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. To guide our analysis, we build a parsimonious model of bank screening and lending that predicts that IT in banking can spur entrepreneurship by making it easier for startups to borrow against collateral. We then empirical show that job creation by young firms is stronger in US counties that are more exposed to IT-intensive banks. Consistent with a strengthened collateral lending channel, entrepreneurship increases by more in IT-exposed counties when house prices rise. In line with the model's implications, higher startup activity does not diminish startup quality. Further, IT weakens the importance of geographical distance between borrowers and lenders, and makes banks' credit supply more responsive to changes in local house prices. These results suggest that banks' IT adoption can increase dynamism and productivity by facilitating the transmission of hard information.

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1 Introduction

The rise of information technology (IT) in the financial sector has dramatically changed how information is gathered, processed, and analyzed (Liberti and Petersen, 2017). This development may have important implications for banks' credit supply, as one of their key function is to screen and monitor borrowers. Financing for opaque borrowers, such as young firms that have produced limited hard information, is likely to be especially sensitive to such changes in lenders' technology. As startups contribute disproportionately to job creation and productivity growth (Haltiwanger, Jarmin and Miranda, 2013; Klenow and Li, 2020), but often rely on bank credit,[1] understanding how the IT revolution in banking has affected startups' access to finance is of paramount importance. Yet, direct evidence on the impact of lenders' IT capability on firm formation is scarce.

This paper analyzes how the rise of IT in the financial sector affects entrepreneurship. We first build a parsimonious model of bank screening and lending to 'old' and 'young' firms that are of heterogeneous quality and opacity. Banks can screen firms by either acquiring information about firms and their projects or by requiring collateral. Crucially, IT makes it relatively cheaper for banks to analyze hard information and thus rely on collateralized lending. This benefits startups, as they have not yet produced sufficient information (i.e. they are *opaque*) and have to be screened through the use of collateral. The model thus predicts that IT in banking spurs entrepreneurship – and the more so when collateral value rises.

To test the model's predictions, we use detailed data on the purchase of IT equipment of commercial banks across the United States in the years before the Great Financial Crisis (GFC).[2] Consistent with the model's implications, we find that counties where IT-intensive banks operate experience stronger job creation by startups, defined as firms of age 0–1. Moreover, the presence of IT-intensive banks strengthens the responsiveness of job creation by entrepreneurs to changes in local real estate values – and especially

[1]For instance, according to the 2007 Survey of Business Owners, the share of business owners who received initial financing through bank loans is more than ten times higher than that of owners who relied on venture capital.

[2]The absence of major financial regulatory changes during our sample period makes it well-suited to identify the effects of IT in banking on entrepreneurship. The period after the GFC is characterized by substantial financial regulatory reform (such as the Dodd-Frank Act and regular stress tests) and encompassing government programs, both of which have affected banks' lending decisions, especially to small firms. A further reason to exclude the GFC and the 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 a potential confounding factor.

within industries that rely more on real estate collateral.

To measure IT adoption in banking, we follow seminal papers on IT adoption among non-financial firms (see Bresnahan et al. (2002), Brynjolfsson and Hitt (2003), Beaudry et al. (2010), or Bloom et al. (2012)). We use the ratio of PCs per employee within each bank as the main measure of bank-level IT adoption. This simple measure of IT adoption, which is based only on hardware availability, is a strong predictor of alternative measures, such as the IT budget or adoption of frontier technologies.[3] Following the literature, we focus on banks' general adoption of IT, rather than specific technologies (e.g. ATMs or online banking as in Hannan and McDowell (1987) or Hernández-Murillo et al. (2010)), because of the multi-purpose nature of IT. Consistently, our analyses aim to shed light on the economic mechanisms behind the effects of IT adoption, rather than on the impact of specific IT applications.

We use banks' IT adoption and historical geographic footprint to compute county-level *exposure* to banks' IT. Specifically, county exposure is computed as the weighted average bank-level IT adoption of banks operating in a given county, with weights given by the initial share of local branches. Constructing local IT exposure from banks' historical footprint ameliorates concerns about banks' selecting into counties based on unobservable county characteristics, such as economic dynamism or growth trajectories. We find that county exposure is not systematically correlated with several county-level characteristics, such as the unemployment rate or level of education, industry composition, or the use of IT in the *non-financial* sector.

The main empirical analysis shows that higher county-level IT exposure is associated with significantly higher entrepreneurial activity, measured as the employment share of new firms (as in Adelino et al. (2017)).[4] 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).

In principle, the positive relation between IT exposure and startup activity could be explained by reverse causality or omitted variable bias. Reverse causality is unlikely to be a major concern in our empirical setting: lending to startups represents only a

[3]Later waves of the same data set provide additional information on the 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).

[4]The results are robust to alternative definitions of entrepreneurship.

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 drive the association between IT and entrepreneurship. For instance, a better-educated workforce may make it easier for banks to hire IT-savvy staff and also create more business opportunities for startups. To mitigate this concern, we first show that including a wide set of county-level controls, such as the industrial composition, education, income, and demographic structure, does not affect the results. Our findings are also robust to accounting for the IT adoption of non-financial firms, and remain near-identical when we exclude counties in which venture capital financing plays an outsized role.

Additionally, we examine the robustness of our findings to the inclusion of granular fixed effects. Exploiting industry heterogeneity, we find that job creation by startups in counties more exposed to IT is relatively larger in industries that depend more on external financing (Rajan and Zingales, 1998). This is true in regressions without and with county fixed effects – suggesting that the relationship between entrepreneurship and IT could be driven by better access to finance, and not unobservable county factors. Similarly, we estimate a long difference specification, in which we show that the local change in entrepreneurship over the course of our sample is positively associated with the increase in IT adoption of banks that are ex-ante present in the same county over the same time horizon. This specification differences out any potential observed and unobserved time-invariant county-specific characteristics that could bias our results.

To further address the concern that exposure to IT could reflect other unobservable county characteristics, we develop an instrumental variable (IV) approach that exploits exogenous variation in banks' market share across counties. 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 counties' 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 IV approach confirms that exposure to IT-savvy banks fosters local entrepreneurship. The estimated coefficients are not statistically different from the OLS estimates, supporting our previous results indicating that the potentially endogenous presence of high-IT banks is not a significant concern for our empirical analysis.

After establishing a robust relationship between county exposure to banks' IT and local entrepreneurship, we investigate potential channels. Guided by our model that highlights the comparative advantage of high-IT banks to lend against collateral, we focus on the importance of collateral. While startups usually do not have pre-existing internal collateral available to post against the loan, entrepreneurs often pledge their home equity as collateral. Following Mian and Sufi (2011) and Adelino et al. (2015), we use changes in county-level home values to test whether higher collateral values foster startup activity, and how this relationship depends on the presence of IT-intensive banks.

Consistent with the model's predictions, we find that job creation by startups increases by more when collateral values rise, and especially so in IT-exposed counties. The positive effect of IT exposure on entrepreneurship during episodes of rising house prices is strongest in industries where home equity is of high importance for startup activity. This is measured either by firms' propensity to use home equity to start or expand their business or the amount of startup capital required to start a business in a given industry (Hurst and Lusardi, 2004; Adelino et al., 2015; Doerr, 2021). Exploiting the heterogeneity in the importance of collateral across industries and its value across regions allows us to control for observed and unobserved heterogeneity at the county and industry level through granular fixed effects. Including these fixed effects has no material effect on our estimated coefficients, further mitigating the concern that unobservable factors explain the correlation between IT in banking and entrepreneurship.

To provide further evidence on the mechanism, we exploit differences in recourse loans across states. Recourse can partially substitute for the need of screening borrowers through collateral, as it allows lenders to recourse borrowers' assets or income in the case of foreclosure, thereby diminishing the misalignment of interests (Ghent and Kudlyak, 2011). This right to recourse varies across states. Consistent with the model's prediction, we show that the positive relationship between IT exposure and entrepreneurship is higher in non-recourse states. We also find that the amplifying effect of IT exposure on the elasticity of entrepreneurship to changes on house prices is muted in recourse states. These findings provide further evidence for the importance of a collateral underlying the relation between IT in banking and entrepreneurship.

In addition to predictions on job creation, the model also predicts that IT in banking does not systematically affect startup quality. In the model, higher startup activity arises from a better screening technology. Financing more startups does thus not lower their quality. Empirically, we find no relation between IT exposure and job creation among young continuing firms (i.e. in the transition rates from firms of age 0–1 to age 2–3, or from 2–3 to 4–5). This indicates that the increase in firm formation in more-exposed counties does not lead to more exits in the following years (which would indicated that firms of lower quality were started). This finding also suggests that IT in banking can have a positive impact on aggregate business dynamism and productivity growth.

In addition to county-level analyses, we use granular bank-county level data on small business lending to shed further light on the role of the ability of IT adoption to improve the use of hard information. Data on small business lending is based on Community Reinvestment Act (CRA) data.

We first focus on the importance of bank-borrower distance in lending. Greater 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 (distant) headquarters (Petersen and Rajan, 2002; Liberti and Petersen, 2017; Vives and Ye, 2020). We study how distance affects bank lending in response to a local increase in business opportunities (i.e., a change in the 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 further away from banks' headquarters – in line with the interpretation that a greater distance implies higher frictions. Consistent with the model, however, we find that banks' IT adoption mitigates the effect of distance on the sensitivity of lending to a rise in business opportunities.

In a second step, we show that small business lending by high-IT banks is more sensitive to changes in local house prices. This evidence suggests that IT banks lend more when real estate collateral values increase, in line with the model's predictions and our findings at the county-level. Note that in these bank-county level specifications, we measure IT at the bank-level directly, instead of exploiting geographic variation in banks' footprints. In addition, granular bank-county level data allow us to carefully control for potentially confounding factors through fixed effects. When we account for unobservable time-varying factors at the bank or county level through bank*time or county*time 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. These findings further provide evidence that IT could increase the importance of hard information in banks' lending decisions and facilitate small firms' access to credit.

We also present additional evidence supporting the assumptions underlying the model. The model assumes that high IT banks have a relative cost advantage in lending against collateral, as they can better verify its value and transmit this information to the headquarters and also abstracts from the role of local competitions between banks. We therefore 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 structure: we find no evidence that the relationship between IT and entrepreneurship is impacted by the local market concentration of the banking industry, indicating that the model's simple approach to competition is appropriate for our research question (while, this interplay may be important for analyzing other issues, such as the impact on financial stability or intermediation costs (Vives and Ye, 2020; De Nicolo et al., 2021)).

In a final step we note that, as IT in banking spurs entrepreneurship (at least partially) through a collateral channel, a potential side effect is that it may also magnify underlying wealth gaps. Banks' IT may strengthen the connection between personal/family wealth and entrepreneurship rather than expanding entrepreneurship opportunities for groups, racial minorities in particular, which face more difficult access to capital (Fairlie et al., 2020), long-lasting discrimination on mortgage markets (Munnell et al., 1996), and a slowdown in wealth accumulation (Wolff, 2018). Consistent, we find suggestive evidence that IT can decrease the share of Black entrepreneurs in a county, highlighting the positive impact on local economic dynamism may come at the expenses of more inequality.

The overall picture emerging from this paper is that greater reliance on information technology in banking decreases the effect of informational frictions on lending markets, at least partly through making screening through the use of collateral more efficient. In turn, IT benefits opaque borrowers—such as startups—disproportionately more.

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, IT adoption could increase banks' reliance on hard information and the distance to borrowers (Petersen and Rajan, 2002; Liberti and Mian, 2009; Liberti and Petersen, 2017).[5] While existing papers have often relied on proxies for banks' use of technology or focused on specific technologies, little evidence exists on the direct impact of banks' overall IT adoption on their lending, the role of collateral, or financing conditions of entrepreneurs.

Our work also relates to papers that analyze the importance of collateral for entrepreneurial activity (Hurst and Lusardi, 2004; Adelino et al., 2015; Corradin and Popov, 2015; Schmalz et al., 2017). 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 (Jiménez et al., 2006; Hollander and Verriest, 2016; Prilmeier, 2017; Vives and Ye, 2020). We contribute to the literature by providing first evidence that banks' IT adoption increases the importance of collateral in banks' financing of young firms.[6]

Finally, we contribute to the recent literature that investigates how the rise of financial technology (FinTech) affects credit scoring and credit supply. Several papers focus on how FinTech changes the way information is processed, as well as the consequences for credit allocation and performance, but focus mostly on consumers and households (Berg et al., 2019; Di Maggio and Yao, 2018; Fuster et al., 2019). While recent work highlights an increasing importance of FinTechs in small business lending (Beaumont et al., 2199; Hau et al., 2018; Erel and Liebersohn, 2020; Gopal and Schnabl, 2020),[7] traditional banks remain an important source of credit for small firms in the US (see also Boot et al. (2021)). An advantage of focusing on variation in IT adoption among banks is that our results are unlikely to be explained by regulatory arbitrage, which has been shown to be an

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

[6] We also relate to the literature on firm dynamics and the macroeconomy. While the slowdown in productivity after the Great Financial Crisis has been attributed to a large extent to frictions in the financial sector, see e.g. Doerr et al. (2018); Manaresi and Pierri (2019); Duval et al. (2020), the impact of changes in the financial sector on firm dynamics before the crisis, especially in terms of IT, has received less attention.

[7] See also Kwan et al. (2021) for the Covid-19 pandemic.

important driver of the growth of FinTechs (Buchak et al., 2018).

The remainder of the paper is structured 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 6 provides additional evidence supporting the model assumptions and its potential implication for inequality. Section 7 concludes.

2 A Model of Bank Screening

We develop a simple model to assess the implications of banks' IT adoption for screening and lending. A key building block is asymmetric information: firms' quality is initially unobserved by banks. To mitigate the arising adverse selection problem, banks screen by either acquiring information about firms to learn their type (unsecured lending) or requesting collateral (secured lending). We describe the consequences of banks' IT adoption for lending to young firms and derive predictions tested in the subsequent analysis.

The agents in the economy are banks and firms. There are two dates $t = 0, 1$, no discounting, and universal risk-neutrality. There are two goods: a good for consumption or investment and collateral that can back borrowing at date 0.

Firms have a new project at date 0 that requires one unit of investment. They are penniless in terms of the investment good but have pledgeable 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 continuous distribution G. The market price of collateral at date 1 (in terms of consumption goods) is P, so the collateral value is PC. Second, firms are either old (O) or young (Y), where we refer to young firms as entrepreneurs. There is mass of firms normalized to one and the share of young firms is $y \in (0, 1)$. For expositional clarity, firm age and collateral are independent.

The key friction is asymmetric information about a firm's type, that is the quality of the project. The project yields $x > 1$ at date 1 if successful and 0 if unsuccessful. Projects of good firms are more likely to be successful: the probability of success is p_G for good firms and p_B for bad ones, where $0 < p_B < p_G < 1$ and only good projects have a positive NPV, $p_B x < 1 < p_G x$. Project quality (type G or B) 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,

$$[qp_G + (1-q)p_B]\, x < 1, \tag{1}$$

so the adverse selection problem is severe enough for banks to choose to screen all borrowers in equilibrium. As a result, all loans granted are made to good firms.

There is a unit mass 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.

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 assume that this cost is lower for old firms than for young firms:[8]

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

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 cost is relatively less important.

Second, the bank can screen by asking for collateral at date 0 that is repossessed and sold at date 1 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 choose to seek funding from banks—reveals their type in equilibrium. We assume that the cost of screening via collateral is lower for high-IT banks than for low-IT banks:[9]

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

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, consistent with hard information lending.[10]

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.

[8] 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.

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

[10] Table A3 provides evidence consistent with this assumption, showing that high-IT banks issue more secured loans in the syndicated loans market.

This assumption simplifies the market structure because it implies that a startup does not make loan application with multiple banks, thus excluding competitive interaction between lenders. Our approach is supported by evidence that the degree of local concentration does not affect the relationship between IT and entrepreneurship (see Table A4).

In what follows, we assume a ranking of screening costs relative to the expected surplus of good projects:

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

In equilibrium, only good firms (a fraction q of all firms) may receive credit. Moreover, young firms (a fraction y of firms) receive credit only when matched with a high-IT bank (a fraction h of banks) and when possessing enough collateral, $C > C_{min}$, which applies to a fraction $1 - G(C_{min})$ of these firms. The bound on the collateral ensures the non-participation of firms with a bad project, making it too costly for them to pretend to be a good firm. This binding incentive compatibility constraint defines C_{min}:

$$p_B(x - r) \equiv (1 - p_B)PC_{min}, \tag{5}$$

where r is the bank's lending rate.[11] Equation 5 has an intuitive interpretation: its left-hand side is the benefit of pretending to be a good type and receiving a loan from a bank, keeping the surplus $x - r$ whenever the project succeeds, while the right-hand side is the cost of forgoing the market value of collateral when the project fails. Since the bad firm fails more often (p_B is low), it is costly for it to pretend to be a good firm. The minimum level of collateral depends negatively on its price, $C_{min} = C_{min}(P)$. In sum, sufficient collateral ($C > C_{min}$) ensures that only good firms receive loans in equilibrium.

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 bank ensures the old firm is of good quality via information acquisition. When matched with a low-IT bank, exclusively screening via information acquisition is used. (For a relaxation of this assumption, see Extension 2 below.)

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

[11] When the bank has adopted IT, its cost of lending is $1 + v_{HighIT}$ and the surplus from lending is $p_G x - (1 + v_{HighIT})$. Since the bank keeps a fraction θ of this surplus, the equilibrium lending rate is $r^*_{HighIT} = \theta p_G x + (1 - \theta)(1 + v_{HighIT})$.

Proposition 1 *The share of lending to young firms equals* $s_Y \equiv \frac{yh[1-G(C_{min})]}{1-y+yh[1-G(C_{min})]}$.

We state comparative static results in terms of the first three predictions.

Prediction 1. A higher share of high-IT banks increases the share of lending to young firms, $\frac{ds_Y}{dh} > 0$.

Prediction 2. Higher collateral values increases the share of lending to young firms, $\frac{ds_Y}{dP} > 0$.

Prediction 3. Higher collateral values increase the share of lending to young firms by more when the share of high-IT banks is higher, $\frac{d^2 s_Y}{dhdP} > 0$.

To gain intuition for these predictions, note that a higher share of high-IT banks implies that good young firms with sufficient collateral can receive funding more often. A higher value of collateral, in turn, increases the range of young firms with sufficient collateral, $C > C_{min}$, increasing expected lending along the extensive margin (lower C_{min}).

In equilibrium, all potential borrowers are screened and only good projects are financed, regardless of the screening choice or the bank type. Thus, the model implies that IT adoption does not affect the quality of firms who are funded by banks, as summarized in the following prediction.

Prediction 4. Bank IT adoption does not affect the quality (default rate) of firms receiving funding in equilibrium.

We will test these predictions below. Some implications are also consistent with evidence documented in other work. The positive impact of collateral values on entrepreneurship is consistent with the evidence in Adelino et al. (2015). Moreover, young firms use collateral more extensively 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 (Gopal, 2019; Chodorow-Reich et al., 2021).

Extension 1: Recourse versus non-recourse states. Recourse can partially substitute for the need of screening borrowers through collateral. To study the role of recourse, we assume that a fraction $i \in (0, 1)$ of firm owners generate an additional external income I and banks may have recourse to this income. However, some banks are located in states with recourse, and others in non-recourse states. In recourse states, banks of all types can obtain this external income, while only high-IT banks have the comparative advantage in lending via collateral. Collateral and recourse to future income are thus substitutes in deterring bad firms from pretending to be good ones. In non-recourse states, banks cannot lay claim to I in the case of failure of the project (and loan default). This implies that in recourse states firms with low collateral but (high) future income can obtain a loan from either bank type, while firms with high collateral and no future income can obtain a loan only from high-IT banks (as in the main model). In consequence, the incentive compatibility constraint changes from Condition (5) to

$$p_B(x - r) \equiv (1 - p_B)[PC^I_{min} + I], \tag{6}$$

so the minimum collateral requirement with recourse is now lower, $C^I_{min} < C_{min}$. Since recourse to future income mitigates the comparative advantage of high-IT banks in using collateral, the next predictions follow directly.

Prediction 5. (a) A higher share of high-IT banks increases the share of lending to young firms by less in recourse states than in non-recourse states, $\frac{ds_Y}{dh}^{Non-recourse} > \frac{ds_Y}{dh}^{Recourse}$; and (b) The positive impact of higher collateral values on entrepreneurship when the share of high-IT banks is higher is less pronounced in recourse states, $\frac{d^2 s_Y}{dhdP}^{Non-recourse} > \frac{d^2 s_Y}{dhdP}^{Recourse}$.

Extension 2: Geographical distance. A large literature in banking highlights the importance of geographical distance between lenders and borrowers and how it affects the relative values of hard and soft information. In our model, high-IT banks have a comparative advantage in screening based on collateral, which can be interpreted as hard-information lending (and is thus unaffected by distance). Low-IT banks lend based on information acquisition instead. To allow for a role of distance, we assume that low-IT banks can screen some young firms, namely those that are close. Hence, we relax Assumption 4 by assuming

$$F_Y^{close} < p_G x - 1 < F_Y^{distant} < v_{LowIT}, \tag{7}$$

where the cost of information acquisition is low enough relative to the expected surplus of a good project when the firm is close to the bank. Let $d \in (0, 1)$ be the fraction of young firms that is distant (d) and the remainder is close (c).

Using these assumptions, we can express for each type of bank the share of credit to young firms as a proportion of total credit, ϕ, and how it depends on the bank's distance to the borrower. For a high-IT bank, this share is invariant to distance:

$$\phi_h = \frac{y[1 - G(C_{min})]}{y[1 - G(C_{min})] + 1 - y} = \phi_h^d = \phi_h^c, \tag{8}$$

because all young firms with sufficient collateral are funded (irrespective of distance). For a low-IT bank, by contrast, this share depends on distance:

$$\phi_l^d = 0 < \frac{y(1-d)}{y(1-d) + 1 - y} = \phi_l^c, \tag{9}$$

because no distant young firms are funded, but geographically close ones are. Note that for a small $1 - d$, such that most young firms are distant, we have $\phi_h > \phi_l^c$. Also note that the shares ϕ_l^c and ϕ_l^d are independent of the price of collateral, so $\frac{d\phi_l}{dP} = 0$.

Prediction 6. Geographic distance between lenders and borrowers matters more for the lending behaviour of low-IT banks than that of high-IT banks. Specifically, the share of lending to young firms varies more with distance for low-IT banks than for high-IT banks, $\phi_l^c - \phi_l^d > \phi_h^c - \phi_h^d = 0$.

That is, the advantage of high-IT banks in hard information lending makes their lending less sensitive to the lender-borrower distance. Of particular relevance for the empirical analysis is how the distance between borrowers and lenders impacts the sensitivity of credit to local economic conditions. Adelino et al. (2017) document that startups strongly respond to changes in economic opportunities and are responsible for a larger share of job creation when local opportunities arise thanks to a positive income shock. As the responsiveness of startup activity to local shocks is larger than for older firms, the more a bank lends to startups in a market, the larger its credit supply should respond to local economic conditions.

Therefore, **Prediction 6** also implies that low IT banks' credit responds less to local economic conditions in counties that are more-distant from the banks' headquarters, while distance does not matter for the responsiveness of lending by high IT banks. We will test this relationship below.

3 Data and Variable Construction

This section explains the construction of the main variables and reports summary statistics. The main analysis focuses on the years from 1999 to 2007. While banks continued to adopt IT in more recent years, the post-crisis period saw substantial financial regulatory reform (such as the Dodd-Frank Act and regular stress tests), which has affected banks' ability to lend to young and small firms. The absence of major financial regulatory changes during our sample period makes it well-suited to identify the effects of banks' IT on entrepreneurship.

IT adoption. Data on banks' IT adoption 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, and 2006. 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 bank-level IT adoption is based on the use of personal computers across establishments in the United States. To construct county-level exposure to bank IT adoption, we proceed as follows. 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 from a regression of the share of personal computers on a bank (group) fixed effect, while controlling for the location of the establishment and other characteristics.[12] We define the variation captured by the bank fixed effects $\widetilde{IT}_b$, which is our main measure of IT adoption at the bank level. The focus on BHCs rather than local branches or banks is due to the facts that (a) most of the variation in branch-level IT adoption is explained by variation at the BHC-level, (b) technology adoption at individual branches could in principle be influenced by the rate of local firm formation, (c) using a larger pool of observations reduces measurement error, and (d) this estimation procedure

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

$$PCs/Emp_{i,t} = \widetilde{IT}_b + \theta_{type} + \theta_c + \theta_t + \gamma \cdot Emp + \epsilon_{i,t} \tag{10}$$

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 are branch-county fixed effects, θ_t are year fixed effects and Emp is the log number of employees in the establishment.

yields bank-level IT adoption measures that are uncorrelated with a bank's business model (assets or funding), size, or profitability, suggesting this approach is able to purge any potential correlation between IT and management quality or other confounding factors (Pierri and Timmer, 2020).

We then merge the resulting Aberdeen-BHC data set to the FDIC summary of deposits (SOD) data that provide information on the number of branches of each bank in a county. To construct a measure on local exposure to IT adoption of banks, we combine $\widetilde{IT}_b$ with the branch network of each bank in 1999, thus before the period of analysis. We then define the average IT adoption of all banks present in a county as:

$$IT_c = \sum_{b=1}^{N} \widetilde{IT}_b * \frac{No.\ branches_{b,c}}{No.\ branches_c}, \tag{11}$$

where $No.\ branches_{b,c}$ is the number of branches of bank b in county c in 1999 and $No.\ branches_c$ is the total number of branches across all banks in 1999 for which $\widetilde{IT}_b$ is available. For the ease of interpretation, IT_c is standardized to a mean of zero and standard deviation of one. Higher values indicate that banks with branches in a given county have adopted relatively more IT. Figure 1, panel (a), shows a map of US counties and their IT exposure.

Our main measure of IT adoption is based on the use of personal computers across bank branches in the United States, as the ratio of PCs per employee has not only the most comprehensive coverage, but also been used extensively in the literature (Bresnahan et al., 2002; Brynjolfsson and Hitt, 2003; Beaudry et al., 2010; Bloom et al., 2012). That said, to examine the validity of our measure, we exploit additional information on banks' IT budget available in the 2016 vintage. The correlation between the IT budget of an establishment and the number of computers as a share of employees is 0.65 in 2016. The R-squared of a cross-sectional regression of PCs per employee on the per capital IT budget is 0.44. There is also a positive correlation between PCs per employee and the probability of the adoption of cloud computing. These correlations provide assurance that the number of PCs per employee is a valid measure of IT adoption.

County and industry data. Data on young firms are obtained from the Quarterly Workforce Indicators (QWI), which provide detailed data on end-of-quarter employment at the county-two-digit NAICS industry-year level. Importantly, they provide a breakdown by firm age brackets. For example, they report employment among firms of age

0–1 in manufacturing in Orange County, CA. Detailed data are available from 1999 onward. QWI are the only publicly available data set that provides information on county employment by firm age and industry.[13]

We follow the literature and define young firms or entrepreneurs as firms aged 0–1 (Adelino et al., 2017; Curtis and Decker, 2018; Doerr, 2021). For each two-digit industry in each county, we use 4th quarter values. Note that the employment of young firms is a flow and not a stock of employment, as it measures the number of jobs created by new firms in a given year. In our baseline specification, we scale the job creation of young firms by total employment in the same county-industry cell, but results are unaffected by other normalization choices. Figure 1, panel (b), shows average job creation by startups across US counties between 2000 and 2006. It shows significant variation both across and within states, and underscores that job creation is also high outside eg tech hubs such as the Silicon Valley.

The 2007 Public Use Survey of Business Owners (SBO) provides 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 out of all firms that reports using home equity financing or personal assets (*home equity* henceforth) to start or expand their business (Doerr, 2021).

County controls include the log of the total population, the share of the black population and the share of the population older than 65 years, the unemployment rate, house price growth, and the log of 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.[14]

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.

We further use Community Reinvestment Act (CRA) data on loan origination at the

[13]Information is unavailable for counties in Massachusetts.

[14]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.

bank-county level, collected by the Federal Financial Institutions Examination Council at the subsidiary-bank level. 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:

$$\Delta CRA_{b,c,t} = \frac{CRA_{b,c,t} - CRA_{b,c,t-1}}{CRA_{b,c,t} + CRA_{b,c,t-1}} \times 2, \tag{12}$$

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.[15]

Descriptive statistics. Table 1 reports summary statistics of our main variables at the county level; Table 2 further reports the balancedness in terms of county-level covariates, where we split the sample 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 industrial 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 most other county-specific variables is reassuring as it suggests that counties' exposure to IT in banking is also uncorrelated with other unobservable county characteristics that could bias our results.[16]

4 IT and Entrepreneurship: Testing the Model's Predictions

This sections proposes a set of empirical tests for the main predictions of the model described in Section 2 and provides results.

[15]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).

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

4.1 IT exposure and local entrepreneurship (Prediction 1)

Prediction 1 implies a positive relation between the share of high-IT banks in a market and local entrepreneurial activity. To test this prediction, we estimate the following cross-sectional regression at the county-industry level:

$$\begin{aligned} \text{startups}_{c,i} = \beta_1 \; IT \; exposure_{c,99} + \beta_2 \; constraint_i \\ + \beta_3 \; IT \; exposure_{c,99} \times constraint_i + controls_{c,99} + \theta_c + \phi_i + \varepsilon_{c,i}. \end{aligned} \tag{13}$$

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.

To mitigate the concern that the relationship between IT exposure and local entrepreneurship is driven by other local characteristics, we include a rich set of county-level controls. Controlling for county size (log of the total population) we avoid comparing small counties to large urban ones. We further control for the share of population age 65 and older, as younger individuals may be more likely to start companies and also have better IT knowledge. Other socio-demographic controls, such as the share of the black population, the unemployment rate, and household income, purge our estimates from a potential correlation between local income or investment opportunities and the variables of interests. We also control for the industrial structure of the county (proxied by employment shares in the major 2-digit industries 23, 31, 44, 62, and 72) in order to compare counties that are similar from the economic point of view, and are subject to similar shocks. We also control for the share of adults with bachelor degree or higher, as human capital may spur entrepreneurship (Bernstein et al., 2021) and could also make it easier to adopt IT. Finally, we control for IT in non-financial firms (measured as the average PCs per employee in non-financial firms) to tackle the concern that startup activity may thrive in location where IT is more readily available, perhaps because many promising startups operate in the IT space or use new technology to quickly scale up.[17] All variables are measured as of 1999. Standard errors are clustered at the county level, and regressions are weighted by county size.

Abstracting from interaction terms, Prediction 1 implies that $\beta_1 > 0$. Before moving

[17]Conversely, we find a negative correlation between local entrepreneurship and IT in non-financial firms, consistent with evidence that High-Tech sectors have been experiencing a particularly severe decline in entrepreneurship (Decker et al., 2016).

to the regression analysis, Figure 2 shows the relation between IT exposure and startup employment in a nonparametric way. It plots the share of employment among firms age 0–1 on the vertical axis against county exposure on the horizontal axis and reveals a significant positive relationship. We now investigate this pattern in greater detail.

Table 3 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 similar in size when we add county-level controls, while the R-squared increases more than 10-fold. Column (3) adds industry fixed effects (at the NAICS2 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 20 pp. This pattern suggests that local IT exposure is orthogonal to industry-specific characteristics. The magnitude of the impact is sizeable: In column (3), a one standard deviation higher IT exposure is associated with a 0.38 pp increase in the share of young firm employment (4% of the mean of 9.3%).

In the model, banks' IT spurs entrepreneurship through a bank lending channel, so we expect the positive correlation shown in columns (1)–(3) to be stronger in industries that depend more on external finance. This is, in Equation (13), we expect $\beta_3 > 0$. 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 exposure 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. In terms of magnitude, a one standard deviation higher IT exposure is associated with a 1 pp increase in the share of young firm employment in industries that depend on more external finance (11% of the mean).

In column (5), we further enrich our specification with county fixed effects to control for any observable and unobservable confounding factors at the local level. Results are near-identical to column (4): the inclusion of county fixed effects changes the estimated impact of IT exposure interacted with financial dependence by only 0.02 pp – despite the fact that the R-squared increases by 10 pp.

Taken together, results in Table 3 provide support for Prediction 1: a larger local presence of IT-intensive banks is associated with more startup activity, and especially so in sectors that depend more on external financing. Findings further suggest that the effect of counties' IT exposure on job creation by startups is orthogonal to observable and unobservable industry and county characteristics, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).

Robustness. A set of robustness tests is presented in Table A1. Column (1) is the baseline (as column (3) of Table 3). 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) 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 (4) excludes employment in startups in the financial and education industries, showing financial companies or universities are not driving our results. Column (5) excludes Wyoming which, perhaps surprisingly, the state with the highest exposure to banks' IT adoption (see Figure 1, panel b). Column (6) includes state fixed effects, showing that our results are driven by within-state variation, rather than variation between different part of the county. Column (7) shows robustness of the specification by normalizing the share of employment in startups by previous year's total employment. Column (8) reveals that our results are due to an impact on the numerator (employment of startups) rather than denominator (total employment).

Our model underscores the role of IT as a technology to facilitate the use of entrepreneurs' real estate as collateral. However, local economic conditions could also be correlated with collateral values and this may create a correlation between local demand and use of collateral. This concern should be mitigated by the fact that we directly control for local income. Additionally, we test whether our main findings is present in industries which are less impacted by local economic conditions, that is "tradable" industries. We rely on the tradable classification of 4 digit industries by Mian and Sufi (2014), which we aggregate at out 2 digit level: two of the 2 digit industries, that is manufacturing and mining and extraction, have most of their employment in tradable sub-industries. As illustrated by column (9) the relationship between IT and entrepreneurship is much stronger within these industries than in baseline, suggesting it is not driven by local demand. As these industries have also high dependence on external finance, this finding further suggest our main result is driven by access to finance rather than local demand.

We then consider the concern that other forms of external financing, venture capital (VC) in particular, may be correlated with IT in banking and have an impact on our results. We exploit the fact that VC funding is highly concentrated in a small fraction of the US territory.[18] We thus repeat our regressions excluding the top 20 counties (representing almost 80% of VC funding at the time) or 7 states with more VC presence, and find results similar to baseline, see columns (10) and (11).

We finally 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 drop the counties in the bottom quartile of coverage or, also include coverage as a control. Results are robust as reported by the last two columns.

Instrumental variable approach. 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 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-

[18] See e.g. https://pitchbook.com/newsletter/28-counties-account-for-80-of-vc-investment-in-the-us.

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:

$$\widehat{IT}_c = \sum_{b=1}^{N} \widetilde{IT}_b * \frac{\widehat{Deposits}_{b,c}}{Deposits_c} \tag{14}$$

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 4. 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. 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

$$\Delta IT_c = \sum_{b=1}^{N} \Delta\widetilde{IT}_b * \frac{No.\ Branches_{b,c}}{No.\ Branches_c}, \tag{15}$$

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 3. 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 A2. 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 (Rampini and Viswanathan, 2010; Adelino et al., 2015; Schmalz et al., 2017; Bahaj et al., 2020). The role of collateral in our model is directly related to this literature. Predictions 2 & 3 of the model state that *i*) higher collateral values increases startup activity, and *ii*) they do so especially in counties with higher IT exposure.

We test these predictions by examining how local IT exposure affects the sensitivity of entrepreneurship to changes in house prices, using a county-year panel from 1999 to 2007.[19] We estimate the following regression:

$$\begin{aligned} \text{startups}_{c,i,t} = &\ \gamma_1\ IT\ exposure_{c,99} + \gamma_2\ \Delta HPI_{c,t} \\ &+ \gamma_3\ IT\ exposure_{c,99} \times \Delta HPI_{c,t} \\ &+ controls_{c,t-1} + \theta_{c,i} + \tau_t + \varepsilon_{c,i,t}. \end{aligned} \tag{16}$$

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 exposure as of 1999. $\Delta HPI_{c,t}$ is the yearly county-level growth in house prices. Controls include 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, and IT adoption among non-financial firms, all lagged by one period. Standard errors are clustered at the county level.

Prediction 1 implies that $\gamma_2 > 0$. Table 5, column (1) confirms that higher IT exposure is associated with a higher share of young firm employment also in our panel (in line with results in Table 3). 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

[19] We complement this analysis with bank-county level data on small business lending below.

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 16. Based on Prediction 3, we expect $\gamma_3 > 0$, ie an increase in house prices leads to an increase in startup-activity, especially in counties more exposed to IT. 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 – the coefficient on IT exposure is now Column (4) shows that $\gamma_3 > 0$, consistent with **Prediction 3**. Columns (5) and (6) add time-varying county controls, as well as industry$\times$year 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 et al., 2015; Doerr, 2021). We exploit this industry heterogeneity to provide further evidence for **Prediction 3**. Focusing on differences between industries within the same county and year also allows us to control for industry$\times$year and county$\times$year fixed effects and thus purge our estimates from the impact of any time-varying industry or county-level shocks. Columns (7) and (8) reveal that the positive effect of rising house prices on startups due to the presence of high-IT banks in a county is more pronounced in those industries whose financing is expected to be more sensitive to changes in collateral values.

In sum, Table 5 provides evidence in line with Predictions 2 and 3: entrepreneurship increases when local collateral values increase, and in particular so in counties with higher exposure to IT-intensive banks.

4.3 IT exposure and startup quality (Prediction 4)

Prediction 4 states that IT exposure should not affect the quality of firms receiving funding in equilibrium. As IT improves the screening process, there is no trade off between the quantity of credit and the marginal quality of the borrower.

In the model firm quality is disciplined by the probability of default, which is unobservable in the data. Instead, we have to rely on the average growth rate of employment of startups during their first few years of life, which can be proxied with "transition rates" (Adelino et al., 2017). As the QWI report employment of firms of eg age 2–3 in a given year, we can substract the employment of startups (firms age 0 or 1 year) two years earlier to obtain the change in jobs created by continuing startups during that period. The transition rate in a county-industry cell is thus defined as:

$$transition^{2-3}_{c,s,t} = \frac{Employment\ Age\ 2-3_{c,s,t+2} - Employment\ Startup_{c,s,t}}{Total\ Employment_{c,s,t}}$$

We construct similar transition rates for firms transitioning from age 2–3 to 4–5. We then estimate a cross-sectional regression similar to Equation 13, where the dependent variable is the average transition rate between 2000 and 2006. Columns (1)-(3) in Table 6 show that there is no systematic correlation between a county's exposure to IT in banking and the transition rates of local startups, neither on average nor in industries that are more dependent on external finance. We find similar effects for the transition rates from 2–3 years to 4–5 years in columns (4)-(6).

The absence of any significant relationship between IT exposure and local startup quality could suggest that our findings have aggregate implications. If the additional startups created due to IT adoption in the financial sector are of similar quality as other startups, this should bring benefits to the wide economy – for example in terms of business dynamism and productivity growth.

4.4 IT and the role of recourse default (Prediction 5)

Recourse – i.e., lenders' ability to possess other borrower assets or future income through a deficiency judgment – can partially substitute for the need of screening borrowers through collateral. The ability to recourse in the case of foreclosure thus diminishes the misalignment of interests (Ghent and Kudlyak, 2011). In the model, this lead to the prediction that the positive relationship between IT exposure and entrepreneurship is more pronounced in non-recourse states.

To test this prediction, we exploit the significant heterogeneity across US states in terms of legal and practical considerations which makes obtaining a deficiency judgment more or less difficult for lenders. We follow Ghent and Kudlyak (2011) to classify states into recourse and non-recourse states and estimate the cross-sectional relationship between IT and entrepreneurship (i.e. Equation 13) for counties in recourse versus non-recourse states.[20] Columns (1) and (2) in Table 7 highlight that the positive relationship between IT exposure and job creation by startups is stronger in non-recourse states, in line with the model's prediction. We confirm this finding in interaction specifications in columns (3) and (4). Columns (3) shows that in recourse states the relationship between IT adoption and entrepreneurship is significantly weaker. Column (4) confirms the finding when we exclude North Carolina, as its classification presents some ambiguity. Moreover, we find that the sensitivity of entrepreneurship to changes in house prices – which is generally higher in counties with higher IT exposure – is lower in recourse states (see the final column in Table 5).

5 IT and small business lending

In this section, we use data on banks' small business lending, provided by the Community Reinvestment Act, to to further test the model's predictions at the bank-county level.

5.1 IT and the role of distance (Prediction 6)

In the model, banks verify the value of collateral at cost v. We assume that v is lower for high-IT banks because they can better verify the existence and market value of collateral, but also because it is cheaper for high-IT to transmit the information on borrowers' collateral to their (distant) headquarters. Following a large literature that shows that informational frictions increase with lender-borrower distance (Liberti and Petersen, 2017), we now investigate the importance of distance in banks' lending decisions.

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; in other words, lending should become more responsive to new investment opportunities in more distant counties.

[20] Ghent and Kudlyak (2011) relies on recourse / non-recourse classifications of states from the 21^{st} edition (2004) of the National Mortgage Servicer's Reference Directory to show that recourse clauses impact borrowers' behavior.

To test whether the relationship between local investment opportunities and lender-borrower distance differs with banks' IT use, we consider the following specification that relates banks' loan growth to local investment opportunities (measured as the change in local income, proxying an increase in local demand for credit):

$$\begin{aligned}\Delta loans_{b,c,t} = {} & \beta_1 \; log(distance)_{b,c} + \beta_2 \; \Delta income \; p.c._{c,t} \\ & + \beta_3 \; log(distance)_{b,c} \times \Delta income \; p.c._{c,t} \\ & + bank \; controls_{b,t-1} + county \; controls_{c,t-1} + \theta + \varepsilon_{b,c,t}, \\ & \text{if IT} = \text{low/high}.\end{aligned} \tag{17}$$

The dependent variable is the log difference in total CRA small business loans by bank b to borrower county c in year t.The variable $log(distance)$ measures the distance between banks' HQ and the county of the borrower (in logs). In general, we expect that an increase in local investment opportunities (and hence the local demand for credit), measured by the log difference of county-level income per capita, increases local lending; and the more so, the shorter the distance between the headquarters county of the lender and the borrower county. That is, we expect $\beta_1 > 0$ and $\beta_3 < 0$. As banks' IT adoption reduces the importance of distance, the model predicts β_3 to be significantly smaller for *high IT* banks.

Results in Table 8 support these hypotheses. Column (1) shows that rising local incomes are associated with higher local loan growth. Distance reduces the sensitivity of banks' small business 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 unobservable time-varying borrower-county characteristics in column (2). Columns (3) and (4) show that the lower responsiveness of banks' lending in counties located further away is present only for low IT banks; for high IT banks, distance has no significant dampening effect. An interaction specifications in column (5) confirms 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 in column (6).

5.2 Banks' IT, house prices and small business lending

To provide further evidence on how banks' IT affects access to finance for entrepreneurs, we investigate how high- and low-IT banks adjust their small business lending in response to house price changes. We thus revisit **Predictions 2–3**, but explicitly analyze changes in lending and IT-adoption at the bank level. We estimate the following regression equation from 1999 to 2007 at the bank-county-year level:

$$\begin{aligned}\Delta loans_{b,c,t} = \beta_1\ IT_b + \beta_2\ \Delta\ HPI_{c,t} + \beta_3\ IT_b \times \Delta HPI_{c,t} \\ + bank\ controls_{b,t-1} + county\ controls_{c,t-1} + \tau_t + \varepsilon_{b,c,t}.\end{aligned} \tag{18}$$

The dependent variable is the growth in total CRA small business loans by bank b to borrower county c in year t. 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 16, 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 at 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. changes in 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$\times$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 local factors, such as employment growth.

Table 9 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 twice as large for the high-IT sample.

Columns (4)–(7) 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 more than fourfold increase in the R-squared, estimated coefficient estimates 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 supply 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.

One caveat of CRA data is that it covers lending to small firms. While the vast majority of young firms are small, not all small firms are young. Despite this limitation, results in Table 9 are consistent with the model's predictions that IT in banking increase the benefits of a rise in collateral values. Note that an additional benefit of these bank-county level regressions is that the measure of IT – which varies at the bank level – differs from the previously used measure of county exposure. Yet, under both measures we find consistent results.

6 Competition, Collateralized Lending, and Minority Entrepreneurs

In this section we present additional evidence that speaks to assumptions and implications of the model. We 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 also show that the effects of IT on startup activity and lending do not depend on local competition among banks. We conclude presenting suggestive evidence on the impact on Black entrepreneurship.

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 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 A2 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:

$$secured_{b,i,t} = \beta \; IT_b + \tau_t + \theta_i + \varepsilon_{b,i,t}, \tag{19}$$

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 A3 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 13, 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 A4. 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 simplistic approach to 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.

Minority Entrepreneurship. Our results indicate that IT can spur entrepreneurship through making it easier to borrow against potential entrepreneurs' own wealth. This suggests that people without personal or family wealth may not be able to benefit from it. Communities, such as racial and ethnic minorities, that have experienced long lasting discrimination in the mortgage market (Munnell et al., 1996) and have thus been accumulated less real estate wealth, may benefit less from the boosts in entrepreneurship stemming from banks' IT. This may be particular problematic as minority entrepreneurs face more hurdles in access to capital (Fairlie et al., 2020).

QWI reports job creation by startups divided by the race of the employees but not by the race of the entrepreneur. However, entrepreneurs are likely to hire from their personal networks, especially during the startup phase, and previous literature extensively documents that job referral are more likely among people of the same ethnic or racial minority (Dustmann et al., 2016). Therefore, it seems reasonable to assume that a startup created/owned by a minority entrepreneur is more likely to hire employees from the same group than a startup created/owned by a different entrepreneur. We therefore investigate the relationship between IT in banking and the share of startups' employees that are Black within a county, normalized by subtracting the same share for White employees.

Table A6, which presents estimates of an equation akin to Equation 13 but with a different dependent variable, reveals that counties more exposed to IT in banking also have a lower share of Black employees among startups' employees (minus the share of startup employees who are White). One standard deviation higher exposure to IT in banking is associated to about .2 percentage point lower difference between share of Black and White startup workers, which is about 15% of the average difference. Given the discussion above, this result suggests that IT in banking is also likely to be associated to a lower share of Black entrepreneurs. IT in banking can foster entrepreneurship and business dynamism but may also magnify inequality across demographic groups.

7 Conclusion

Over the last decades, banks have invested in information technology at a grand scale. However, there is very little evidence on the effects of this 'IT revolution' in banking on lending and the real economy. In this paper we focus on startups because of their importance for business dynamics and productivity growth, and because they are opaque borrowers and thus may be sensitive to technologies that change information frictions.

We show that IT adoption in the financial sector has spurred entrepreneurship. In regions where banks that with more IT-adoption have a larger footprint, job creation by startups was relatively stronger; this relationship is particularly pronounced in industries that rely more on external finance. We show – both theoretically and empirically – that collateral plays an important role in explaining these patterns. As IT makes it easier for banks to assess the value and quality of collateral, banks with higher IT adoption are more likely to lend against increases in entrepreneurs' collateral.

Our results have important implications for policy. Banks' enthusiasm towards technology adoption has been very strong during the last years,[21] 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 the need for collateral and firms' access to credit (Gambacorta et al., 2020). Our findings suggest that IT in lending decisions can spur job creation by young firms by making lending against collateral cheaper. 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. As a caveat, however, we also present suggestive evidence that IT in banking may magnify wealth inequalities and exacerbate the effects of past racial discrimination on the credit markets.

[21] 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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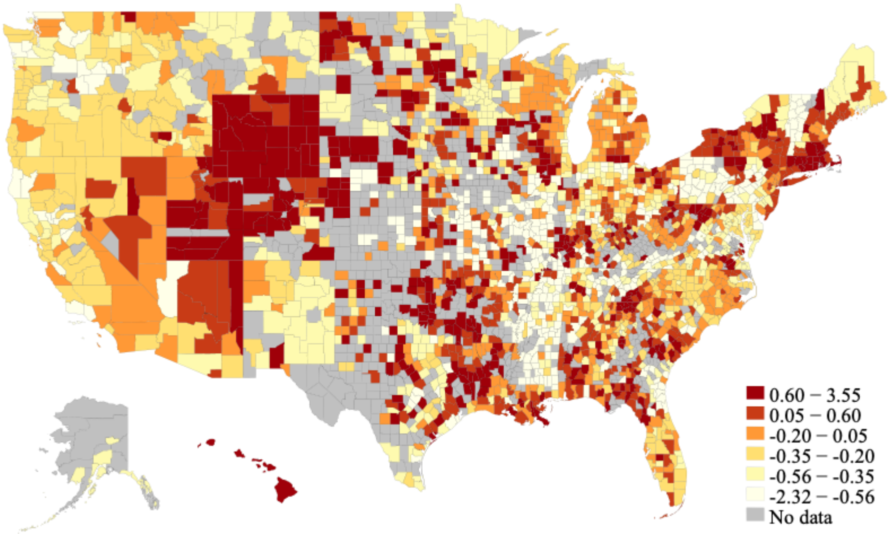
Figures and Tables

Figure 1: **Spatial distribution of startups and IT exposure**

(a) County exposure to IT in Banking



(b) Job creation by startups

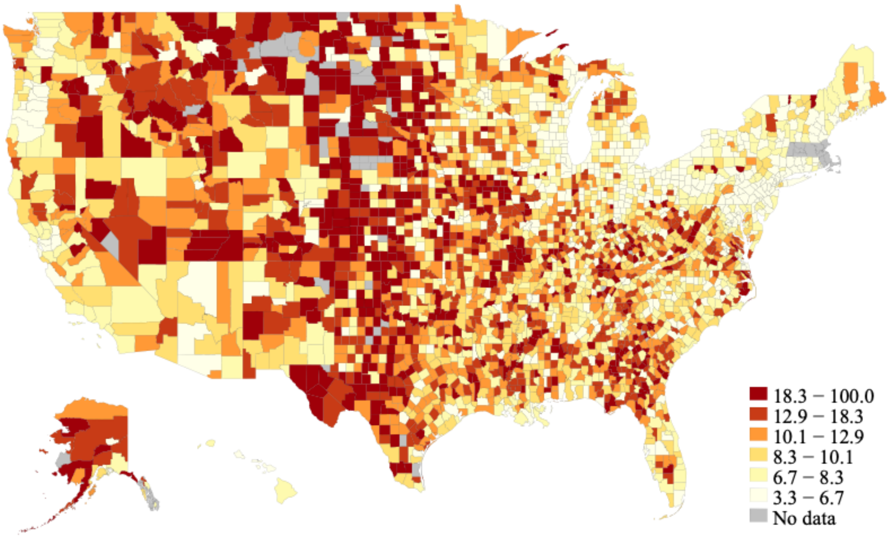
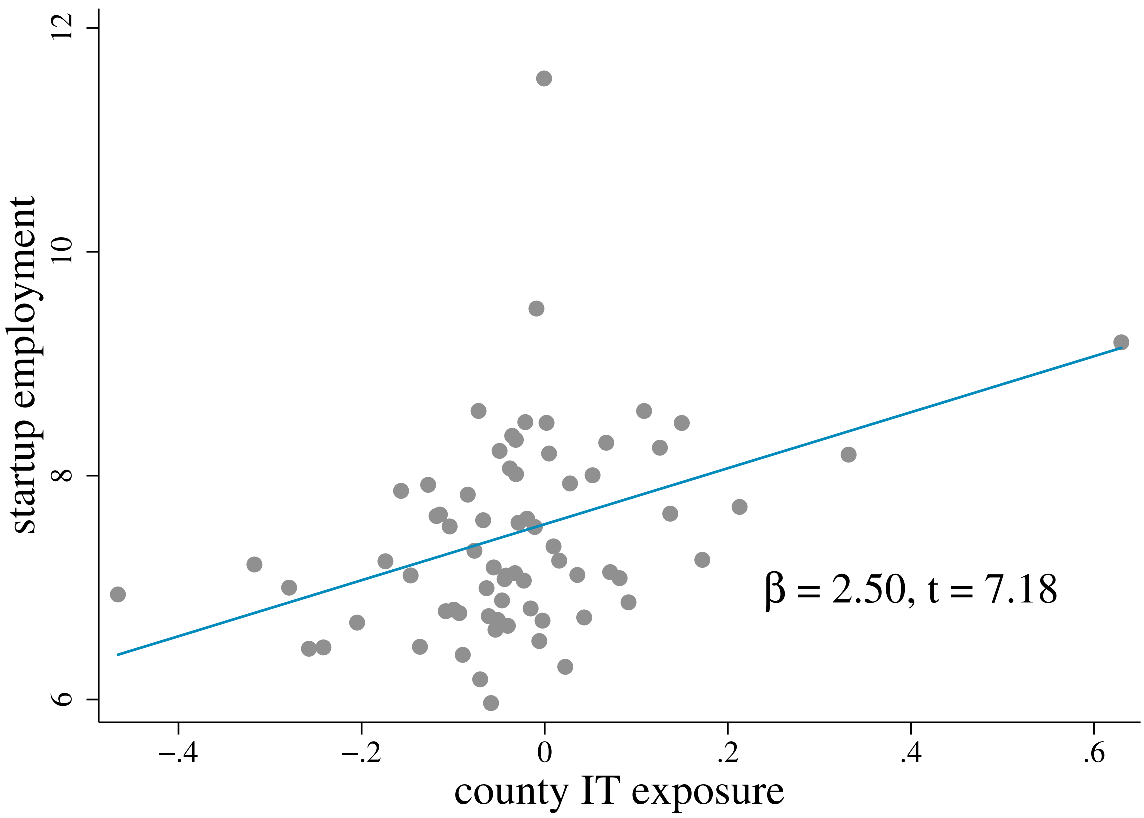
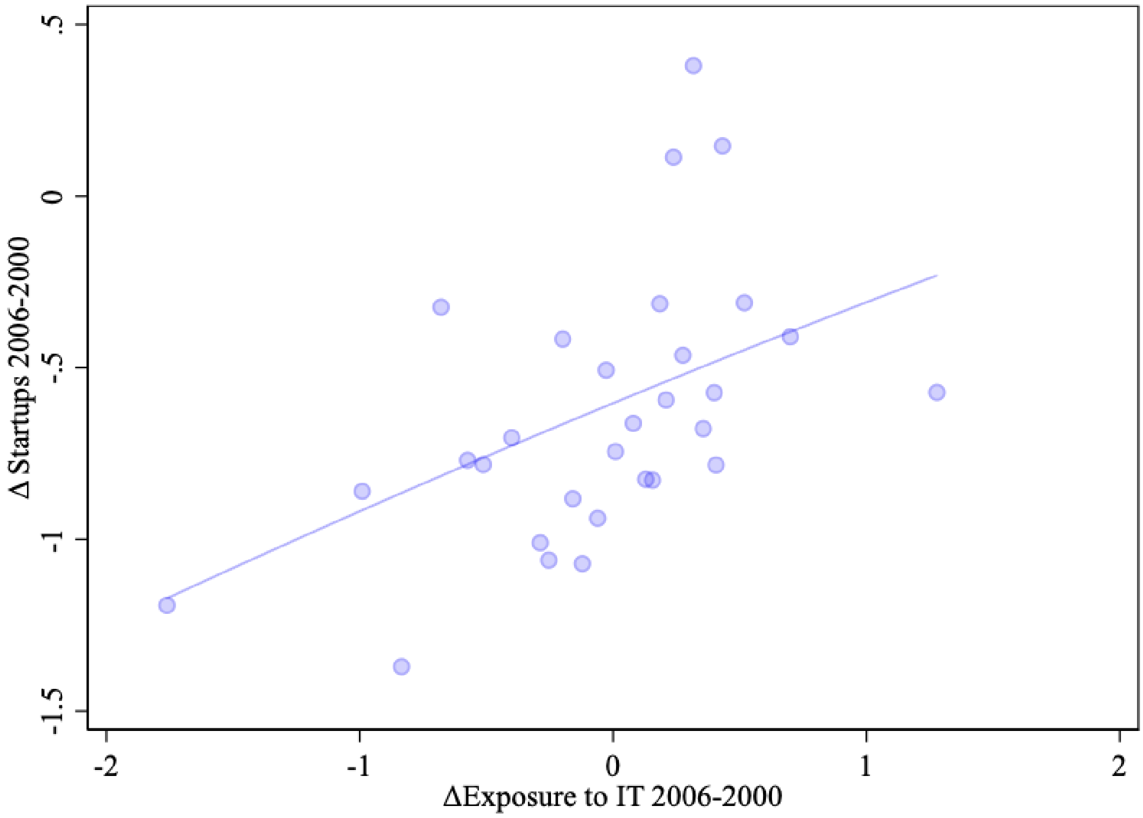


Figure 2: Job Creation by Young Firms and Banks' IT adoption



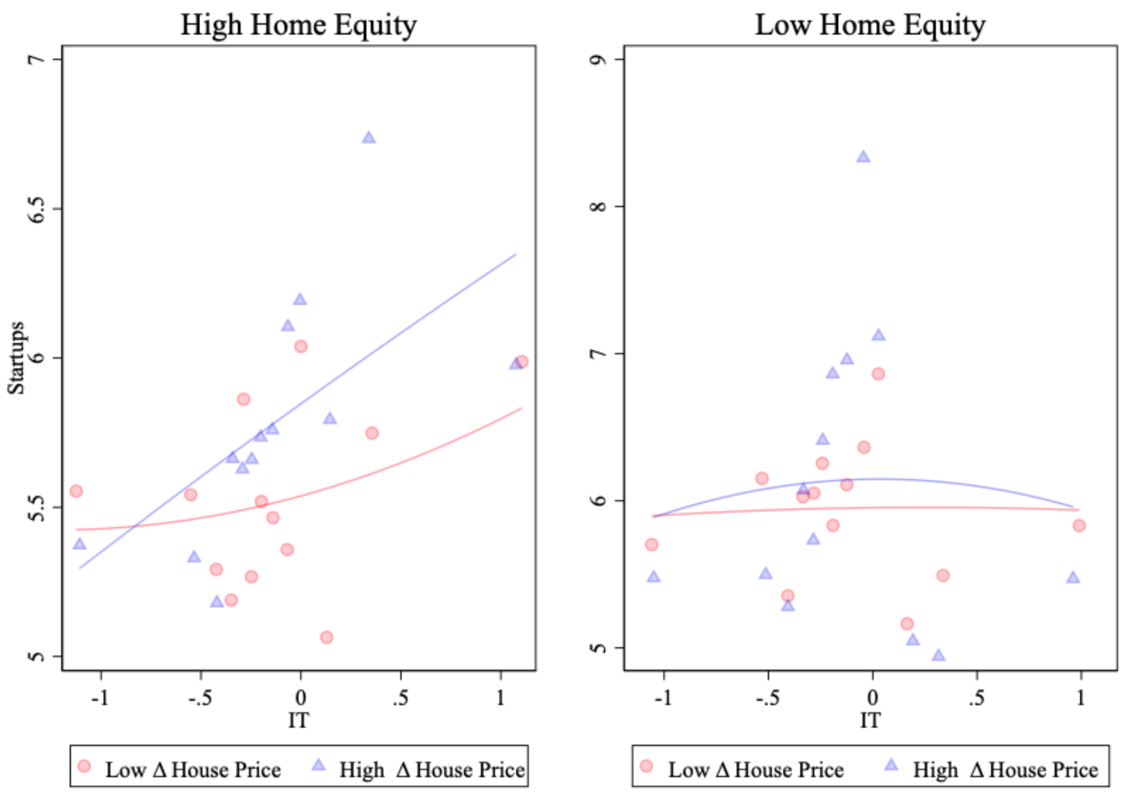
This figure shows a binscatter of the share of employment by young firms over total employment in a county-industry cell across 2000 and 2007 on the vertical axis and the county-level exposure to Bank IT adoption as defined in Section 3 on the horizontal axis.

Figure 3: 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 4: 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.

Table 1: **Descriptive statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
IT exposure	1774	-.001	.235	-.562	.964	-.108	-.041	.067
log(pop)	1774	10.995	1.135	8.501	16.06	10.186	10.774	11.651
log(income pc)	1774	10.062	.206	9.493	11.305	9.929	10.039	10.163
bachelor or higher	1774	.183	.083	.06	.605	.122	.16	.223
share pop old	1774	.138	.037	.029	.349	.114	.137	.158
share pop black	1774	.091	.133	0	.855	.006	.03	.114
unemployment rate	1774	4.671	2.388	.7	29.7	3.1	4.1	5.8
employment share NAICS 23	1774	.059	.03	.004	.369	.04	.052	.071
employment share NAICS 31	1774	.216	.131	.003	.685	.114	.194	.297
employment share NAICS 44	1774	.158	.04	.052	.512	.131	.155	.181
employment share NAICS 62	1774	.137	.052	.01	.448	.101	.132	.165
employment share NAICS 72	1774	.097	.045	.02	.568	.072	.088	.111
PCs per employee (non-fin)	1774	.497	.092	.251	.767	.44	.499	.553

This table reports summary statistics at the county level

Table 2: **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
log(income pc)	10.05	(0.20)	10.04	(0.21)	1.09
bachelor or higher	0.18	(0.09)	0.18	(0.08)	1.24
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 3: **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	0.455***	0.397***	0.370***	0.373***	
	(0.118)	(0.098)	(0.098)	(0.098)	
IT exposure × ext. fin. dep				0.698***	0.677***
				(0.179)	(0.176)
Observations	25,742	25,742	25,742	25,742	25,742
R-squared	0.003	0.047	0.252	0.252	0.354
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 13). 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 4: **County IT exposure and entrepreneurship: IV approach**

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

The dependent variable is the share of the employment in firms of age 0-1 in county c and industry i in column (1), (3), and (4). $ITExposure_c$ 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. This table reports results from cross-sectional regressions at the county-industry level (see Equation 13). Column (1) presents the baseline estimate on this sample of counties. Column (2) is the first stage between exposure to IT and predicted exposure to IT based on the gravity RS approach. Column (3) is the reduce-form regression of the instrument on the variable of interest. Column (4) is the second stage regression. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **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	(9) share 0-1
IT exposure	0.325***		0.320***						
	(0.111)		(0.110)						
Δ HPI		0.025**	0.024**	-0.024**	-0.041***	-0.034***			-0.028**
		(0.010)	(0.010)	(0.011)	(0.014)	(0.011)			(0.012)
IT exposure × Δ HPI				0.075***	0.070**	0.075**			0.271***
				(0.027)	(0.033)	(0.030)			(0.086)
IT exposure × Δ HPI × Low SU capital							0.136***		
							(0.051)		
IT exposure × Δ HPI × home equity								0.175**	
								(0.087)	
IT exposure × Δ HPI × Recourse									-0.264***
									(0.092)
Observations	192,402	192,402	192,402	192,402	152,904	152,904	192,097	192,097	152,904
R-squared	0.008	0.007	0.008	0.564	0.579	0.599	0.621	0.621	0.599
County × NAICS FE	-	-	-	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	-	-	-	-
NAICS × Year FE	-	-	-	-	-	✓	✓	✓	✓
County × Year FE	-	-	-	-	-	-	✓	✓	-
County Controls	-	-	-	-	✓	✓	-	-	✓
Cluster	County	County	County	County	County	County	County	County	County

This table reports results for regressions at the county-industry-year level (see Equation 16). 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. $lowSU\ capital_i$ is a dummy where low amounts of capital required to start a company. $home\ equity_i$ 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 6: **County IT exposure and transition rates**

VARIABLES	(1) tr 0/1-2/3	(2) tr 0/1-2/3	(3) tr 0/1-2/3	(4) tr 2/3-4/5	(5) tr 2/3-4/5	(6) tr 2/3-4/5
IT exposure	-0.000	-0.000		-0.000	-0.000	
	(0.000)	(0.000)		(0.000)	(0.000)	
IT exposure × ext. fin. dep		-0.001	-0.001		-0.001	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Observations	23,696	23,696	23,696	22,643	22,643	22,643
R-squared	0.070	0.070	0.140	0.048	0.048	0.120
County Controls	✓	✓	-	✓	✓	-
NAICS FE	✓	✓	✓	✓	✓	✓
County FE	-	-	✓	-	-	✓
Cluster	County	County	County	County	County	County

The dependent variable is the transition rate of firms of age 0–1 to 2–3 (columns 1–3) and of age 2–3 to 4–5 (columns 4–6) 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 7: **Recourse**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1
IT exposure	0.305***	0.471***	0.700***	0.673***
	(0.0966)	(0.176)	(0.203)	(0.204)
Recourse State × IT exposure			-0.463**	-0.434**
			(0.220)	(0.220)
Observations	20,046	5,696	25,742	24,630
R-squared	0.275	0.359	0.272	0.273
County Controls	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓
Cluster	County	County	County	County
Specification	Recourse	Non-Recourse	Interaction	No NC

This table reports results from cross-sectional regressions at the county-industry level (see Equation 13). 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. $RecourseState_s$ a dummy that is one if the state is a recourse state. Column (1) shows the baseline specification only for recourse states. Column (2) shows the baseline specification only for non-recourse states. Column (3) and (4) show. the regression with an interaction between a $RecourseState_s$ and $ITExposure_c$. Column (4) excludes North Carolina, as its classification presents some ambiguity. Standard errors are clustered at the county level *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **CRA lending – distance**

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 17). 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. Δ $Income_{c,t}$ 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.

Table 9: **Banks' IT, house prices and CRA lending**

VARIABLES	(1) Δ loans	(2) low IT Δ loans	(3) high IT Δ loans	(4) Δ loans	(5) Δ loans	(6) Δ loans	(7) Δ loans
IT	0.031***			0.007*	0.006		
	(0.002)			(0.004)	(0.004)		
Δ HPI	0.172***	0.078	0.159*	0.031			
	(0.055)	(0.089)	(0.097)	(0.058)			
IT × Δ HPI				0.213***	0.244***	0.310***	0.178**
				(0.066)	(0.068)	(0.103)	(0.087)
Observations	338,857	87,414	60,152	194,317	194,003	183,654	183,623
R-squared	0.028	0.020	0.049	0.019	0.126	0.250	0.331
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 18). The dependent variable is the change in CRA loans by bank b to county c in year t, featuring entry and exit. 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.

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	(9) share 0-1	(10) share 0-1	(11) share 0-1	(12) share 0-1	(13) share 0-1
IT exposure	0.377***	0.163**		0.398***	0.375***	0.333***	0.418***	0.054	0.809*	0.247***	0.349***	0.344***	0.405***
	(0.098)	(0.073)		(0.106)	(0.099)	(0.092)	(0.126)	(0.065)	(0.421)	(0.088)	(0.095)	(0.097)	(0.103)
IT exposure (deposit weighted)			0.342***										
			(0.094)										
Observations	25,779	25,779	25,779	21,735	25,544	25,779	25,440	25,774	2,105	21,150	25,519	24,900	18,652
R-squared	0.248	0.252	0.248	0.252	0.248	0.268	0.208	0.215	0.279	0.283	0.247	0.251	0.242
County Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Spec	Baseline	No Weights	Deposit Share	No Finance	NoWyoming	State FE	Lagged Denominator	Δ Total Employment	Only Tradable	No High-VC States	No High-VC Counties	Coverage: control	No Low Coverage Counties
Cluster	County	County	County	County	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. In Column (3) we project bank IT adoption by the deposit share rather than the number of branches on the county. In column (4) we exclude finance and education as a sector. In (5) We exclude Wyoming. (6) We include state FE. (7) We divide employment creation of young firms by lagged total employment in the county sector cell. In Column (8) we use the change in total employment as a dependent variable. Standard errors are clustered at the county level. In (9) we restrict our sample to firms in tradable industries. In (10) and (11) we exclude high venture capital states and counties, respectively. In column (12) we control for the coverage. In (13) we exclude low coverage counties. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: **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 A3: **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.

Table A4: **The role of local competition**

VARIABLES	(1) share 0-1	(2) share 0-1	(3) share 0-1	(4) share 0-1
IT exposure	0.393***	0.415***	0.372***	0.372***
	(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
R-squared	0.249	0.249	0.252	0.252
County Controls	✓	✓	✓	✓
NAICS FE	✓	✓	✓	✓
Cluster	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 A5: **Banks' IT, house prices and home equity loans**

VARIABLES	(1) Δ HE loans	(2) low IT Δ HE loans	(3) high IT Δ HE loans	(4) Δ HE loans	(5) Δ HE loans	(6) Δ HE loans	(7) Δ HE loans
IT	-0.022***			-0.066***	-0.061***		
	(0.005)			(0.010)	(0.010)		
Δ HPI	2.158***	2.811***	5.013***	2.248***			
	(0.090)	(0.231)	(0.408)	(0.106)			
IT × Δ HPI				0.343***	0.376***	0.465***	0.931***
				(0.085)	(0.090)	(0.143)	(0.150)
Observations	50,036	9,725	3,194	31,408	28,810	40,534	40,143
R-squared	0.089	0.189	0.329	0.139	0.280	0.358	0.633
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

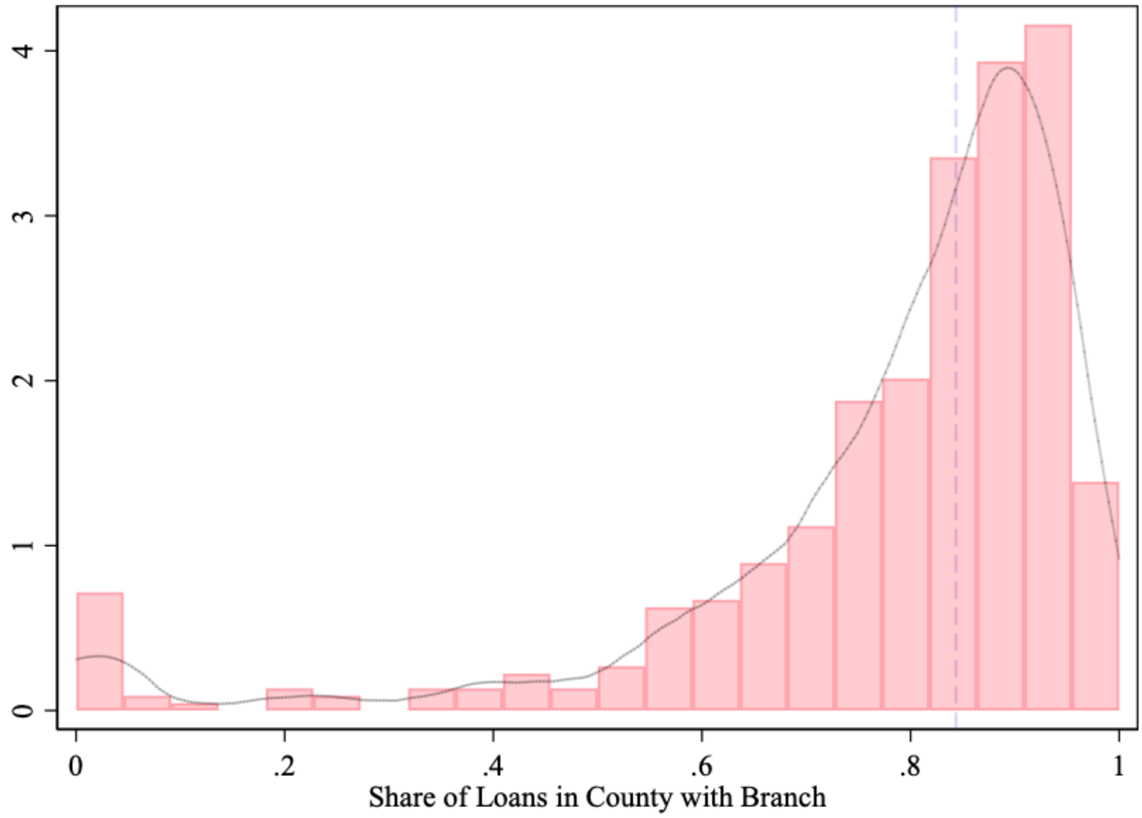
This table reports results for regressions at the bank-county-year level (see Equation 18). The dependent variable is the change in business-related home equity loans by bank b to county c in year t, based on HMDA data. IT_b is the IT adoption of bank b, $\Delta HPI_{c,t}$ is the yearly change in house 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 A6: **Black Entrepreneurship**

	(1)	(2)	(3)
VARIABLES	Share of startup employees who are Black (minus share of White)		
IT exposure	-0.259***	-0.257***	-0.245***
	(0.098)	(0.094)	(0.094)
Observations	21,714	21,714	21,714
R-squared	0.001	0.013	0.047
County Controls	-	✓	✓
NAICS FE	-	-	✓
Cluster	County	County	County

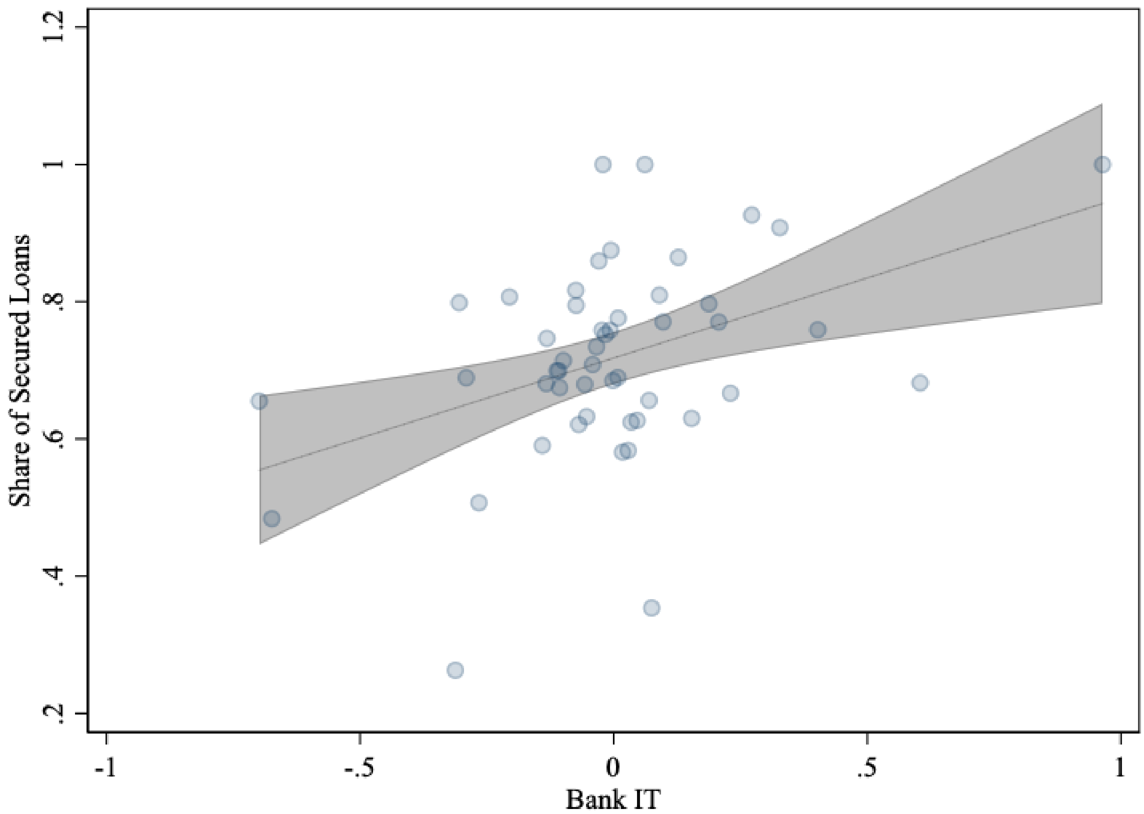
The left hand side variable is defined as the difference between the minority young employment share and non-minority young employment share, where young employment share is the share of employees in young firms in a demographic group relative to total employees in demographic group in a county sector. 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.

Figure A2: Share of Loans Secured



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