Does IT help?
Information Technology in Banking and Entrepreneurship

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Abstract

This paper analyzes the importance of information technology (IT) in banking for entrepreneurship. We build a parsimonious model of bank screening that predicts that IT in banking can spur entrepreneurship by making it easier for startups to borrow against collateral. Empirically, we find that job creation by young firms is stronger in US counties that are more exposed to IT-intensive banks, as measured through banks' historical geographical footprint. We also show that entrepreneurship increases by more in IT-exposed counties when house prices rise, and especially so in home equity-intensive sectors. These results suggest that banks' IT facilitates collateralized lending. Further highlighting IT's role in improving the use of hard information, we establish that small business lending by banks with higher IT adoption is *i*) more sensitive to changes in local house prices, and *ii*) less-affected by the distance between the bank headquarters and its borrowers. These findings are robust to controlling for unobservable time-varying county or bank factors.

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1 Introduction

The United States have witnessed a declining rate of firm creation since the 1980s (Decker et al., 2014), dragging down productivity growth (Decker et al., 2016; Klenow and Li, 2020). Yet, the reasons for this decline in entrepreneurship are far from completely understood. One possible culprit could be banks' massive investment in information technology (IT) over the same period (see Figure 1). As young firms are usually opaque and have produced limited hard information, their financing is sensitive 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.

In this paper, we analyse how the rise of IT in the financial sector affects entrepreneurship. We develop a parsimonious model of bank screening and lending to firms of heterogeneous quality and opacity. Screening can be performed through information acquisition or by requiring collateral. Old firms can be screened in either way, while startups have not yet produced sufficient hard information and thus can obtain funds only if entrepreneurs post their own house as collateral. The model predicts that IT in banking can facilitate entrepreneurship by making it easier for entrepreneurs to borrow against collateral. The underlying channel is that IT makes it relatively cheaper for banks to verify the value of collateral. Further, high-IT banks are more willing to lend to young firms especially when collateral values rise.

To systematically examine how banks' IT adoption affects startups, we use detailed data on the purchase of IT equipment of commercial banks across the United States in the years prior to the Great Financial Crisis (GFC).[1] We use these data to compute county-level *exposure* to banks' IT based on banks' historical geographic footprint. Consistent with the model's implications, we find that counties more exposed to IT-intensive banks through banks' historical geographical footprint experience stronger job creation by young firms during this period. This is especially so in industries that rely more on external financing, pointing towards better access to finance as the underlying chanell. Exploiting the rise in IT adoption during the 2000s, we show that in counties exposed to banks that have *increased* their IT adoption experienced a *weaker decline* in startup rates.

[1]We focus on the pre-GFC period because it is characterized by light regulation and the absence of major policy changes. Detailed data on local entrepreneurship are available only from 1999 on, making it difficult to extend the analysis back in time. A further reason to exclude the GFC and following years from the analysis is that during the crisis IT adoption determined the performance of mortgages originated by banks (Pierri and Timmer, 2020), thus creating an important potential confounding factor.

Examining the channels through which IT in banking fosters entrepreneurship, we document that an increase in local house prices boosts startup employment by more in counties with higher exposure to banks' IT—and even more so in industries in which startups depend relatively more on home equity financing to start or expand their operations. These findings are in line with the model's predictions and highlight the importance of collateral as a channel through which IT in banking affects entrepreneurship. Exploiting granular bank-county level data on banks' small business lending, we also show that lending by high-IT banks is more sensitive to changes in local house prices. This finding further provides evidence that IT could increase the importance of collateral in banks' lending decisions. We also provide evidence that IT increases the importance of hard information by showing that distance matters less for small business lending by high-IT banks when local investment opportunities arise (Petersen and Rajan, 2002; Liberti and Petersen, 2017).

In our theoretical framework, firms have heterogeneous collateral values, differ in their age (old firms and startups), and their new investment projects are of a quality unobserved to banks. To overcome this adverse selection problem, banks engage in screening by either acquiring information about the firm or requiring sufficient collateral. Old firms can be screened in either way, while startups have not yet produced enough hard information and thus can obtain funds only if entrepreneurs post their own house as collateral. Banks differ in their adoption of information technology that, in turn, lowers the cost of screening. In particular, as in the empirical analysis we find that high IT banks are more likely to issue corporate loans against collateral (even controlling for borrower identity), we assume that IT makes it relatively cheaper for banks to verify and communicate the existence and the value of collateral. When firms and banks are randomly matched, a higher share of IT-banks increases the expected lending to entrepreneurs in the economy. As in Adelino et al. (2015), a raise in collateral values boosts local entrepreneurship. In our framework, however, it is the high IT banks that lend to more young firms when collateral values rise, so the relationship between collateral values and entrepreneurship is stronger where banks adopt more IT.

Our measure of IT adoption in banking is closely related to seminal papers on IT adoption for non-financial firms, for example Bresnahan et al. (2002), Brynjolfsson and Hitt (2003), Beaudry et al. (2010), or Bloom et al. (2012). 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 the IT budget or adoption of frontier technologies.[2] County-level exposure to banks' IT is then computed as the weighted average bank-level IT adoption of banks operating in a given county, with weights given by the historical share of local branches. Constructing local IT exposure based on banks' historical geographic footprint ameliorates concerns about banks' selecting into counties based on unobservable county characteristics, such as dynamism or growth trajectories.

We start our empirical analysis by documenting that higher county-level IT exposure is associated with significantly higher entrepreneurial activity, measured as the employment share of new firms (Adelino et al., 2017). This finding is consistent with the prediction from our theoretical model and shows that the simple negative correlation between banks' IT adoption and startup activity over time is likely to reflect other secular trends. We further 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), suggesting that the relation could be explained by firms' better access to finance. Economically, our estimates imply that a one-standard-deviation higher IT exposure is associated with a 4 pp higher employment share in new firms (around 4% of the mean). These findings suggest that while the positive impact of IT adoption in banking have stimulated entrepreneurship significantly, it was likely not strong enough to offset other forces that have slowed down business dynamism.

In principle, the positive relation between IT exposure and startup activity could be explained by reverse causality or omitted variable bias. Arguably, reverse causality is unlikely to be a major concern in our empirical setting: lending to startups represents only a small fraction of banks' overall lending, which makes it unlikely that banks adopt IT solely because they expect an increase in startup activity. Yet, confounding factors could spuriously drive the association between IT and local entrepreneurship. For instance, a better-educated workforce may make it easier for banks to hire IT-savvy staff and also create more frequent business opportunities for new startups. To mitigate this concern, we start by including a wide set of county-level controls for differences in local characteristics. For instance, we control for industrial composition, education, income, and demographic structure. We also control for IT adoption of non-financial firms, to

[2]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 in 2016. For example, the bank-level correlation between the per capita share of PCs and the IT budget is 65%. 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 (Bresnahan et al., 2002; Beaudry et al., 2010; Bloom et al., 2012).

avoid that entrepreneurship clustering in high-tech areas might drive the results.

Additionally, we exploit the granularity of our county-industry data to include a battery of fixed effects. For example, we can control for local observable and unobservable county characteristics, such as income, consumption or dynamism, by including county fixed effects. Further, we can include industry fixed effects to absorb any unobservable industry factors, such as changes in import penetration or export demand. 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. Importantly, including controls and fixed effects does not materially affect the magnitude of our coefficients, despite increasing the R^2 substantially. These findings suggest that IT exposure is uncorrelated with observable and unobservable county and industry characteristics, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).

Our results suggest that IT in banking facilitates entrepreneurship. However, exposure to IT could reflect other unobservable county characteristics. We thus develop an instrumental variable (IV) approach that exploits exogenous variation in banks' market share across counties to establish causality. Specifically, we instrument banks' geographical footprint with a gravity model interacted with state-level banking deregulation, as in Doerr (2021). That is, we first predict banks' geographic distribution of deposits across counties with a gravity model based on the distance between banks' headquarters and branch counties, as well as their relative market size (Goetz et al., 2016). In a second step, predicted deposits are adjusted with an index of staggered interstate banking deregulation to take into account that states have restricted out-of-state banks from entering to different degrees (Rice and Strahan, 2010). The cross-state and cross-time variation in branching prohibitions provides exogenous variation in the ability of banks to enter other states. Predicted deposits are thus plausibly orthogonal to unobservable county characteristics. The instrumental variable approach confirms that exposure to IT-savvy banks leads to more local entrepreneurship. The estimated coefficients are not statistically different from the OLS estimates, indicating that the endogenous presence of high IT banks is not a main concern for our empirical analysis.

What drives the relationship between IT and entrepreneurship? Our model highlights the comparative advantage of IT banks to lend against collateral. We therefore investigate the role of collateral as a source of hard information in lending decisions empirically. While startups often do not have pre-existing collateral available to post against the loan, entrepreneurs often post their home equity as collateral. Following Mian and Sufi (2011) and Adelino et al. (2015), we exploit home value increases at the county-level to identify higher collateral values that, in turn, enable borrowers to take on more debt.

Consistent with the model's predictions, we show that the presence of IT-intensive banks spurs entrepreneurship *more* when collateral values rise. 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. In fact, we find that the positive interaction between IT in banking and house price raises on entrepreneurship is strongest in industries where collateral is of high importance for startup activity measured by (i) the industry propensity to use home equity to start and expand their business or (ii) the amount of startup capital required to start a business in an industry (Hurst and Lusardi, 2004; Adelino et al., 2015; Doerr, 2021). Exploiting heterogeneity in the importance of collateral across regions and industries allows us to control for observed and unobserved time-variant and invariant heterogeneity at the county and industry level through granular fixed effects, further mitigating the concern that unobservable factors explain the correlation between IT in banking and entrepreneurship.

To further highlight the importance of collateral, we use Community Reinvestment Act (CRA) data on banks' small business lending at the bank-county level. We find that small business lending by high-IT banks is more sensitive to changes in local house prices, suggesting that they lend more when real estate collateral values increase. In these specifications, we measure IT at the bank-level directly, instead of exploiting geographic variation in banks' footprints. When we account for unobservable time-varying factors at the bank or county level through bank×year or county×year fixed effects, we essentially compare small business lending by two similar banks that differ in their IT intensity to borrowers in the *same* county, mitigating concerns that the relation between bank lending and house prices is due to (unobservable) confounding factors, such as employment growth. Accounting for possible confounding factors does not materially affect our estimates. This finding further provides evidence that IT could increase the importance of collateral in banks' lending decisions and facilitate small firms' access to credit.

In a final step, we present additional evidence supporting the intuition and the assumptions underlying the model. In particular, the model (a) builds on the idea that a bank's IT adoption ameliorates information frictions between lender and borrower (especially when collateral is used), (b) assumes that high IT banks have a relative cost advantage in lending against collateral, (c) abstracts from the role of local competitions between banks.

To shed further light on the role of the ability of IT adoption to improve the use 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; Vives and Ye, 2020). To this end, we study how distance affects banks' lending in response to a local increase in business opportunities (i.e., 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 arise, even if they arise distant from the headquarter.

We then rely on loan-level data on corporate lending to show that banks with higher degree of IT adoption are more likely to request collateral for their lending, even controlling for borrower identity. This is consistent with a cost advantage of these banks with respect to other screening approaches. We finally analyze how our specifications are impacted by local market concentration: we find no evidence that the relationship between IT and entrepreneurship is impacted by the county-level market structure of the banking industry.

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. In turn, IT benefits opaque borrowers, such as startups, disproportionately.

Literature and contribution. Our results relate to the literature investigating 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). 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.[3] 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.[4] Yet, use of actual data on banks' IT adoption to test these hypotheses is scarce. 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 could 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).[5] 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 1980s 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);

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

[4] 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.

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

Manaresi and Pierri (2019); Duval, Hong and Timmer (2020), the impact of the financial 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 how 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 businesses. 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 relatively small, compared to credit supplied by traditional providers (see Boot et al. (2021) for an overview). In this paper, we differentiate ourselves from the FinTech literature by focusing on traditional banks in the US, which are still a key provider of credit to small firms and have also invested heavily in IT.

The remainder of the paper proceeds as follows. Section 2 presents a simple model of bank screening and lending. Section 3 provides an overview over our data. Section 4 presents empirical tests for the main implications of the model. Section 5 provides additional evidence supporting the model intuition and assumptions. Section 6 concludes.

2 Model

We develop a simple model to assess the implications of bank IT adoption for lending and screening. A key building block is asymmetric information, whereby firm quality is initially unobserved by banks. To mitigate the arising adverse selection problem, banks can screen via acquiring information about firms (unsecured lending) or by requesting collateral (secured lending). We describe how the IT adoption of banks and changes in collateral values affect the share of lending to young firms (entrepreneurs) and the type of screening. In particular, we derive three specific implications to be tested in the subsequent empirical analysis.

There are two dates $t = 0, 1$, no discounting, and universal risk-neutrality. There are two goods: a good for consumption / investment and collateral that can back borrowing at date 0. There are banks and firms, each of which with preferences of $u(c_0, c_1) = c_0 + c_1$, where c_t is consumption at date t.

Firms have a new project at date 0 that requires one unit of investment. Firms are penniless in terms of the investment good but have collateral C at date 0. Firms are heterogeneous at date 0 along two publicly observable dimensions. First, a firm's collateral is drawn from a distribution $G(C)$. The entire collateral can be pledged. The market price of collateral at date 1 is P. Second, firms differ in their age: firms are either old (O) or young (Y), where we refer to young firms as entrepreneurs. In total, there is mass of firms normalized to one and the share of young firms is $y \in (0, 1)$. For expositional simplicity, firm age and collateral are independent.

The key friction is asymmetric information about the firm's type, that is the quality of the project. The project yields $x > 1$ at date 1 if successful and 0 if unsuccessful. Good projects are more likely to be successful and, for simplicity, we focus on the limiting case in which all good projects are successful and all bad ones are unsuccessful. Project quality (good or bad) is privately observed by the firm but not by banks. The share of good projects at date 0 is $q > 0$, which is independent of bank or firm characteristics. We assume that the share of good projects is low,

$$q\,x < 1, \tag{1}$$

so the adverse selection problem is severe enough for banks to screen borrowers.

There is a mass K of banks endowed with one unit of the investment good at date 0 to grant a loan. An exogenous fraction $h \in (0, 1)$ of banks adopted IT in the past and is therefore a high-IT bank, while the remainder is a low-IT bank.[6] Our focus is on the implications of bank IT adoption, especially for lending to young firms.

Each bank has two tools to screen borrowers. First, the bank can pay a fixed cost F to learn the type of the project (screening by information acquisition). This cost can be interpreted as the time cost of a loan officer identifying the quality of the project. We

[6]The type of a bank may be either publicly observed or inferred from the equilibrium lending rates.

assume that this cost is lower for old firms than for young firms:[7]

$$F_O < F_Y, \tag{2}$$

which captures that old firms have (i) a longer track record and thus lower uncertainty about future prospects; or (ii) larger median loan volumes, so the (fixed) time cost is relatively less relevant.

Second, the bank can screen by asking for collateral that is repossessed and sold if the firm defaults on the loan. In this case, the bank does not directly learn the firm's type but the self-selection by firms—whereby only firms with good projects seek funding from banks—also reveals their type in equilibrium. We assume that the cost of verifying collateral is lower for high-IT banks than for low-IT banks:[8]

$$v_{HighIT} < v_{LowIT}, \tag{3}$$

which captures that it is easier or cheaper for a high-IT bank to (i) verify the existence of collateral; (ii) determine its market value; or (iii) document or convey these pieces of information to its headquarters. Table A6 provides evidence consistent with this assumption, showing that high-IT banks issue more secured loans in the syndicated loans market. Moreover, Table 5 shows that distance matters less for high-IT banks in their response to better local opportunities, consistent with the idea that information can be transmitted more cheaply to (distant) headquarters of high-IT banks.

We assume that banks and firms are randomly matched. The lending volume maximizes joint surplus, where banks receive a fraction $\theta \in (0, 1)$ of the surplus generated by lending. The assumption that a bank's share of surplus does not depend on their IT adoption is supported by evidence in Table A2. Specifically, the interaction term between competition and IT exposure of banks is insignificant. In what follows, we assume a ranking of screening costs:

$$v_{HighIT} < F_O < x - 1 < \min\{F_Y, v_{LowIT}\}. \tag{4}$$

In equilibrium, only firms of high quality (a fraction q of them) may receive credit. Moreover, young firms (a fraction y of firms) receive credit only when matched with a

[7]For simplicity, we assume that these fixed costs are independent of the bank's type. Our results can be generalized as long as the high-IT bank has a comparative advantage in screening via collateral.

[8]For simplicity, we assume that these verification costs are independent of firm age.

high-IT bank (a fraction h of banks) and when possessing enough collateral, $C \geq C_{min} \equiv \frac{1}{P}$, which applies to a fraction $1-G(C_{min})$ of these firms. Old firms always receive credit. When matched to a high-IT bank, lending is backed by collateral if the old firm has enough of it, otherwise the high-IT ensures the high quality via information acquisition. When matched with a low-IT firm, screening via information acquisition is also used.

Taken these results together, we can state the model's implications about the share of expected lending to young firms s_Y and how it depends on the share of high-IT firms h, the price of collateral P, and both factors simultaneously.

Proposition 1 *The share of lending to young firms is* $s_Y \equiv \frac{yh[1-G(C_{min})]}{1-y+yh[1-G(C_{min})]}$. *We have the following comparative statics:*

1. $\frac{ds_Y}{dh} > 0$*: a higher share of high-IT banks increases the share of lending to young firms.*
2. $\frac{ds_Y}{dP} > 0$*: a higher collateral value increases the share of lending to young firms.*
3. $\frac{d^2 s_Y}{dhdP} > 0$*: a higher collateral value increases the share of lending to young firms more when the share of high-IT banks is higher.*

To gain intuition for these results, note that a higher share of high-IT banks implies that young firms of good quality and with sufficient collateral can receive funding more often. A higher value of collateral, in turn, increases the range of young firms that have sufficient collateral, increasing expected lending on the extensive margin.

We test these three implications in section 4, while section 5 provides additional evidence supporting the main assumptions of the model. Before going there, however, we discuss another implications of the model. Young firms use more collateral than old firms in equilibrium. Since firm age and size are correlated in the data, this implication is consistent with recent evidence on the greater importance of collateral for lending to small businesses (Chodorow-Reich et al., 2021; Gopal, 2019).

3 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 excluding savings institutions and credit unions). We end up with 143,607 establishment-year observations.

Our main measure of IT adoption is based on the use 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 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.

Our measure of county-level exposure to bank IT adoption is estimated through the following steps. We first 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. We then compute a BHC-level measure of IT adoption based on a regression of the share of personal computers on a bank (group) fixed effect controlling for the geography of the establishment and other characteristics.[9] We define this measure as $\widetilde{IT}_b$. The focus on BHC rather than local branches or banks is due to the facts that (a) most of variation in branch-level IT adoption is explained by the BHC (b) technology adoption at both local branches, back offices, local and national headquarter may impact screening ability (c) using a larger pool of observations reduces measurement error (d) this estimation procedure delivers bank-level IT adoption measures that are uncorrelated with banks' business model (assets or funding), size, or

[9]That is, we estimate the following regression for years 1999, 2003, 2004, and 2006:

$$PCs/Emp_{i,t} = \widetilde{IT}_b + \theta_{type} + \theta_c + \theta_t + \gamma \cdot Emp + \epsilon_{i,t} \quad (5)$$

where $PCs/Emp_{i,t}$ is the ratio of computers per employee in branch i survey wave t (capped at top 1%), $\widetilde{IT}_b$ is a bank fixed effect, θ_{type} is a establishment-type (HQ, standalone, branch) fixed effects, θ_c is a county fixed effect, θ_t is a year fixed effect and Emp is the log number of employees in the establishment.

profitability, suggesting it is not correlated with management quality or other confounding factors (Pierri and Timmer, 2020).

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.[10] 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:

$$IT_c = \sum_{b=1}^{N} \widetilde{IT}_b * \frac{No.Branches_{b,c}}{No.Branches_c} \tag{6}$$

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.

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.

[10] The results are qualitatively the same on the MSA-level.

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). In some specifications we split industries along the median in high- and low-home equity dependent industries.

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 (FHFA) House Price Index (HPI), and Bureau of Economic Analysis Local Area Personal Income.[11]

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 origination at the bank-county level, collected by the Federal Financial Institutions Examination Council at the subsidiary-bank level. The CRA data contain 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:

$$\Delta CRA_{b,c,t} = \frac{CRA_{b,c,t} - CRA_{b,c,t-1}}{CRA_{b,c,t} + CRA_{b,c,t-1}} \times 2, \tag{7}$$

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.[12]

[11]The FHFA house price index is a weighted, repeat-sales index and it measures average price changes in repeat sales or refinancing on the same properties.

[12]While the log difference is symmetric around zero, it is unbounded above and below, and does not

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.[13]

4 IT adoption, Entrepreneurship and Collateral Value

This sections proposes a set of empirical tests for the main predictions of the model described in section 2.

4.1 IT exposure and local entrepreneurship (Prediction 1)

The first prediction of the model connects the share of high-IT banks in a market with local entrepreneurship.

Prediction 1. $\frac{ds_Y}{dh} > 0$: *a larger local presence of high-IT banks increases local lending to young firms.*

To investigate this prediction, we estimate the following cross-sectional regression at the county-industry level:

$$\begin{aligned} \text{startups}_{c,i} = {} & \beta_1 \; IT\ exposure_{c,99} + \beta_2 \; constraint_i \\ & + \beta_3 \; IT\ exposure_{c,99} \times constraint_i + controls_{c,99} + \theta_c + \phi_i + \varepsilon_{c,i}. \end{aligned} \tag{8}$$

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

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).

[13] Banks' predominantly lend in counties where they have branches, see Figure A2.

deviation of one. All regression control 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), education (share of adults with bachelor degree or higher), and IT adoption in non-financial firms (PCs in non-financial firms over total employment). All variables are measured as of 1999. Standard errors are clustered at the county level, and regressions are weighted by county size.

Our model predicts $\beta_1 > 0$, while aggregate time series correlation suggests $\beta_1 < 0$. Consistent with the model, 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 a significantly higher share of employment among young firms. Column (2) shows that the coefficient remains stable when we add county-level controls. Column (3) includes industry fixed effects (at the NAICS 2 level) to control for unobservable confounding factors at the industry level. Including these fixed effects does not change the coefficient of interest in a statistically or economically meaningful way, despite a sizeable increase in the R-squared by 40 p.p. This pattern suggests that local IT exposure is orthogonal to industry-specific characteristics. The magnitude of the impact is not trivial: a one standard deviation higher IT exposure is associated with a 0.4 to 0.38 pp increase in the share of young firm employment. This is an increase of 4% with respect to the average (9.3%).

Moreover, as the model connects banks' IT with entrepreneurship through a lending channel, we might expect this effect to be stronger in industries where external finance is more important. We therefore augment the regression 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). In column (4), the coefficient on the interaction term between IT adoption and external financial dependence is positive, and economically and statistically significant. Counties with higher IT exposure have a higher share of employment among young firms precisely in those industries that depend more on external finance, consistent with the notion that the correlation is driven by the impact of banks' IT on startups' financing.

So far, we have included industry fixed effects to purge the estimation from observable and unobservable confounding factors at the industry level. In column (5), we further enrich our specification with county fixed effects to control for confounding factors at the local level, for example changes in consumption of government expenditure. Results are remarkably similar across specifications: relative to column (5), the inclusion of county fixed effects changes the estimated impact of IT exposure interacted with financial dependence by only 0.02 – despite the fact that the R-squared increases by 11 pp.

Robustness. The Appendix presents a set of robustness tests 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) uses an alternative exposure measure that 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).

We then investigate the potential role of data coverage in the analysis. In fact, the IT variable is constructed from survey rather than administrative data. The high quality of the survey collected by Harte-Hanks/Aberdeen over a few decades is disciplined by market forces as the information are sold to IT supplier to direct their marketing efforts. However, it is still possible that the survey effort or success might be heterogeneous across different locations. We therefore compute a measure of local coverage, which is equal to the ratio between the establishments belonging to the banking industry surveyed by the marketing company in a county in a year and the total number of branches present according to FDIC data. We then average these across the four years (1999, 2003, 2004, 2006) to have a measure of average coverage for each county. The average value is 13.6%, with a standard deviation of 8.4%. To test how heterogeneity in local coverage might impact our results we first augment Equation 8 by including the coverage ratio as a control, and then we exclude low-coverage counties, that is counties in the bottom quartile in terms of coverage, so to focus on counties where the IT data are more reliable. Results are presented in Table A3 and indicate that (i) our results are robust to controlling for differences in survey coverage across the US, and (ii) the impact of IT adoption on entrepreneurship appears to be dampened if one does not control for coverage.

Instrumental Variable. The inclusion of detailed controls and the across-industries heterogeneity approach (Rajan and Zingales, 1998) help mitigate the concern that local factors might impact both the presence of high IT banks and entrepreneurship. Yet, IT exposure could still be correlated with such local unobservable factors, preventing us from drawing causal implications. To this end, we follow Doerr (2021) and adopt an instrumental variable approach. In a first step, we predict banks' geographic distribution of deposits across counties with a gravity model based on the distance between banks' headquarters and branch counties, as well as their relative market size (Goetz, Laeven and Levine, 2016). In a second step, predicted deposits are adjusted with an index of staggered interstate banking deregulation to take into account that states have restricted out-of-state banks from entering to different degrees (Rice and Strahan, 2010). The cross-state and cross-time variation in branching prohibitions provides exogenous variation in the ability of banks to enter other states. Predicted deposits are thus plausibly orthogonal to unobservable county characteristics during our sample period. We thus compute a predicted county-level measure of exposure to IT in banking as:

$$\widehat{IT}_c = \sum_{b=1}^{N} \widetilde{IT}_b * \frac{\widehat{Deposits}_{b,c}}{Deposits_c} \tag{9}$$

We estimate a two-stage least square model considering IT_c as an endogenous regressor and $\widehat{IT}_c$ as an excluded instrument. Using $\widehat{IT}_c$ as an instrument allows us to purge our specification from the bias introduced by unobservable factors that might attract high-IT banks and also impact local startup activity. Results are presented in Table A4. Column (1) presents the baseline estimate on this sample of counties. Column (2) is the first stage and shows a positive correlation between exposure to IT and predicted exposure to IT. Column (3) is the reduce-form regression of the instrument on the variable of interest, showing a positive impact of predicted exposure to IT in banking on entrepreneurship. Finally, column (4) is the second stage regression: the IV estimate of the impact of IT in banking on entrepreneurship is qualitatively similar than baseline and larger in magnitude. However, we cannot reject the null hypothesis that the difference between OLS and IV estimates is zero, suggesting biases coming from unobservable factors at the local level are not significantly biasing the baseline estimates.

Increase in IT adoption over time. The period of study also is a time of robust technology adoption in the banking sector (Figure 1). Thus, another approach to test **Prediction 1** is to analyze the relationship between increase in IT adoption and change in entrepreneurship at the county-level. To do so we compute the county exposure as

$$\Delta IT_c = \sum_{b=1}^{N} \Delta \widetilde{IT}_b * \frac{No.Branches_{b,c}}{No.Branches_c}, \tag{10}$$

where $\Delta \widetilde{IT}_b$ is the increase of IT adoption between 1999 and 2006 of bank b.

We find that counties more exposed to the increase in IT in banking also experienced less negative decreases in startup rates, as illustrated by Figure A1. The positive correlation between changes in IT adoption in banking and changes in startup rates is also confirmed by more formal regression analysis presented in Table A5. These results further confirm **Prediction 1**. Moreover, this first-difference approach implicitly controls any county-level (time invariant) observable and unobservable characteristics by differencing them out.

4.2 IT, house prices and entrepreneurship (Predictions 2 & 3)

A large literature highlights the importance of the collateral channel for employment among small and young firms: rising real estate prices increase collateral values, thereby mitigating informational frictions and relaxing borrowing constraints for opaque firms (Rampini and Viswanathan, 2010; Adelino, Schoar and Severino, 2015; Schmalz, Sraer and Thesmar, 2017; Bahaj, Foulis and Pinter, 2020).

Following this literature, the use of collateral has a prominent role in our theoretical model. In fact, predictions 2 & 3 of the model presented in section 2 predict the following relationships between entrepreneurship, collateral values, and IT adoption:

Prediction 2. $\frac{ds_Y}{dP} > 0$: *a higher collateral value increases the share of lending to young firms.*

Prediction 3. $\frac{d^2 s_Y}{dhdP} > 0$: *a higher collateral value increases the share of lending to* *young firms more when the share of high-IT banks is higher.*

To test these hypotheses, we investigate the interaction between IT and collateral in two complementary analyses: first, we estimate county-level regressions to investigate how local IT adoption affects the sensitivity of entrepreneurship to house prices. Second, at the bank-county level, we analyze how banks' IT affects their supply of small business lending when local house prices change.

4.2.1 County IT exposure and local house prices.

We estimate the following regression at the county-industry-year level from 1999 to 2007:

$$\begin{aligned} \text{startups}_{c,i,t} = &\ \gamma_1\ IT\ exposure_{c,99} + \gamma_2\ \Delta HPI_{c,t} \\ &+ \gamma_3\ IT\ exposure_{c,99} \times \Delta HPI_{c,t} \\ &+ controls_{c,t-1} + \theta_{c,i} + \tau_t + \varepsilon_{c,i,t}. \end{aligned} \tag{11}$$

The dependent variable is the employment share of firms of age 0-1 out of total employment in county (c) and 2-digit industry (i) in given year (t). $IT\ exposure_c$ denotes counties' IT as of 1999, standardized to mean zero and a standard deviation of one. $\Delta HPI_{c,t}$ is the yearly county-level growth in house prices. Controls (included when county fixed effects are not) are county size (log total population), the share of population age 65 and older, the share of black population, education, the unemployment rate, the industrial structure (measured by employment shares in the major 2-digit industries 23, 31, 44, 62, and 72), and IT adoption in non-financial firms (PCs per employee in non-financial firms), all of which lagged by one period. Standard errors are clustered at the county level.

Table 3 reports the estimation results. To start, column (1) shows that higher IT exposure is associated with a higher share of young firm employment in the cross-section – in line with Table 2. We then explicitly test **Prediction 2**. Column (2) shows that a rise in house prices is associated with an increase in entrepreneurship at the local level, conditional on year fixed effects that absorb common trends. Column (3) confirms this finding when controlling for IT adoption at the county level. These findings provide support for Prediction 2.

We then test **Prediction 3** by augmenting the equation with an interaction term between changes in local house prices and county exposure to IT in banking. That is, we focus on the coefficient γ_3 in Equation 11. To isolate the variation of interest and controlling for any confounding factor at the local or industry level, we include county-industry fixed effects and exploit only the variation within each county-industry cell. As reported in column (4) of Table 3, we find $\gamma_3 > 0$, consistent with **Prediction 3**. Columns (5) and (6) add time-varying county controls, as well as industry*time fixed effects that account for unobservable changes at the industry level. The interaction coefficient remains positive and similar in size across specifications.

Previous literature has highlighted that young firms are more responsive to changes in collateral values 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). Therefore, we exploit industry heterogeneity to provide further evidence on **Prediction 3**. Focusing on differences between industries within the same county and year allows us to control for industry×year and county×year fixed effects and thus purge our estimates from the impact of any time-varying industry or local shock. Results, presented in columns (6) and (7), reveal that the larger benefits of house prices increase due to the presence of high IT banks occur exactly in those industries whose financing should be more sensitive to collateral values.

4.2.2 Banks' IT adoption and small business lending.

To further investigate whether the different sensitivity of startup rates to house prices in counties more exposed to IT in banking is really due to high IT banks, we study how high- and low-IT banks adjust their lending in response to house price changes. While we have no detailed data on bank-level lending to startups, we can study the behavior of total CRA small business loans. We estimate the following regression equation from 1999 to 2007 at the bank-county-year level:

$$\begin{aligned}\Delta loans_{b,c,t} = \beta_1\ IT_b + \beta_2 \Delta\ HPI_{c,t} + \beta_3\ IT_b \times \Delta HPI_{c,t} \\ + bank\ controls_{b,t-1} + county\ controls_{c,t-1} + \tau_t + \varepsilon_{b,c,t}.\end{aligned} \tag{12}$$

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 described in Section 3. $\Delta HPI_{c,t}$ measures the yearly change in house prices. County-level controls are the same as in Equation 11, while bank-level controls are the log of assets, deposits over total liabilities, the share non-interest income, securities over total assets, return on assets, the equity ratio (Tier 1), and the wholesale funding ratio. We cluster standard errors on the county level to account for serial correlation among banks lending to the same county.

If banks that use IT more 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. That is, we expect $\beta_3 > 0$. Since borrower counties could differ along several dimension, we enrich our specifications with time-varying fixed effects at the county level. These fixed effects absorb unobservable county characteristics, for example loan demand. With county×year fixed effects, we essentially compare small business lending by two banks that differ in their IT intensity to borrowers in the *same* county, mitigating concerns that the relation between bank lending and house prices is due to (unobservable) confounding factors, such as employment growth.

Table 4 shows that small business lending is more responsive to changes in local house prices for high-IT banks. To begin, column (1) illustrates that high-IT banks have higher small business lending growth on average, and that loan growth for the average bank is higher in counties with stronger house price growth. Columns (2) and (3) split the sample into banks with a low value of IT (bottom tercile of the distribution) and a high value (top tercile). A rise in house prices is associated with faster loan growth among 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 increasingly saturated specifications. In column (4), small business lending reacts by significantly more to a change in house prices for banks with higher IT adoption. This finding is conditional on bank and county controls as well as year fixed effects to account for common trends. To further account for unobservable time-varying changes in unobservables across counties, we include county×year fixed effects in column (5). Despite a fourfold increase in the R-squared, estimated coefficients remain similar (the coefficient on the change in house prices is now absorbed). Column (6) further absorb time-invariant factors at the bank-county level (e.g. bank-borrower distance) and shows that the size of the coefficient of interest increases when we exploit within bank-county variation only. The coefficient on IT is now absorbed. Finally, column (7) controls for time-varying bank fundamentals through bank×year 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 local house prices rise.

Despite the limitation of not directly observing lending to startups, these empirical exercises provide additional support to the model's predictions that IT in banking increase the benefits of a rise in collateral values.

5 The role of Competition, Distance, and Colleteralized Lending

In this section we present additional evidence that speaks to assumptions and implications of the model. We first build on the literature on the importance of the physical distance between borrower and lender to provide evidence that IT could increase the importance of hard information. We then provide evidence that high-IT banks are more likely to provide collateralized loans even when controlling for unobservable borrower characteristics through fixed effects, supporting the assumption that IT provides an advantage in collateralized lending. We finally provide evidence that the effects of IT on startup activity and lending do not depend on local competition among banks.

IT in banking and the role of distance. Our modelling effort builds on the premise that banks' IT adoption ameliorates information frictions between borrower and lender. A large literature shows that informational frictions increase with lender-borrower distance (Liberti and Petersen, 2017). Consequently, even if there is an increase in local investment opportunities, banks that are located further away might increase their lending by less than banks that are located closer to potential borrowers. The literature suggests that IT adoption by banks could reduce the importance of distance (Petersen and Rajan, 2002; Vives and Ye, 2020), as it enables a more effective transmission of hard 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' with more or less IT use, we consider the following model that relates banks' loan growth to local investment opportunities (measured as the change in local income):

$$
\begin{aligned}
\Delta loans_{b,c,t} = & \beta_1 \, log(distance)_{b,c} + \beta_2 \, \Delta income \; p.c._{c,t} \\
& + \beta_3 \, log(distance)_{b,c} \times \Delta income \; p.c._{c,t} \\
& + bank \; controls_{b,t-1} + county \; controls_{c,t-1} + \theta + \varepsilon_{b,c,t}, \\
& \text{if IT} = \text{low/high}
\end{aligned}
\tag{13}
$$

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.[14] $log(distance)$ measures the distance between banks' HQ and the county of the borrower. 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 smaller the log distance between the lender and the borrower. That 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. Column (1) shows that rising local incomes are indeed associated with higher local loan growth; and 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 findings holds when we include county×year fixed effects to control for any local shock in column (2). Columns (3) and (4) show that the lower responsiveness of banks' lending to income shocks in counties located further away is present only for low IT banks; for high IT banks, distance has no dampening effect. Interaction specifications in columns (5) and (6) confirm this finding: 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 in the decision to grant a loan in response to local shocks to investment opportunities. Results are similar when we enrich the specification with bank fixed effects.

IT and the use of collateral. Our model builds on the assumption that high IT banks have a relative cost advantage in screening through collateral with respect to information acquisition. We investigate the soundness of this assumption by looking at whether banks

[14] 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.

which adopt more IT are also more likely to use collateral in their lending, controlling for borrower characteristics. While we do not have loan-level information on lending to startups, as a second best we can perform such empirical test on large corporate loans data from DealScan as in Ivashina and Scharfstein (2010), for example.

Consistent with the model's assumption, Figure A3 shows that the share of loans that are collateralized is positively correlated with bank IT adoption. To test whether this correlation is really driven by banks' IT rather than borrowers heterogeneity, we estimate the following linear probability model:

$$secured_{b,i,t} = \beta \; IT_b + \tau_t + \theta_i + \varepsilon_{b,i,t}, \tag{14}$$

where b is a bank that granted a loan in year t to (large) corporate borrower i and $secured_{b,i,t}$ is a dummy equal to one whenever the loan is collateralized. Results are presented in Table A6 and confirm that more IT intense banks are more likely to lend through a secured loan than other banks, even when controlling for borrower fixed effects.

The role of local competition. The model assumes that local bank competition is independent of bank IT adoption. In fact, bank and potential borrowers are assumed to be matched and to share the surplus from lending—if a loan is granted. To understand how this simplified market structure might impact our results, we re-estimate the main equation of interest, Equation 8, and augment it with a term for bank concentration (in terms of deposits or CRA lending) in a county, and the interaction between local IT exposure and concentration. Results are presented in Table A2. Higher concentration is associated with more startup activities. This might be due to the fact that banks might be more prone to lend to startups when competition is low if they know they can gain larger information rent and extract more surplus as these firms grow (Petersen and Rajan, 1995). However, we find no significant interaction between concentration and local IT adoption in banking. The positive impact of IT on startups does not seem to depend on the local market structure. This result mitigates the concern that the absence of market power in the model is severely harming its ability to describe the relationship between IT adoption and entrepreneurship, which is the aim of this paper.

6 Conclusion

Over the last decades, banks have invested in information technology at a grand scale. This 'IT revolution' in lending has raised concerns about banks' ability to serve small and young firms.

In this paper we show that IT in the financial sector has spurred entrepreneurship. In regions where banks that adopt more IT are present, entrepreneurship was stronger than in other regions; this relationship is stronger in industries that rely more on external finance and in regions where more business opportunities arose. We show – both theoretically and empirically – that the collateral lending channel, as described in Adelino et al. (2015), is a major explanation for the results. 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-intensive banks.

Our results have important implications for policy. Banks' enthusiasm towards technology adoption has been very strong during the last years,[15] and the role of FinTech companies as lenders of small businesses has been increasing since the GFC (Gopal and Schnabl, 2020). This has triggered a debate on the impact of IT in finance on the economy, for example through its impact on firms' access to credit. 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. From a policy perspective, this finding raises the hope that improvements in financial technology help young and dynamic firms to get financing.

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.

[15] For instance, many banks' top executives have been arguing they lead technology companies with a banking license, see Pierri and Timmer (2020) and https://www.sepaforcorporates.com/payments-news-2/technology-companies-what-big-banks-spend-say-about-tech/.

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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
IT exposure	0.462***	0.405***	0.378***	0.380***	
	(0.118)	(0.100)	(0.099)	(0.100)	
IT exposure × ext. fin. dep				0.714***	0.692***
				(0.185)	(0.181)
Observations	25,779	25,779	25,779	25,779	25,779
R-squared	0.003	0.046	0.248	0.248	0.350
County Controls	-	✓	✓	✓	-
NAICS FE	-	-	✓	✓	✓
County FE	-	-	-	-	✓
Cluster	County	County	County	County	County

This table reports results from cross-sectional regressions at the county-industry level (see Equation 8). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i. $ITExposure_c$ 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. $Ext.fin.dep_i$ the dependence on external finance in an industry. 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) share 0-1	(6) share 0-1	(7) share 0-1	(8) share 0-1
IT exposure	0.348***		0.341***					
	(0.111)		(0.110)					
Δ HPI		0.020**	0.024**	-0.024**	-0.041***	-0.034***		
		(0.010)	(0.010)	(0.011)	(0.014)	(0.011)		
IT exposure × Δ HPI				0.075***	0.064**	0.071**		
				(0.027)	(0.032)	(0.029)		
IT exposure × Δ HPI × Low SU							0.136***	
							(0.051)	
IT exposure × Δ HPI × Homeequity								0.175**
								(0.087)
Observations	195,220	214,327	194,535	192,402	168,836	168,836	192,097	192,097
R-squared	0.008	0.006	0.008	0.564	0.581	0.597	0.621	0.621
County × NAICS FE	-	-	-	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	-	-	-
Year FE × NAICS FE	-	-	-	-	-	✓	✓	✓
County × Year FE	-	-	-	-	-	-	✓	✓
Cluster	County	County	County	County	County	County	County	County

This table reports results for regressions at the county-industry-year level (see Equation 11). The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i in year t. $ITExposure_c$ 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. $\Delta HPI_{c,t}$ is the yearly change in house prices in county c. $lowSU_i$ is a dummy where low amounts of capital required to start a company. $Homequity_i$ refers to the dependence on home equity of an industry as a source to start or expand operations. 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

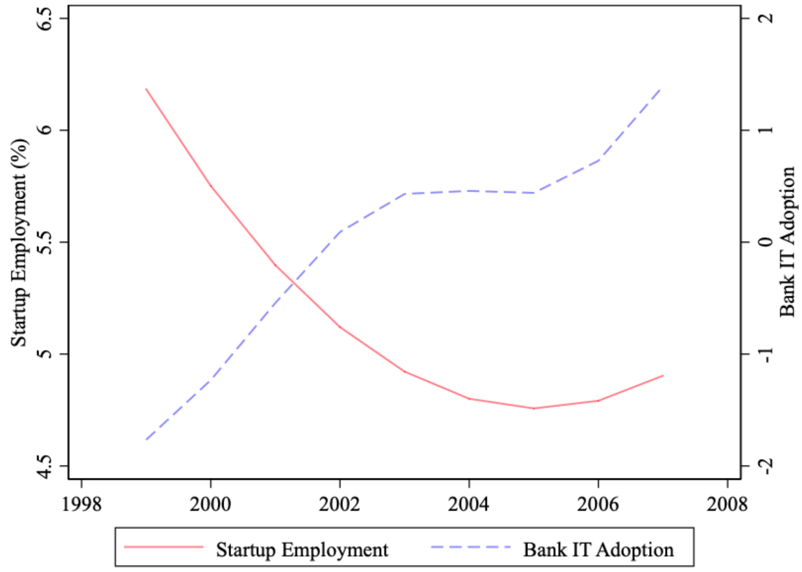
This table reports results for regressions at the bank-county-year level (see Equation 12). The dependent variable is the change in CRA loans by bank b to county c in year t. IT_b is the IT adoption of bank b, $\Delta HPI_{c,t}$ is the yearly change in house prices in county c. *low/high IT* refers to 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 13). The dependent variable is the change in CRA loans by bank b to county c in year t. IT_b is the IT adoption of bank b. $\Delta\ Income_{c,t}$ is the change in per capita income in county c between year $t-1$ and t. $log(distance)_{b,c}$ 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**



The red solid line plots the median employment share of young firms across MSAs as described in section 3. The blue dashed dotted line plots the year fixed of bank-level IT adoption.

Figure 2: Startups

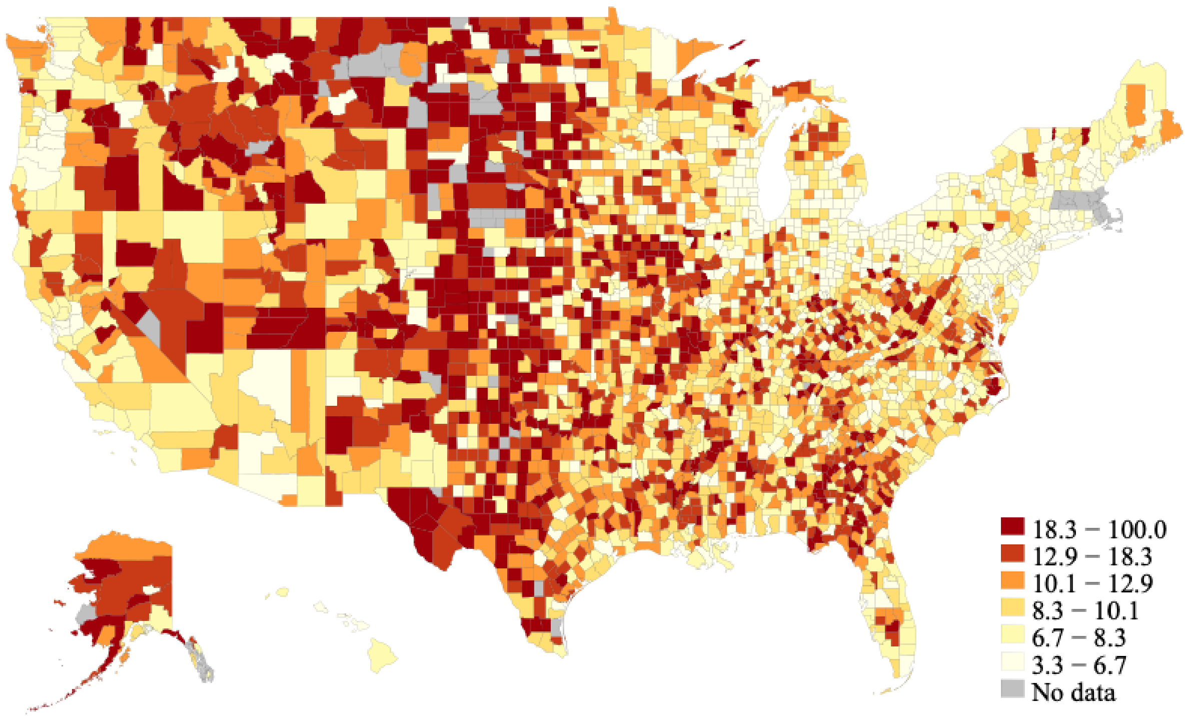


Figure 3: Exposure to IT in Banking

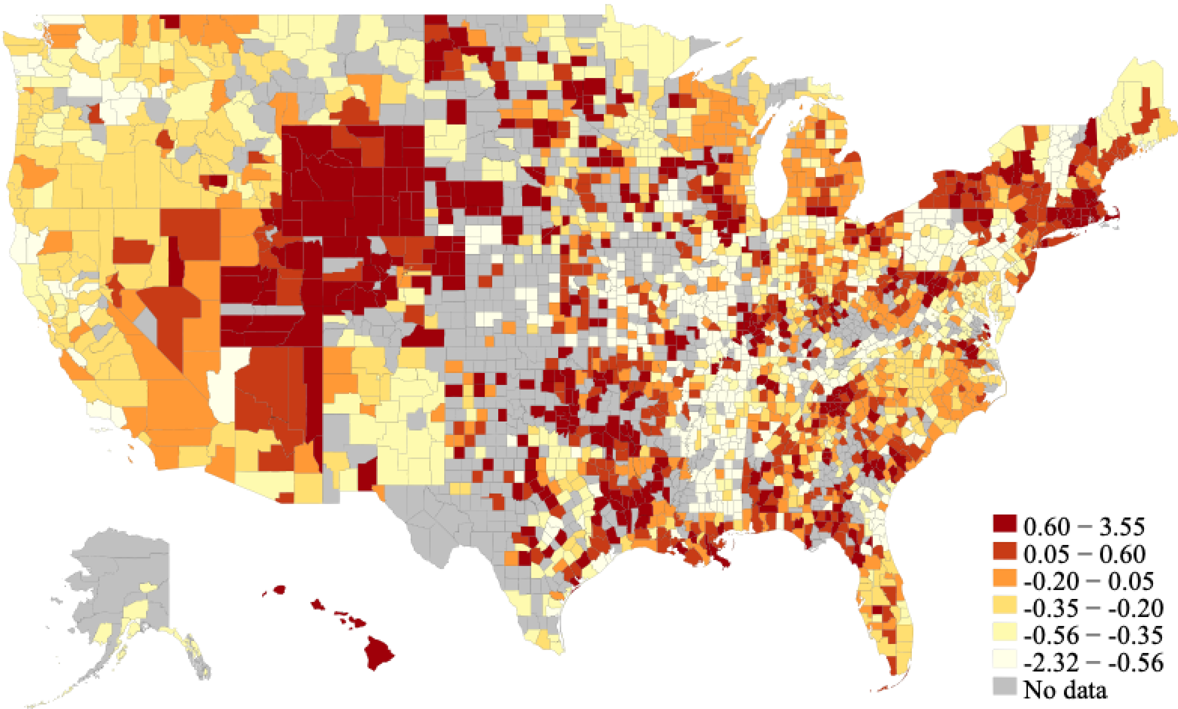
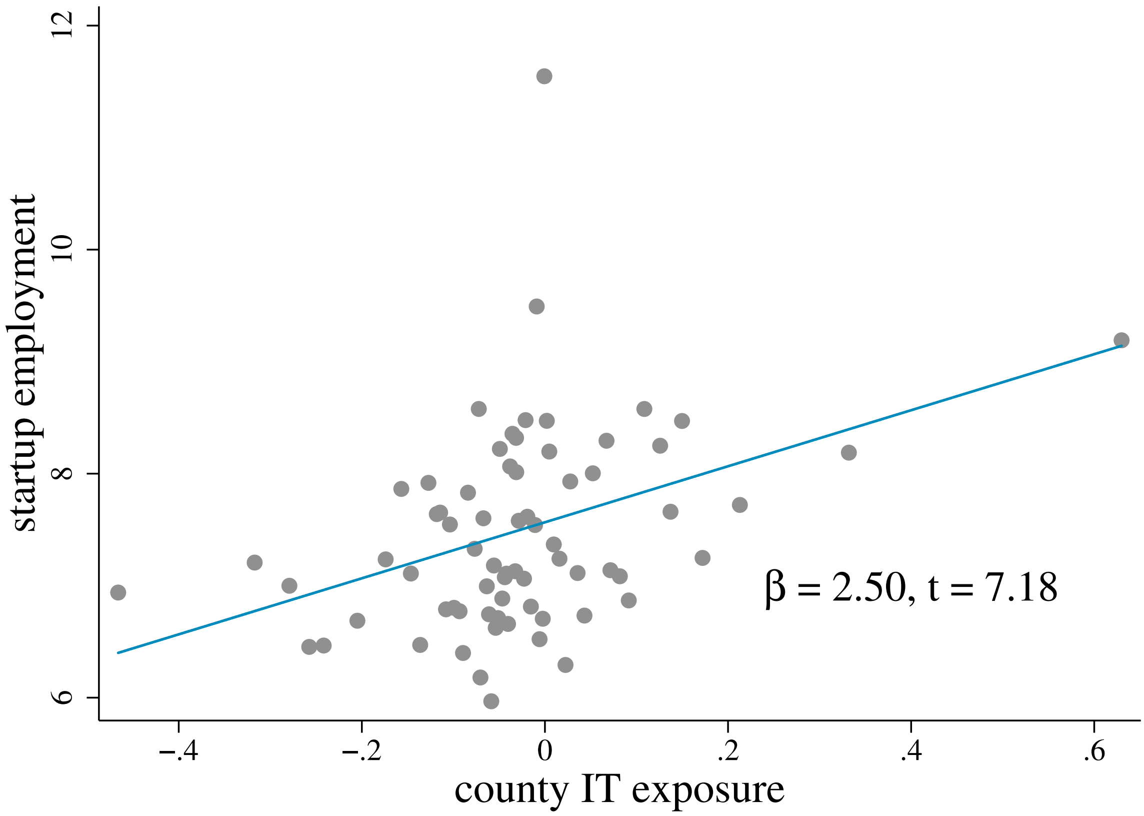
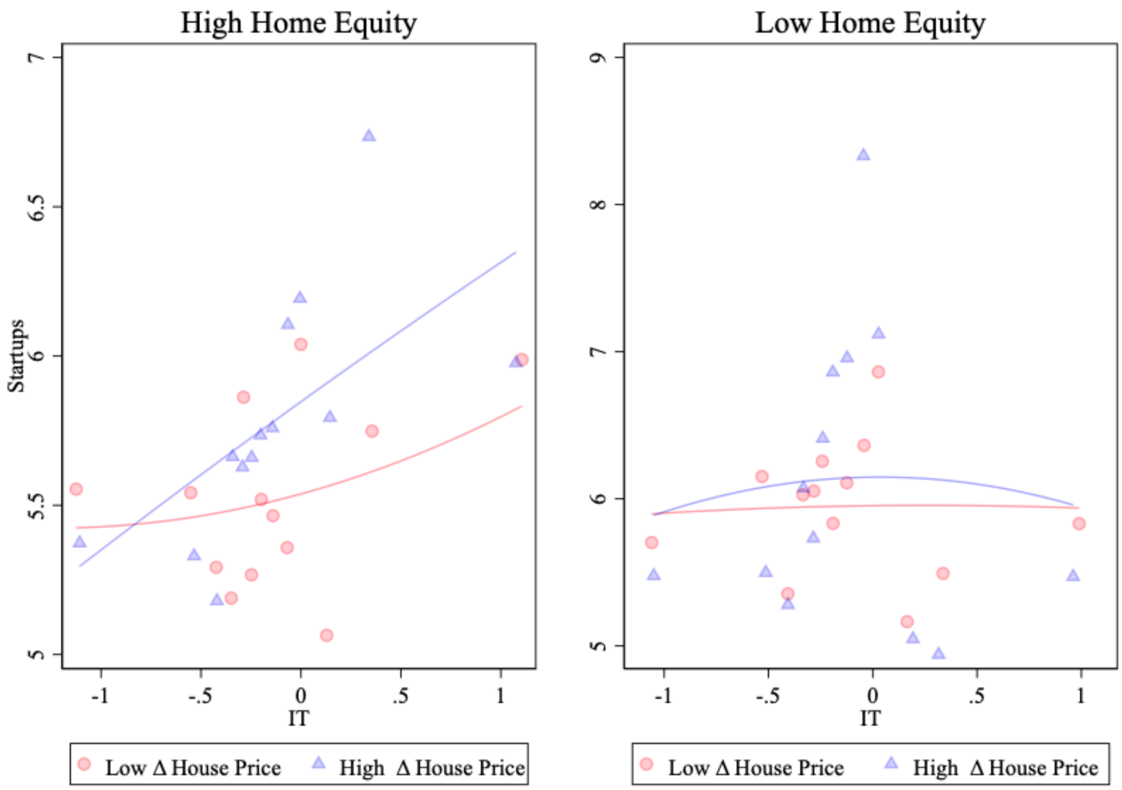


Figure 4: Job Creation by Young Firms and Banks' IT adoption



This figure shows a binscatter of the share of employment by young firms over total employment in an a county-industry cell across 2000 and 2007 on the vertical axis and the county-level exposure to Bank IT adoption as defined in section 3 on the horizontal axis.

Figure 5: Job Creation by Young Firms, Banks' IT adoption, House Prices, and Home Equity



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 3 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 (lagged)	(8) Δ Employment
IT exposure	0.377***	0.163**	0.377***	0.398***	0.375***	0.333***		0.054
	(0.098)	(0.073)	(0.098)	(0.106)	(0.099)	(0.092)		(0.065)
IT exposure (branch weighted)							0.381***	
							(0.114)	
Observations	25,779	25,779	25,779	21,735	25,544	25,779	25,440	25,774
R-squared	0.248	0.252	0.248	0.252	0.248	0.268	0.208	0.215
County Controls	✓	✓	✓	✓	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓
Spec	Baseline	No Weights	Branch Share	No Finance	NoWyoming	State FE	Lagged Denominator	Δ Total Employment
Cluster	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.

Table A2: **The role of local competition**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1	(5) share 0-1
IT exposure	0.436***	0.393***	0.415***	0.372***	0.372***
	(0.114)	(0.110)	(0.100)	(0.113)	(0.113)
HHI		2.439***	2.483***	4.895***	4.893***
		(0.910)	(0.906)	(1.019)	(1.017)
HHI × IT exposure			0.646		-0.015
			(0.603)		(0.954)
Observations	25,779	25,779	25,779	25,779	25,779
R-squared	0.248	0.249	0.249	0.252	0.252
County Controls	✓	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓	✓
County FE	-	-	-	-	-
Cluster	County	County	County	County	County
HHI	-	CRA lending	CRA lending	FDIC deposits	FDIC deposits

This table reports results for the following regression: $\text{startups}_{c,i} = \beta\ IT\ exposure_{c,99} + \delta\ HHI_{c,99} + \gamma\ IT\ exposure_{c,99} \times HHI_{c,99} + controls_{c,99} + \phi_i + \varepsilon_{c,i}$, 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. $HHI_{c,99}$ is the Herfindahl-Hirschman Index in county c, where market shares are computed from either small business lending in 1999 (from CRA data) or deposits in 1999 (from FDIC data). Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: **County IT exposure, entrepreneurship, and survery coverage**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1
IT exposure	0.472***	0.393***	0.557***	0.429***
	(0.139)	(0.113)	(0.149)	(0.113)
(mean) coverage	0.105***	0.0594***	0.121***	0.0570***
	(0.0199)	(0.0179)	(0.0193)	(0.0177)
Constant	6.234***	7.968	6.018***	20.72**
	(0.207)	(6.917)	(0.247)	(8.951)
Observations	24,900	24,900	18,652	18,652
R-squared	0.012	0.252	0.016	0.243
County Controls	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓
County FE	-	-	-	-
Cluster	County	County	County	County
Sample	All	All	Exclude low-coverage	Exclude low-coverage

Table A4: **County IT exposure, entrepreneurship, and collateral**

VARIABLES	(1) share 0-1	(2) IT exposure	(3) share 0-1	(4) share 0-1
IT exposure	0.319***			0.526***
	(0.109)			(0.143)
IT exposure - gravity RS approach		0.640***	0.337***	
		(0.0667)	(0.0889)	
Observations	19,293	19,293	19,293	19,293
R-squared	0.246	0.536	0.247	0.051
County Controls	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓
County FE	-	-	-	-
Cluster	County	County	County	County
Estimator	OLS	OLS	OLS	IV
Instrument	-	-	-	Gravity/RS

Table A5: **County IT exposure and Entrepreneurship-Differences**

VARIABLES	(1) Δ share 0-1	(2) Δ share 0-1	(3) Δ share 0-1	(4) Δ share 0-1	(5) Δ share 0-1
Δ IT exposure	0.153*	0.241***	0.248***	0.210**	
	(0.084)	(0.085)	(0.085)	(0.088)	
Δ IT exposure × ext. fin. dep				0.258*	0.201
				(0.142)	(0.136)
Observations	15,952	15,952	15,952	15,952	15,952
R-squared	0.000	0.007	0.021	0.014	0.144
County Controls	-	✓	✓	✓	-
NAICS FE	-	-	✓	✓	✓
County FE	-	-	-	-	✓
Cluster	County	County	County	County	County

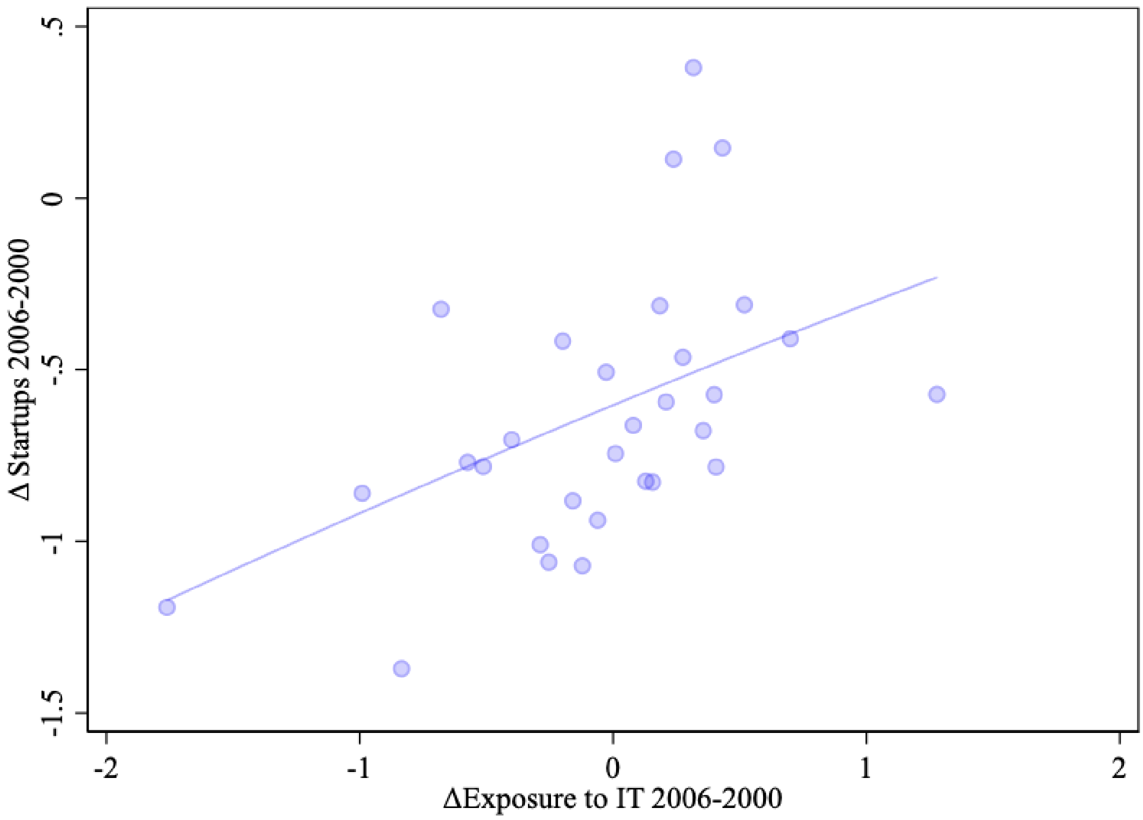
This table reports results from cross-sectional regressions at the county-industry level. The dependent variable is the change in the share of the employment in firms of age 0-1 in county c and industry i between 2006 and 2000. ΔIT $Exposure_b$ is the change in the IT adoption of banks in the county, measured by the change in IT adoption of banks historically present in the county (between 2006 and 2000), and standardized with mean zero and a standard deviation of one. $ext.fin.dep_i$ the dependence on external finance in an industry. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Table A6: **Secured Loans and Bank IT adoption**

VARIABLES	(1) Secured	(2) Secured	(3) Secured	(4) Secured	(5) Secured
Bank IT	0.230***	0.279***	0.039*	0.046**	0.033*
	(0.051)	(0.057)	(0.022)	(0.019)	(0.017)
Observations	211,796	211,795	207,889	207,888	147,212
R-squared	0.018	0.049	0.820	0.824	0.822
Borrower FE	-	-	✓	✓	✓
Year FE	-	✓	-	✓	✓
Cluster	Bank	Bank	Bank	Bank	Bank
Sample	All	All	All	All	Pre-GFC

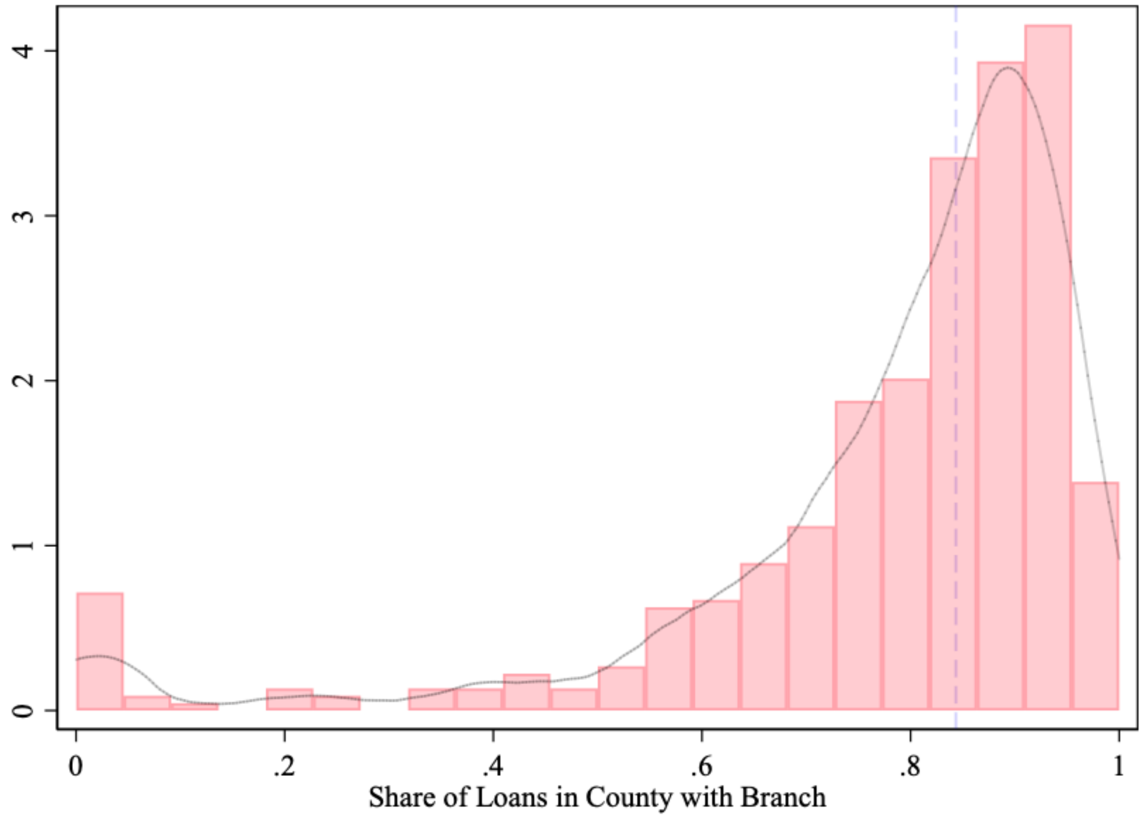
This table reports results from syndicated loan-level regression using data from Dealscan. The dependent variable is a dummy that equals one if the loan is secured and 0 otherwise. Standard errors are clustered at the bank-level *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: IT in Banking and Startup Rate - Differences



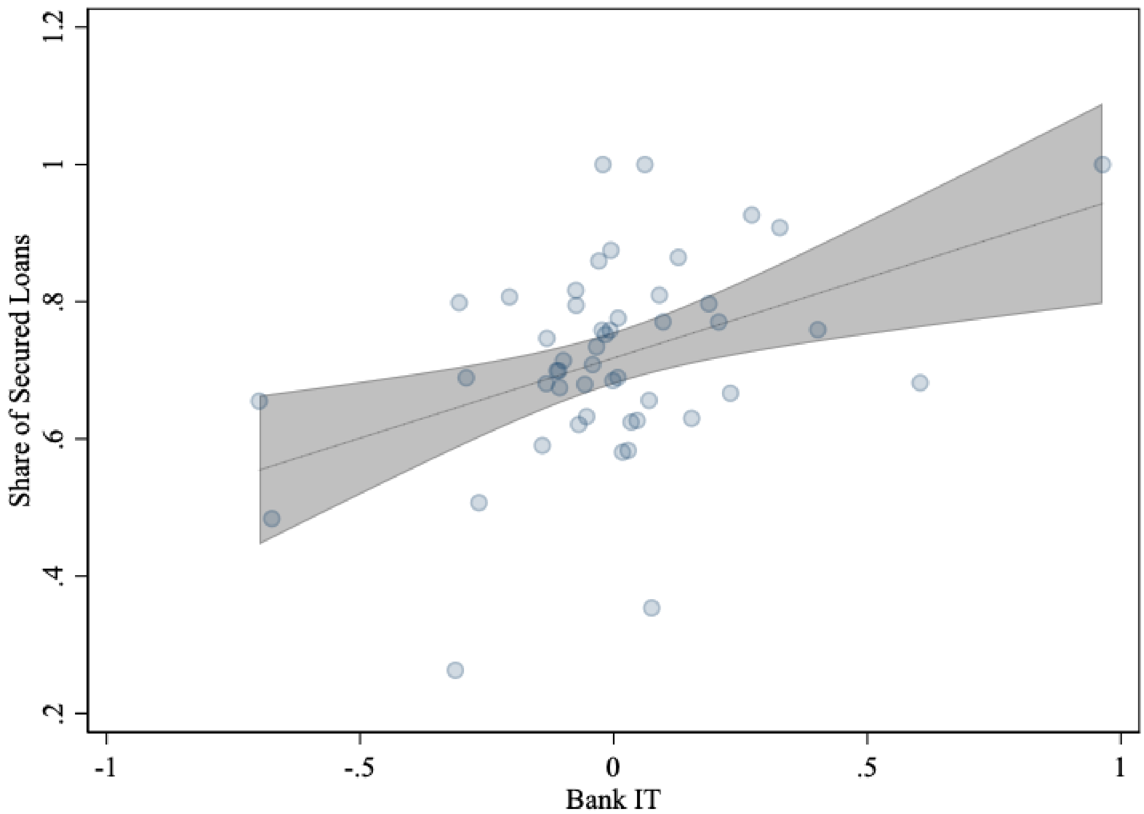
This figure shows a binscatter of the change in the startup rate in a county-industry between 2006 and 2000 (in percentage points) on the y-axis and the exposure of a county to banks *change* in IT adoption between 2006 and 2000 (standardized) on the x-axis.

Figure A2: 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.

Figure A3: Share of Loans Secured



This figure shows the share of secured loans in the Dealscan syndicated loan data and banks' IT adoption.