. Petersen and Rajan (2002) argue that increasing capital intensity because of greater usage computers and communication equipment account for the growing lender-borrower distance.[2] Liberti and Petersen (2017) also argue that the increase in distance is partly explained by new technologies such as credit scoring, fax machines, or internet that enabled banks to expand geographically. Liberti and Mian (2009) show that greater hierarchical distance within banks makes hard information more valuable.[3] Yet, few papers use actual data on banks' IT adoption to test these hypotheses. Our results, based on unique information on banks' IT adoption at the branch level, suggest that higher IT intensity is associated with an increase in job creation among young firms, especially if they are more collateral dependent. These results imply that banks rely more on hard information (i.e. collateral) if they adopt more IT.

Our work also relates to papers that analyze the importance of collateral for entrepreneurial activity (Hurst and Lusardi, 2004; Adelino, Schoar and Severino, 2015; Corradin and Popov, 2015; Schmalz, Sraer and Thesmar, 2017).[4] Problems of asymmetric information about the quality of new borrowers are especially acute for young firms that are costly to screen and monitor (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). To overcome the friction, banks require hard information, often in the form of collateral, until they have better private information about borrowers, see also Jiménez, Salas and Saurina (2006); Hollander and Verriest (2016); Prilmeier (2017). We contribute to the literature by showing that banks' IT adoption increases the importance of collateral.

We further relate to the literature on firm dynamics and the macroeconomy, which has established that startups are an important driver of U.S. job creation Haltiwanger, Jarmin and Miranda (2013) and productivity growth Klenow and Li (2020). Decker et al. (2014) document that the share of employment of young firms declined by around 30% between the late 80s and just before the Global Financial Crisis in 2008. In the 2000s this trend has been particularly pronounced for high-tech firms, which are playing an extremely important role for productivity growth (Haltiwanger, Hathaway and Miranda, 2014). While the slowdown in productivity after the Great Financial Crisis has been attributed to a large extent to frictions in the financial sector, e.g. Doerr, Raissi and Weber (2018); Manaresi and Pierri (2019); Duval, Hong and Timmer (2020), the impact of the financial

[2] DeYoung, Glennon and Nigro (2008) show that the distance between borrowers and lenders increased over recent years. For a summary, see also Boot (2016).

[3] Petersen (1999); Berger and Udell (2002); Hauswald and Marquez (2006) provide theoretical motivation and evidence on when and why banks rely on hard information, and how distance affects the decision.

[4] Hombert, Schoar, Sraer and Thesmar (2020) show that unemployment insurance can spur entrepreneurial activity.

sector on firm dynamics before the crisis has received less attention. We show that areas with a stronger presence of IT-intensive banks experience more job creation by start-ups, especially in industries that are more dependent on external finance. These findings suggest that technological progress in the banking sector increased dynamism in the US economy and counteracted the secular decline in job creation among young firms.

Finally, we contribute to the recent literature that investigates how the rise of financial technology (FinTech) affects credit scoring and credit supply. Recent papers have focused on FinTech has changed the way information is processed, as well as the consequences for credit allocation and performance; for instance, see Berg et al. (2019); Di Maggio and Yao (2018); Fuster et al. (2019). However, the majority of papers examines the role of FinTech credit for consumers instead of business. While notable exceptions include Beaumont, Tang and Vansteenberghe (2199); Hau, Huang, Shan and Sheng (2018); Erel and Liebersohn (2020); Gopal and Schnabl (2020), the share of FinTech credit to small firms is still tiny, relative to credit provided by traditional banks.[5] In this paper, we differentiate ourselves from the FinTech literature by focusing on traditional banks in the US which are still the main provider of credit to small firms and have also invested heavily in IT.

The remainder of the paper proceeds as follows. Section 2 provides an overview over our data. Section 3 reports our main results and sheds light on the channels. Section 4 concludes.

2 Sample and variable construction

IT adoption Data on banks' IT use come from an establishment-level survey on personal computers per employee by CiTBDs Aberdeen (previously known as "Harte Hanks") for the years 1999, 2003, 2004, 2006, and 2016. We focus on establishments in the banking sector (based on the SIC2 classification) and exclude savings institutions and credit unions. We end up with 143,607 establishment-year observations.

Our main measure of IT adoption is based on the average share of personal computers across establishments in the United States. However, for the year 2016, we also have information on the IT budget and the usage of cloud computing of the establishment. The data also contain information about the type of establishment, i.e. whether it is the

[5] See Boot et al. (2021) for an overview.

headquarters (HQ), a branch or a standalone establishment, the number of employees in the establishment, as well as its location. The correlation between the IT budget of the establishment and the number of computers as a share of employees is high for later years, e.g. 65% in 2016. The R-squared of a cross-sectional regression of PCs per Employee on the per capital IT budget is 44%. There is also a positive correlation between PCs per Employee and the adoption of cloud computing. These correlations provide assurance that the number of personal computers per employee is a good measure of IT adoption in recent years, a relation that is likely even more pronounced in earlier years when other forms of IT adoption were less common.

We hand merge the CiTBD Aberdeen data with data on bank holding companies (BHCs) collected by the Federal Reserve Bank of Chicago. We use the Financial Institution Reports which provide consolidated balance sheet information and income statements for domestic BHCs. For the years 1999, 2003, 2004, and 2006 for which we have IT data available we take the average across the 361 banks that we merge.[6] We define this measure as $\widetilde{IT}_b$.

We then map banks from the merged Aberdeen-BHC data set to the FDIC summary of deposits (SOD) data set that provides information on the number of branches (and deposits) of each bank in a county, which we aggregate to the county level.[7] To construct a measure on local exposure to IT adoption of banks, we combine $\widetilde{IT}_b$ with the branch distribution of each banks in the first year available (1994) to mitigate reverse causality concerns. We then define the average IT adoption of the banks' present in each county by:

$$IT_c = \sum_{b=1}^{N} \widetilde{IT}_b * \frac{No.Branches_{b,c}}{No.Branches_c} \tag{1}$$

where $No.Branches_{b,c}$ is the number of branches of bank b in county c in 1994 and $No.Branches_c$ is the total number of branches across all banks in 1994 for which we have $\widetilde{IT}_b$ available. To ease interpretation IT_c is standardized with mean zero and standard deviation of one. Higher values indicate that banks with branches in a given county have adopted relatively more IT.

[6]See Pierri and Timmer (2020) for more details on the merging procedure.
[7]The results are qualitatively the same on the MSA-level.

County and industry data Data on young firms are obtained from the Quarterly Workforce Indicators (QWI). QWI provide detailed data on end-of-quarter employment at the county-two-digit industry-year level. Importantly, they provide a breakdown by firm age brackets. For example, they report employment among firms of age 0–1 or 2–3 in manufacturing in Orange county. Detailed data are available from 1999 onward. QWI is the only publicly available data set that provides information on county employment by firm age.

We follow the literature and define young firms or entrepreneurs as firms aged zero to one (Adelino et al., 2017; Curtis and Decker, 2018; Doerr, 2021). For each two digit industry in each county, we use 4th quarter values. As these firms have been created in this year and would not be in our young firm category in the same year, the employment of young firms is a flow and not a stock of employment. In our baseline specification we scale the job creation of young firms by total employment in the same county-industry cell.

We use the 2007 Public Use Survey of Business Owners (SBO) for firm-level information on sources of business start-up and expansion capital, broken down by two-digit NAICS industries. For each industry i we compute the fraction of young firms that reports using home equity financing or personal assets (*home equity* henceforth) to start or expand their business, out of all firms (Doerr, 2021).

County controls include log population, the share of black population and share of population older than 65 years, the unemployment rate, house price growth, and log per capita income. The respective data sources are: Census Bureau Population Estimates, Bureau of Labor Statistics Local Area Unemployment Statistics, Federal Housing Finance Agency House Price Index (HPI), and Bureau of Economic Analysis Local Area Personal Income. The house prices used in the regressions come from the Federal Housing Finance Agency (FHFA) House Price Index (HPI) data at the county level. The FHFA house price index is a weighted, repeat-sales index and it measures average price changes in repeat sales or refinancings on the same properties.

Bank data The Federal Deposit Insurance Corporation (FDIC) provides detailed bank balance sheet data in its Statistics on Depository Institutions (SDI). We collect second quarter data for each year on banks' total assets, Tier 1 capital ratio, non-interest and total income, total investment securities, overhead costs (efficiency ratio), non-performing loans, return on assets, and total deposits.

To capture the response of small business loan to changes in local house prices, we exploit Community Reinvestment ACT (CRA) data on loan originations at the bank-county level, collected by the Federal Financial Institutions Examination Council at the subsidiary-bank level. The CRA data contains information on loans with commitment amounts below \$1 million originated by financial institutions with more than \$1 billion in assets. We aggregate the data to the BHC-county level. To mitigate the effect of outliers we normalize the year-to-year change in lending volume by the mid-point of originations between the two years:

$$\Delta CRA_{b,c,t} = \frac{CRA_{b,c,t} - CRA_{b,c,t-1}}{CRA_{b,c,t} + CRA_{b,c,t-1}} \times 2, \tag{2}$$

where b refers to BHC, c to county and t to year. This definition bounds growth rates to lie in $[-2, 2]$, where -2 implies that a bank exited a county between $t-1$ and t, and 2 that it entered.[8]

Descriptive statistics Table 1 reports summary statistics of our main variables at the county level, split into counties in the bottom and top tercile of IT exposure. Except for population, we do not find significant differences across counties. Counties with high and low exposure to IT banks are similar in terms of their industry employment structure, but also in terms of the IT adoption of non-financial firms in the county. The absence of a correlation between IT exposure to banks and other county-specific variables is reassuring as it suggests that the exposure to IT in banking is also uncorrelated with other unobservable county characteristics that could bias our results.[9]

3 Empirical strategy and results

This section lays out the empirical strategy and reports our main results. First, we establish that counties with higher IT exposure have a higher share of employment among small firms – especially in industries that depend on external finance. We then provide evidence at the county and bank-county level that higher IT adoption is associated with

[8]While the log difference is symmetric around zero, it is unbounded above and below, and does not easily afford an integrated treatment of entry and exit. The growth rate used in this paper is divided by the simple average in $t-1$ and t. It is symmetric around zero, lies in the closed interval [-2,2], facilitates an integrated treatment of entry and exit, and is identical to the log difference up to a second order Taylor series expansion (Davis and Haltiwanger, 1999).

[9]Banks' predominantly lend in counties where they have branches, see Figure A1.

a stronger increase in employment among young firms and small business lending when local house prices rise. We argue that the higher sensitivity to rising real estate values arises because IT adoption increases the importance of hard information (i.e., collateral) in banks' decision to lend to young firms.

3.1 County IT exposure and entrepreneurship

To investigate the relation between county-level IT exposure and entrepreneurship, we estimate the following cross-sectional regression at the county-industry level:

$$\begin{aligned}\text{startups}_{c,i} = {} & \beta_1 \; IT\ exposure_{c,99} + \beta_2 \; constraint_i \\ & + \beta_3 \; IT\ exposure_{c,99} \times constraint_i + controls_{c,99} + \theta_c + \phi_i + \varepsilon_{c,i}.\end{aligned} \tag{3}$$

The dependent variable is the employment share of firms of age 0-1 (startups) out of total employment in county (c) and 2-digit industry (i), averaged over 1999-2007. $IT\ exposure_c$ denotes county exposure to IT-intensive banks as of 1999, measured by the IT adoption of banks' historical presence in the county. It is standardized to mean zero and a standard deviation of one. Standard errors are clustered at the county level.

If banks' IT adoption has a positive effect on startup activity, we expect $\beta_1 > 0$. Importantly, we expect this effect to be stronger in industries where external finance is more important or where it is easier to start a company. To this end, we interact $IT\ exposure_c$ with a measure of financial constraints at the industry level, $constraint_i$. We use the Rajan and Zingales (1998) measure of external financial dependence, as well as the average capital required to start a company, following Hurst and Lusardi (2004) and Adelino et al. (2015). We define an industry to be constrained if it lies in the top (bottom) quartile of external financial dependence (start-up capital). We expect a more-pronounced relation between IT exposure and startup activity in constrained industries, so $\beta_3 > 0$.

To control for heterogeneity in characteristics at the county or industry level, whenever possible we include county (θ_c) and industry (ϕ_i) fixed effects. When we do not include county fixed effects, we controls instead for: county size (log of the total population), the share of population age 65 and older, the share of black population, the unemployment rate, and the industrial structure (proxied by employment shares in the major 2-digit industries 23, 31, 44, 62 and 72), as IT adoption in non-financial firms (PCs in non-financial firms over total employment). All variables are measured as of 1999.

Table 2 shows a positive relation between county IT adoption and startup activity. Column (1) shows that counties with higher levels of IT exposure also have have a higher share of employment among young firms. Column (2) adds county controls but the coefficient remains stable and if anything increases slightly in magnitude. In terms of economic magnitudes, a one standard deviation higher IT exposure is associated with a 0.21 pp increase in the share of young firm employment. However, to compare the job creation of young firms across two counties with differing level of banks' IT adoption during the time period, the estimated coefficient needs to be multiplied by the number of sample years (seven). This calculation suggests that a county with a one standard deviation larger IT adoption of banks would have had a ($0.22 \times 7 =$) 1.47 percentage points higher employment share of young firms, or 16% of the average share (1.54%/9.34%).

The positive correlation between the IT adoption of banks present in a county and the larger share of young firm employment could be driven by confounding factors at the industry level. For example if counties that have a larger exposure to IT banks also differ in terms of their industries' import competition, a positive coefficient on IT bank exposure could spuriously be driven by differences in import competition. Column (3) thus includes industry fixed effects (at the NAICS 2 level) to control for the potential correlation between the IT adoption of banks present in a city and the local industry composition. Including fixed effects does not change the coefficient of interest in a statistically or economically meaningful way.

To assess whether the correlation between IT in banking and entrepreneurship is driven by IT's impact on financial frictions rather than spurious correlation, we follow Rajan and Zingales (1998) and study heterogeneity across industries. Specifically, we augment the estimating equation with an interaction term between IT adoption and industry-level dependence on external finance (which, as in Rajan and Zingales (1998), is measured by capital expenditure minus cash flow over capital expenditure) The coefficient on the interaction term between IT adoption and external financial dependence is economically large and statistically significant. Indeed, counties with higher IT exposure experience a higher share of employment among young firms precisely in those industries that depend more on external finance, suggesting the correlation is indeed driven by the impact of banks'IT on startups' financing.

Heterogeneity across industries allows us to purge the estimated impact of IT adoption in banking from other–observable or observable–confounding factors at the local level. In fact, we saturate the estimating equation with both industry and county fixed effects. Results are remarkably robust to focusing on within-county variation. In fact, as reported by column (5), the inclusion of county fixed effects change the estimated impact of IT exposure interacted with financial dependence by only 0.001, or about 0.3% of the estimated impact–despite the fact that the explanatory power of the regression increase by 20% with the inclusion of such controls. Finally, columns (6)–(7) show that the correlation is also stronger within industries in which it is cheaper to start a company, irrespective of the included controls.

A set of robustness exercises is presented in Table A1. Column (1) is the baseline (as column (3) of Table 2). In column (2) the IT exposure measure is the unweighted average of the IT adoption of banks that operate in a county, rather weighted by banks' number of branches in that county. Column (3) substitute the "shift-share" IT exposure measure with the simple average of PC per employees of the bank branches in a county. Column (4) use an alternative exposure measure which use the share of local deposits from FDIC, rather than the number of branches, as a weighting variable. The results of these empirical exercises are in line with baseline and thus highlight that our findings are not driven by any specific choice of the construction of the IT adoption measure. Column (5) excludes employment in startups in the financial and education industries, showing financial companies or universities are not driving our results. Column (6) excludes Wyoming which, perhaps surprisingly, the state with the highest exposure to banks' IT adoption, see Figure 3. Column (7) includes state fixed effects, showing that our results are driven by within-state variation, rather than variation between different part of the county. Column (8) shows robustness of the specification by normalizing the share of employment in startups by previous year's total employment. Column (9) reveals that our results are due to an impact on the numerator (employment of startups) rather than denominator (total employment).

In conclusion, Table 2 provides evidence that local IT adoption in the financial sector is associated with higher startup activity, especially in industries that rely more on external finance. This evidence is consistent with the hypothesis that IT adoption in banking alleviates the financial frictions that constrain entrepreneurship activity.

3.2 IT, house prices and entrepreneurship

This section provides further evidence on the mechanisms behind the relationship between IT in banking and entrepreneurial activity. A large literature highlights the importance of the collateral channel for small and young firms: rising real estate prices lead to an increase in firm formation, as higher collateral values relax firms' borrowing constraints (Adelino, Schoar and Severino, 2015; Schmalz, Sraer and Thesmar, 2017; Bahaj, Foulis and Pinter, 2020), which are particularly severe for small and young firms as they are informationally opaque. In other words, information asymmetries between banks and entrepreneurs can be mitigated by posting collateral (Rampini and Viswanathan, 2010).

Collateral and banks' IT adoption could in principle interact in several ways. On the one hand, collateral may be more more important for high-IT adoption banks, as IT adoption increases banks' reliance on hard relative to soft information (Liberti and Petersen, 2017). On the other hand, better screening technology could mitigate informational frictions, as IT in banking serves as a substitute for collateral, thereby reducing the sensitivity of young firm employment to collateral values (Hauswald and Marquez, 2003; Gambacorta, Huang, Li, Qiu and Chen, 2020).

We investigate the interaction between IT and collateral in two complementary analyses: first, we study the relationship between IT in banking and the sensitivity of entrepreneurship to house prices at the local level. We then analyze how IT shapes the elasticity of a bank's supply of small business loans in response to counties' local house prices.

County IT exposure and local house prices. We estimate the following regression at the county-industry-year level from 1999 to 2007:

$$\begin{aligned} \text{startups}_{c,i,t} = {} & \gamma_1 \ \textit{IT exposure}_{c,99} + \gamma_2 \ \Delta \textit{house prices}_{c,t} \\ & + \gamma_3 \ \textit{IT exposure}_{c,99} \times \Delta \textit{house prices}_{c,t} \\ & + \textit{controls}_{c,t-1} + \theta_{c,i} + \tau_t + \varepsilon_{c,i,t}. \end{aligned} \tag{4}$$

The dependent variable is the employment share of firms of age 0-1 (startups) out of total employment in county (c) and 2-digit industry (i) in given year (t). $\textit{IT exposure}_c$ denotes county exposure to IT-intensive banks as of 1999, measured by the IT adoption of banks' historical presence in the county. It is standardized to mean zero and a standard deviation of one. $\Delta \textit{house prices}_{\ c,t}$ is the yearly county-level growth in house prices. Controls are the same as in Equation 3, although we include them with a one-year lag rather than fixed at the 1999 level. Standard errors are clustered at the county level.

The coefficient on the interaction term (γ_3) reveals whether startup employment reacts by more or less in response to a change in house prices. If $\gamma_3 > 0$, then employment among young firms is more sensitive to changes in local collateral values in countries where banks use IT more intensively, suggesting that the 'hard information channel' dominates. The underlying argument is that rising house prices raise collateral values of firms (or of their owners' private residence), and this relaxation of collateral constraints stimulates entrepreneurship.

Table 3 reports the estimation results. Column (1) shows – in line with Table 2 – that higher IT exposure is associated with a higher share of young firm employment in general. Columns (2)–(9) refer to a set of specification including county-industry fixed effects and therefore exploit only the variation within each county-industry cell; the coefficient on IT exposure is thus absorbed. Column (2) shows that a rise in house prices increase entrepreneurship by more in IT-exposed counties, conditional on year fixed effects. Column (3) confirms this finding when including county times year fixed effects.

Finally, columns (5)-(9) investigate whether the positive effect of IT during periods of rising house prices is stronger in industries in which average start-up capital is lower, or in industries in which a larger share of firms relies on home equity to start or expand their business (Adelino, Schoar and Severino, 2015; Doerr, 2021). Within these industries, young firms should be more responsive to changes in collateral values. Results show this to be the case: the coefficient on the interaction effect is positive and significantly larger in industries that require lower startup capital and depend more on home equity to start or expand operations. Taken together, results in Table 3 suggest that the local presence of IT banks *increases* the sensitivity of local startup employment to changes in collateral values. This is in line with the argument that IT-intensive banks rely more on hard information, e.g. collateral, when making the decision whether to finance a firm.

Banks' IT adoption and small business lending While the county-level analysis suggests that rising house prices stimulate entrepreneurship by more in counties with higher IT exposure, unobservable time-varying characteristics at the lender or borrower level could confound the estimates. To address this issue, we investigate the sensitivity of small business lending to local house prices and whether the sensitivity is different for more or less IT-intensive banks. To do so, we estimate the following linear equation from 1999 to 2007 at the bank-county-year level:

$$\Delta loans_{b,c,t} = \beta_1\ IT_b + \beta_2 \Delta house\ prices_{c,t} + \beta_3\ IT_b \times \Delta house\ prices_{c,t} + bank\ controls_{b,t-1} + county\ controls_{c,t-1} + \varepsilon_{b,c,t}. \tag{5}$$

The dependent variable is the growth in total CRA small business loans by bank b to borrower county c in year t. We follow Davis and Haltiwanger (1999) and compute the growth rate along the extensive margin that accounts for bank entry into and exit out of counties over the sample period. The main explanatory variable IT_b measures the use of IT at the bank level as discussed in the data section. To measure the yearly change in house prices, we compute $\Delta house\ prices_{c,t}$ as the log difference in the county-level house price index. We cluster standard errors on the county level to account for serial correlation among banks lending to the same county.

If banks that use more IT rely more on hard information, as indicated by the count-level analysis, we expect their lending to be more sensitive to changes in local collateral values, i.e. when local house prices rise. This is, we expect $\beta_3 > 0$. Yet, borrower counties could differ along several dimension. We thus enrich our specifications with time-varying fixed effects at the county level. With county*time fixed effects, we essentially compare small business lending by two banks that differ in their IT intensity to the *same* county County-level controls are as in Equation 4, while bank-level controls are: log assets, deposits over total liabilites, share non-interest income, securities over total assets, return on assets, equity ratio (Tier 1), and wholesale funding ratio.

Table 4 shows that small business lending is more responsive to changes in local house prices for high-IT banks. Column (1) illustrates that high-IT banks experience a stronger small business lending growth and that the average bank lends more to counties with stronger house prices increases. Columns (2) and (3) split the bank sample into a low-IT (bottom tercile) and high-IT (top tercile) groups. For a given change in house prices, lending is more responsive by high IT banks. The coefficient of house price's growth is about 50% larger for the high-IT sample. Columns (4)–(6) confirm the larger responsiveness of high-IT banks when we interact banks' IT adoption with the change in house prices using a set of more and more saturated specifications. In column (4), small business lending reacts by more to a change in house prices for banks with higher IT adoption. This finding holds when we include bank and county controls, as well as year fixed effects to account for common trends. To further account for unobservable time-varying changes across counties, we include county*time fixed effects in column (5) and results remain similar. Column (6) absorb time-invariant factors at the bank-county level (eg bank-borrower distance) and shows that the size of our coefficient increases when we exploit within bank-county variation only. Finally, column (7) controls for time-varying bank fundamentals through bank*time fixed effects. Essentially, comparing loan growth by the same bank to the same county for different levels of IT, we find that high-IT banks adjust their loan supply by more than low-IT banks when house prices rise.

These results suggest that IT-intensive banks rely more on hard information. Young firms are informationally opaque, so they often pledge collateral in the form of real estate to obtain a loan. If high-IT banks rely more on hard information to make loan decisions – of which real estate collateral is a prime example – we expect that their loan volume reacts more to changes in collateral values (proxied by changes in county-level house prices). Instead, if banks would rely purely on soft information to grant loans, lending would be unresponsive to changes in local house prices.

3.3 IT, distance and lending

To further investigate the impact of IT on informational frictions, we analyze the interaction of lenders' IT adoption and the distance between lenders and borrowers in granting loans when local investment opportunities arise.

A large literature shows that information frictions increase with lender-borrower distance. Consequently, even if there is an increase in local county-level investment opportunities, banks that are located further away from the county will increase their lending by less than banks that are located closer. The literature suggests that IT adoption by banks could reduce the importance of distance (Petersen and Rajan, 2002), as it enables a more effective transmission of information; consequently, the informational frictions associated with distance become less important.

To test whether the relationship between local investment opportunities and lender-borrower distance is different for banks' adopting more IT, we consider the following linear model:

$$\begin{aligned}\Delta loans_{b,c,t} = {} & \beta_1\ log(distance)_{b,c} + \beta_2\ \Delta income\ p.c._{c,t} \\ & + \beta_3\ log(distance)_{b,c} \times \Delta income\ p.c._{c,t} \\ & + bank\ controls_{b,t-1} + county\ controls_{c,t-1} + \theta + \varepsilon_{b,c,t}, \\ & \text{if IT} = \text{low/high}\end{aligned} \tag{6}$$

We estimate (6) separately for banks in the high-IT and low-IT groups (top and bottom tercile of the IT distribution). The dependent variable is the log difference in total CRA small business loans by bank b to borrower county c in year t along the intensive margin.[10] In general, we expect that an increase in local investment opportunities, measured by the log difference of county-level income per capita, increases local lending; and the more so, the small the log distance between the lender and the borrower. This is, we expect $\beta_1 > 0$ and $\beta_3 < 0$. If banks' IT adoption reduces the importance of distance, we expect β_3 to be significantly smaller for *high IT* banks.

Results in Table 5 for all small business loans support these hypotheses. Columns (1) and (2) show that distance reduces the sensitivity of banks' CRA lending in response to local investment opportunities as the interaction terms between changes in income and distance is negative. This is true whether we include county times year fixed effects to control for any local shock. Moreover, many banks' expansion during the sample period results in higher growth rate of loans in further away from the headquarter (i.e. $\beta_1 > 0$). Columns (3) and (4) show that the lower responsiveness of further away banks to local economic shocks is present only for low IT banks; for high IT banks, distance has no dampening effect. Finally, columns (5) and (6) interact the log distance with changes in income per capita and banks IT adoption. Results confirm that – while distance reduces the sensitivity of lending to changes in local investment opportunities for low IT banks – among high IT banks, distance matters significantly less.

Taken together, results in Table 4 and Table 5 suggest that small business lending by banks that rely more on IT is *i*) more responsive to changes in collateral values, and *ii*) reacts by more to local investment opportunities, irrespective of the lender-borrower distance. These results suggest that IT banks rely more on hard information, which disproportionately benefits small firms that rely on collateral to start or expand their operations.

4 Conclusion

IT investment of banks have increased massively in the last few decades. This IT revolution in lending has raised concerns that banks increase their reliance on hard information,

[10] We cannot investigate growth along the extensive margin when we use distance as explanatory variable. As banks expanded geographically during the sample period, they are mechanically more likely to enter counties that are located further away from their HQs.

making it harder to small and young entrepreneurs to obtain credit as they are naturally opaque and have little collateral available.

In this paper we study the effect of the IT revolution in banking during the 2000s on entrepreneurship. We do not find evidence that IT in banking halts job creation by startups. Instead we find that in regions where banks that adopt more IT are present, entrepreneurship was stronger than in other regions. We show that this relationship is stronger in industries that rely more on external finance and in regions where more business opportunities arose. Moreover, we show that the collateral lending channel, as described in Adelino et al. (2015), is one potential explanation for the results. Young entrepreneurs pledge the increased value of their home equity as collateral when house prices rise. Our results suggest that this effect is stronger for IT-reliant banks.

Our results have important implications for policy. Technology adoption in lending especially due to the global rise in FinTech has triggered a debate on its impact on the economy. At the same time, policy makers have been struggling with low productivity growth for decades. Contrary to what the simple time series correlation would suggest, we show that IT in lending decisions can spur rather than drag job creation by young firms.

Given the strong rise in house prices since the pandemic and larger reliance on IT systems due to a reduction in physical interactions, our evidence also suggests that the adoption of IT in banking can spur entrepreneurship and productivity growth in the post-pandemic world.

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Figures and Tables

Table 1: **Balancedness at the county level**

	low IT		**high IT**		**mean diff.**
	mean	sd	mean	sd	t
log(pop)	10.94	(1.11)	10.82	(1.10)	2.00
share pop old	0.14	(0.04)	0.14	(0.04)	-1.63
share pop black	0.09	(0.14)	0.09	(0.13)	0.47
unemployment rate	4.71	(2.31)	4.60	(2.25)	0.84
employment share NAICS 23	0.06	(0.03)	0.06	(0.03)	-0.20
employment share NAICS 31	0.22	(0.13)	0.21	(0.13)	0.12
employment share NAICS 44	0.16	(0.04)	0.16	(0.04)	-0.13
employment share NAICS 62	0.14	(0.05)	0.14	(0.05)	-0.12
employment share NAICS 72	0.09	(0.04)	0.10	(0.05)	-1.62
PCs per employee (non-fin)	0.50	(0.10)	0.49	(0.09)	1.04
Observations	592		591		1183

This table reports summary statistics at the county level, split into counties in the bottom and top tercile of the distribution of IT exposure. *mean diff* denotes the t-value for the difference in means.

Table 2: **County IT exposure and entrepreneurship**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1	(5) share 0-1	(6) share 0-1	(7) share 0-1
IT exposure	0.217**	0.240***	0.244***	0.240***		0.175***	
	(0.109)	(0.077)	(0.071)	(0.071)		(0.068)	
IT exposure × ext. fin. dep				0.095**	0.085**		
				(0.040)	(0.035)		
IT exposure × low startup capital						0.318***	0.288***
						(0.112)	(0.108)
Observations	25,779	25,779	25,779	25,779	25,779	25,779	25,779
R-squared	0.001	0.060	0.490	0.491	0.602	0.491	0.602
County Controls	-	✓	✓	✓	-	✓	-
NAICS FE	-	-	✓	✓	✓	✓	✓
County FE	-	-	-	-	✓	-	✓
Cluster	County	County	County	County	County	County	County

This table reports results from cross-sectional regressions at the county-industry level (see Equation 3). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i. *IT* is the IT adoption of banks in the county, measured by the IT adoption of banks historically present in the county, and standardized with mean zero and a standard deviation of one. *ext. fin. dep* is a dummy with value one for industries with high dependence on external finance, *low startup capital* is a dummy with value one for industries with low amounts of capital required to start a company. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **County IT exposure, entrepreneurship, and collateral**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1	(5) high SU share 0-1	(6) low SU share 0-1	(7) low HE share 0-1	(8) high HE share 0-1	(9) share 0-1
IT exposure	0.241**								
	(0.105)								
Δ HPI		-0.012	-0.023**	-0.024***	-0.026***	-0.018	-0.024***	-0.024**	
		(0.008)	(0.009)	(0.009)	(0.008)	(0.013)	(0.008)	(0.011)	
IT exposure × Δ HPI		0.082***	0.087**	0.087***	0.073**	0.132**	0.067*	0.104**	
		(0.031)	(0.035)	(0.033)	(0.034)	(0.053)	(0.038)	(0.040)	
IT exposure × Δ HPI × High HE									0.012***
									(0.004)
Observations	195,220	192,402	168,836	168,836	113,087	55,749	81,119	87,717	168,569
R-squared	0.010	0.617	0.634	0.650	0.683	0.527	0.602	0.698	0.698
County × NAICS FE	-	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	-	-	-	-	-	-
Year FE × NAICS FE	-	-	-	✓	✓	✓	✓	✓	✓
County × Year FE	-	-	-	-	-	-	-	-	✓
Cluster	County	County	County	County	County	County	County	County	County

This table reports results for regressions at the county-industry-year level (see Equation 4). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i in year t. IT is the IT adoption of banks in the county, measured by the IT adoption of banks historically present in the county, and standardized with mean zero and a standard deviation of one. ΔHPI is the yearly change in house prices in county c. *high/low SU* refers to industries with high/low amounts of capital required to start a company. *low/high HE* refers to industries with low/high dependence on home equity as a source to start or expand operations. $High\ HE$ is a dummy equal to one if the industry i is an industry where where startups have a high reliance on home-equity. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Banks' IT, house prices and CRA lending**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		low IT	high IT				
VARIABLES	Δ loans	Δ loans	Δ loans	Δ loans	Δ loans	Δ loans	Δ loans
IT	0.031***			0.024***	0.026***		
	(0.002)			(0.003)	(0.003)		
Δ HPI	0.002***	0.002***	0.003***	0.002***			
	(0.001)	(0.001)	(0.001)	(0.001)			
IT × Δ HPI				0.001**	0.001**	0.004***	0.002**
				(0.001)	(0.001)	(0.001)	(0.001)
Observations	338,857	141,495	112,831	338,857	338,857	338,857	338,857
R-squared	0.028	0.022	0.044	0.028	0.082	0.172	0.407
Bank Controls	✓	✓	✓	✓	✓	-	-
County Controls	✓	✓	✓	✓	-	-	-
Year FE	✓	✓	✓	✓	-	-	-
County × Year FE	-	-	-	-	✓	✓	✓
Bank × County FE	-	-	-	-	-	✓	✓
Bank × Year FE	-	-	-	-	-	-	✓
Cluster	County-Bank	County-Bank	County-Bank	County-Bank	County-Bank	County-Bank	County-Bank

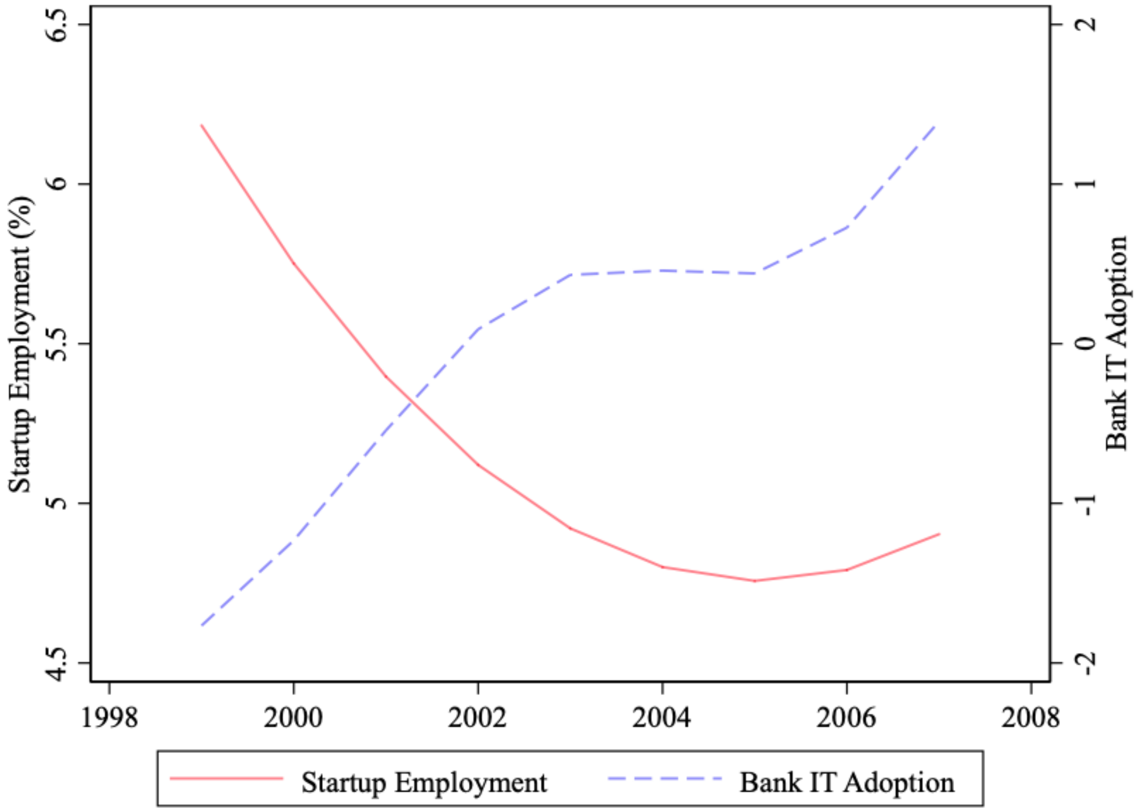
This table reports results for regressions at the bank-county-year level (see Equation 5). The dependent variable is the change in CRA loans by bank b to county c in year t. IT is the IT adoption of bank b, ΔHPI is the yearly change in house prices in county c. *low/high IT* refers to banks in the bottom/top tercile of the IT distribution. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **CRA lending – distance all loans**

VARIABLES	(1) Δ loans	(2) Δ loans	(3) low IT Δ loans	(4) high IT Δ loans	(5) Δ loans	(6) Δ loans
Δ Income	0.019***					
	(0.003)					
log(distance)	0.016***	0.018***	0.055***	-0.003	0.017***	0.017***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)
Δ Income × log(distance)	-0.003***	-0.004***	-0.009***	0.002*	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IT					0.060***	
					(0.014)	
Δ Income × IT					-0.014***	-0.011***
					(0.003)	(0.003)
IT × log(distance)					-0.009***	-0.011***
					(0.003)	(0.003)
Δ Income × log(distance) × IT					0.003***	0.002***
					(0.001)	(0.001)
Observations	194,655	194,341	84,902	54,278	194,771	194,768
R-squared	0.019	0.126	0.234	0.286	0.127	0.150
Bank Controls	✓	✓	✓	✓	✓	✓
County Controls	✓	-	-	-	-	-
Year FE	✓	-	-	-	-	-
County × Year	-	✓	✓	✓	✓	✓
Bank FE	-	-	-	-	-	✓
Cluster	Bank-County	Bank-County	Bank-County	Bank-County	Bank-County	Bank-County

This table reports results for regressions at the bank-county-year level (see Equation 6). The dependent variable is the change in CRA loans by bank b to county c in year t. *IT* is the IT adoption of bank b. $\Delta income$ is the change in per capita income in county c between year $t-1$ and t. $log(distance)$ is the log of the number of miles between bank b's headquarter and county *low/high IT* refers to banks in the bottom/top tercile of the IT distribution. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Startups and Banks' IT adoption- Time Series



The red solid line plots the median employment share of young firms across MSAs as described in section 2. The blue dashed dotted line plots the year fixed of bank-level IT adoption.

Figure 2: Startups

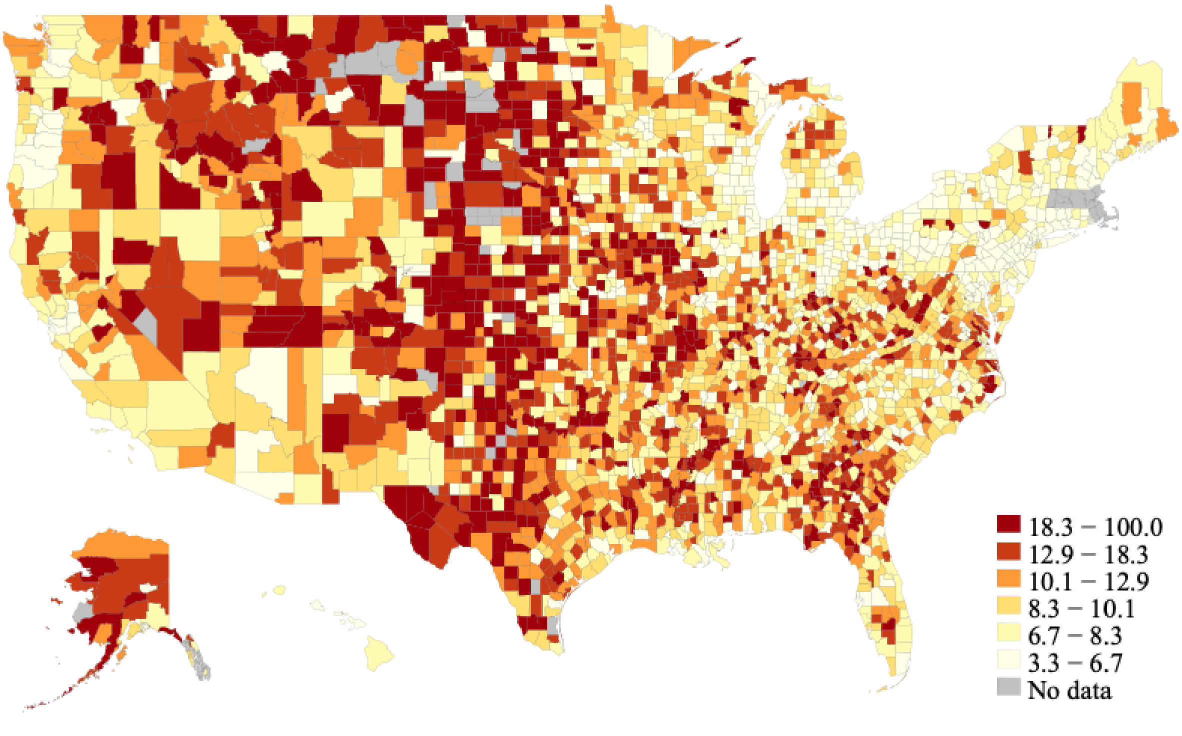


Figure 3: Exposure to IT in Banking

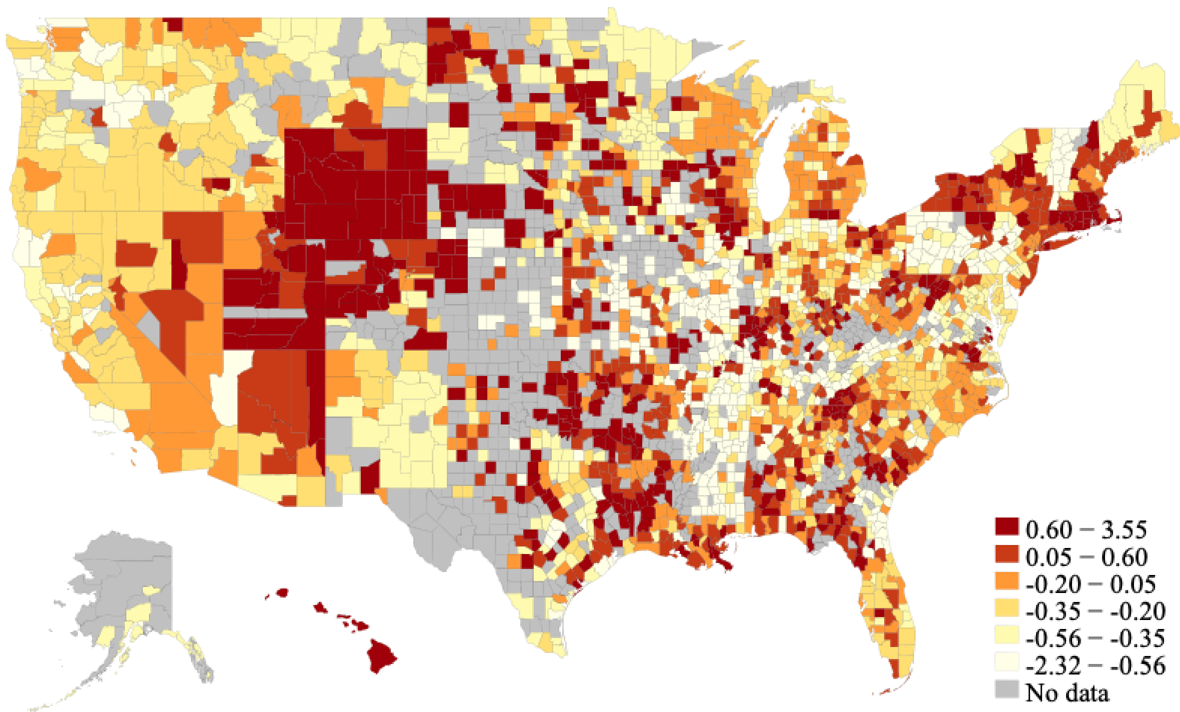
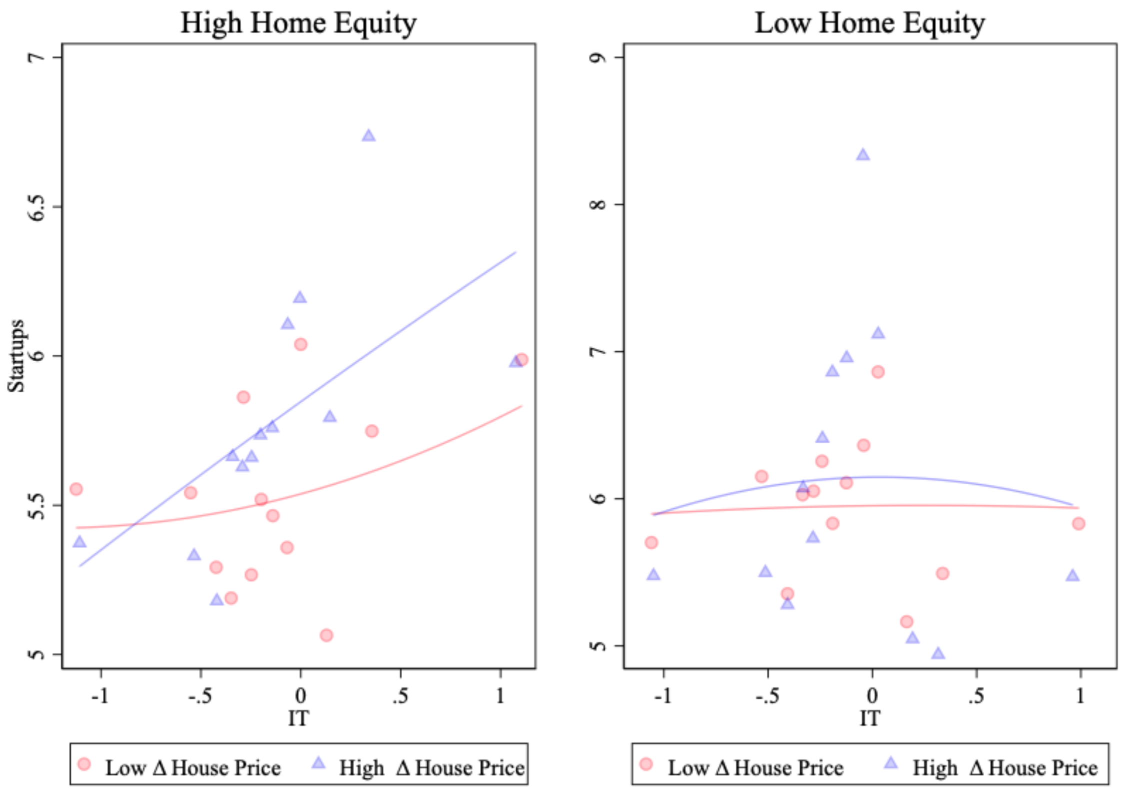


Figure 4: Job Creation by Young Firms and Banks' IT adoption



This figure shows a binscatter of the share of employment by young firms over total employment in an a county across 2000 and 2007 on the vertical axis and the county level exposure to Bank IT adoption as defined in section 2 on the horizontal axis. The left (right) panel shows the data for industries with above (below) median home equity usage. The blue triangles reflect areas where house prices rose above the median and the red dots reflect areas where house price rose below the median.

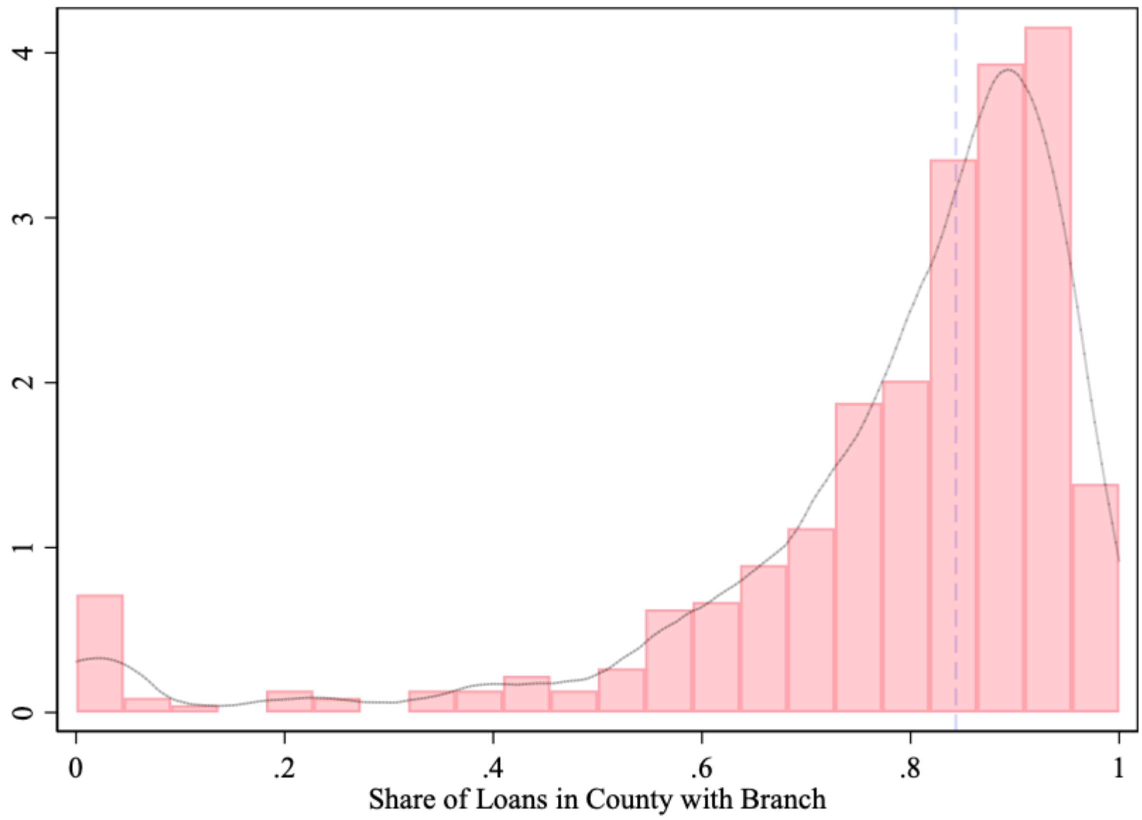
Appendix

Table A1: **Robustness**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1	(5) share 0-1	(6) share 0-1	(7) share 0-1	(8) share 0-1 (lagged)	(9) Δ Employment
PCs per employee			0.147**						
			(0.060)						
IT exposure	0.244***	0.189**			0.268***	0.236***	0.228***	0.266***	-0.001
	(0.071)	(0.084)			(0.069)	(0.071)	(0.064)	(0.076)	(0.073)
IT exposure (deposit weighted)				0.178***					
				(0.063)					
Observations	25,779	25,779	25,711	25,779	21,735	25,544	25,779	25,440	25,774
R-squared	0.490	0.252	0.490	0.490	0.496	0.491	0.531	0.445	0.367
County Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Spec	Baseline	No Weights	PC/Emp	Deposit Share	No Finance	NoWyoming	State FE	Lagged Denominator	Δ Total Employment
Cluster	County	County	County	County	County	County	County	County	County

This table reports results for the following regression: $\text{startups}_{c,i} = \beta \ IT\ exposure_{c,99} + controls_{c,99} + \theta_c + \phi_i + \varepsilon_{c,i}$, where $\text{startups}_{c,i}$ is defined as the share of the employees in county c and industry t which is employed at a firm with at most 1 year of life. The share is then averaged across the years 2000 and 2007. IT_c is the IT adoption of banks in the county, measured by the IT adoption of banks historically present in the county, and standardized with mean zero and a standard deviation of one. The Table report results from a set of robustness exercises. (1) Is the baseline regression. Column (2): local IT adoption is the unweighted average of the IT adoption of banks present in the county. Column (3) uses the simply measure PC per Employee in the county as an independent variable. In Column (4) we project bank IT adoption by the deposit share rather than the number of branches on the county. In column (5) we exclude finance and education as a sector. (6) We exclude Wyoming. (7) We include state FE. (8) We divide employment creation of young firms by lagged total employment in the county sector cell. In Column (9) we use the change in total employment as a dependent variable. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: Share of Loans in County with a Branch by Bank



This figure shows the distribution of the share of CRA loans that are granted in a county where the bank has a branch. The vertical dashed line represents the median across banks.